Applications of Ultrawideband in Communications and Ranging

DISSERTATION

zur Erlangung des akademischen Grades eines

DOKTOR-INGENIEURS
(DR.-ING.)

der Fakultät für Ingenieurwissenschaften
und Informatik der Universität Ulm

von

THANAWAT THIASIRIPHET
AUS CHIANG MAI

Betreuer: Prof. Dr.-Ing. Jürgen Lindner
Gutachter: Prof. Dr.-Ing. habil. Reiner Thomä
Amtierender Dekan: Prof. Dr. Tina Seufert

Ulm, 16. July 2014
Acknowledgments

This thesis represents my work at the Institute of Information Technology (since October 2011 Institute of Communications Engineering) at Ulm University. This work was done within the project UWB in Medicine, which was financially supported under the priority program Ultrabreitband-Funktechniken fuer Kommunikation, Lokalisierung und Sensorik (UKoLos) of the German Research Foundation (Deutsche Forschungsgemeinschaft, DFG). In this program our institute collaborated with the Institute of Electron Devices and Circuits and the Institute of Microwave Techniques, both from Ulm University. This thesis would not be possible without support from many people and I would like to express my gratitude to all of them.

First, I would like to express my most sincere gratitude and appreciation to Prof. Jürgen Lindner for everything he has done for me during my time in Ulm. He has always been supportive and gave me a lot of help as well as valuable advices. I have learned many things from him and will always value his guidance. I would also like to thank Prof. Hermann Schumacher and Prof. Wolfgang Menzel. I have learnt a great deal from our collaboration in the project UWB in Medicine. Furthermore, I would like to thank Prof. Reiner Thomä from Technische Universität Ilmenau for his time and effort of being the second reviewer for this thesis.

I would like to give special thanks to Dr. Werner Teich for many helpful advises and supports. I would also like to thank him for his effort for helping me with proofreading several parts of this thesis.

My special regards go to colleagues from the UKoLos project. In particular, I am deeply grateful to Bernd Scheilcher, Lin Dayang, Mario Leib and Michael Mirbach for several helpful discussions, for providing me with measurement data and results and also for the all the good time we spent together in our meeting and travel. Addition-
ally, I would like to thank Rahmi Salman from Universität Duisburg for providing me
with measurement data and results from his image algorithm. Many thanks also go
to the DFG for financial support.

I would also like to thank several colleagues at the institute. Especially, Christian
Senger, Zoran Utkovski, Mohammed Mostafa, Eva Peiker, Rui Zhan, Matthias Wetz,
Alexander Linduska, Doris Yacoub, Henning Zoelin and Mohammed Khider for all
their help, support, proof-reading and also for their friendship over the years.

I am indebted to all the students who wrote their thesis under my supervision for
all their contribution to my work.

Last but not least, my sincere gratitudes go to my parent and my wife for all their
unconditional love, motivation and support throughout my life.
# Contents

1 Introduction 1

2 Fundamentals of Ultrawideband Systems 7  
   2.1 Brief History of UWB .......................... 8  
   2.2 UWB Regulations .............................. 8  
   2.3 UWB Transmission Model ....................... 11  
   2.4 Impulse Shapes for UWB Systems ............... 13  
   2.5 Basic UWB Modulation Techniques ............. 16  
      2.5.1 Pulse Amplitude Modulation ............... 16  
      2.5.2 Pulse Position Modulation ............... 18  
      2.5.3 Transmitted Reference .................... 18  
   2.6 UWB Propagation Channels ..................... 19  
      2.6.1 AWGN Channel ............................ 20  
      2.6.2 Multipath Propagation Channel .......... 20  
      2.6.3 Wireless Personal Area Network Channel Models ............ 22  
      2.6.4 Wireless Body Area Network Channel Models ......... 24  
   2.7 Basic Receiver Concepts ....................... 26  
      2.7.1 Correlation Based Receiver ................ 27  
      2.7.2 Energy Detector ........................... 31  
      2.7.3 Autocorrelation Receiver ................. 34  
   2.8 Spread Spectrum Techniques in UWB ........... 35  
      2.8.1 Direct Sequence - UWB .................... 35  
      2.8.2 Time Hopping - UWB ...................... 37
<table>
<thead>
<tr>
<th>Section</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.9</td>
<td>UWB Systems for Ranging Applications</td>
<td>38</td>
</tr>
<tr>
<td>2.9.1</td>
<td>Performance Bounds</td>
<td>40</td>
</tr>
<tr>
<td>2.9.2</td>
<td>Sampling of UWB signals</td>
<td>42</td>
</tr>
<tr>
<td>3</td>
<td>Transmission with Impulse Radio Ultrawideband</td>
<td>45</td>
</tr>
<tr>
<td>3.1</td>
<td>Performance of Basic UWB Receivers</td>
<td>46</td>
</tr>
<tr>
<td>3.2</td>
<td>Comb Filter Based System Concept for UWB Transmissions</td>
<td>51</td>
</tr>
<tr>
<td>3.2.1</td>
<td>Basic Concept of Comb Filter</td>
<td>51</td>
</tr>
<tr>
<td>3.2.2</td>
<td>Comb Filter Receiver Structure</td>
<td>54</td>
</tr>
<tr>
<td>3.2.3</td>
<td>Comparison to Conventional Correlation Detection</td>
<td>62</td>
</tr>
<tr>
<td>3.2.4</td>
<td>Bit Error Rate Performance of Comb Filter Receiver</td>
<td>64</td>
</tr>
<tr>
<td>3.3</td>
<td>Shortened Delay Comb Filter Receiver Structure</td>
<td>68</td>
</tr>
<tr>
<td>3.3.1</td>
<td>Problem Statement</td>
<td>68</td>
</tr>
<tr>
<td>3.3.2</td>
<td>Signal Analysis</td>
<td>70</td>
</tr>
<tr>
<td>3.3.3</td>
<td>Rake-like Comb Filter Based Receiver</td>
<td>78</td>
</tr>
<tr>
<td>3.4</td>
<td>A Novel Detection Method for Code-Reference UWB Transmission</td>
<td>83</td>
</tr>
<tr>
<td>3.4.1</td>
<td>State of The Art</td>
<td>84</td>
</tr>
<tr>
<td>3.4.2</td>
<td>Comb Filter Based Receiver for Code-Reference UWB</td>
<td>85</td>
</tr>
<tr>
<td>3.4.3</td>
<td>Simulation Results</td>
<td>88</td>
</tr>
<tr>
<td>4</td>
<td>Advanced Concepts for UWB Ranging Systems</td>
<td>93</td>
</tr>
<tr>
<td>4.1</td>
<td>Particle Filtering</td>
<td>95</td>
</tr>
<tr>
<td>4.1.1</td>
<td>Recursive Bayesian Filtering Algorithm</td>
<td>96</td>
</tr>
<tr>
<td>4.1.2</td>
<td>Sampling Importance Resampling Particle Filtering</td>
<td>99</td>
</tr>
<tr>
<td>4.1.3</td>
<td>Particle Filtering for UWB Radar</td>
<td>101</td>
</tr>
<tr>
<td>4.1.4</td>
<td>Simulation Results</td>
<td>106</td>
</tr>
<tr>
<td>4.2</td>
<td>Compressed Sensing</td>
<td>110</td>
</tr>
<tr>
<td>4.2.1</td>
<td>Fundamentals</td>
<td>111</td>
</tr>
<tr>
<td>4.2.2</td>
<td>Reconstruction Algorithms</td>
<td>117</td>
</tr>
<tr>
<td>4.2.3</td>
<td>Compressed Sensing for UWB Ranging Systems</td>
<td>122</td>
</tr>
<tr>
<td>4.2.4</td>
<td>Simulation Results from Simulated Channels</td>
<td>125</td>
</tr>
<tr>
<td>4.2.5</td>
<td>Simulation Results from Measurement Data</td>
<td>131</td>
</tr>
<tr>
<td>4.3</td>
<td>Comb Filter Receiver for UWB Ranging Systems</td>
<td>139</td>
</tr>
<tr>
<td>5</td>
<td>Summary and Conclusion</td>
<td>143</td>
</tr>
<tr>
<td>A</td>
<td>Shortened Delay Comb Filter Received Signal</td>
<td>147</td>
</tr>
<tr>
<td>B</td>
<td>List of Abbreviations</td>
<td>152</td>
</tr>
</tbody>
</table>
Contents

C  List of Frequently Used Symbols and Functions  155

Bibliography  159
Chapter 1

Introduction

Ultrawideband (UWB) systems have been gaining a lot of interest in several research fields during the last decade [1–5]. This interest was largely triggered by the introduction of the world’s first commercial regulation on this technology by the Federal Communications Commission (FCC) in 2002 [6].

UWB systems are usually based on short time sub-nanosecond impulses. These type of impulses have potentials to achieve high data rates as well as high accuracy for distance and position estimation (ranging), while promising devices with low complexity and low power consumption. Compactness and longevity are very important focal points in the development of future wireless technologies. Transmission with a short duration impulse signal also means that UWB systems usually operate with a low duty cycle, i.e. long empty period between impulses. The devices can be shut-off
for most of the time, thus the power consumption is low. These attractive properties
make UWB systems a very good choice for many areas of application, e.g. medicine,
military, rescue operation, sport and entertainment [7–15].

The UWB technology is well-suited for short-range transmission. It is often con-
sidered to be used in indoor personal-area and body-area systems. As an example,
several small UWB sensing/communication nodes can be attached to different parts
of a human body to form a body area network. The nodes capture some information,
e.g. body temperature, blood pressure, and then transmit them to a central node via
the UWB communication links. The information is then forwarded for further pro-
cessing by the central node. Another example for the use of UWB technology are
sensors for a contact-free detection of vital signals like breathing rate or heart beat.
For medical applications, this method gives an advantage in cases where conven-
tional wired electrodes cannot be used, e.g. for patients with burnt skin. For accident
prevention, sensors can be placed in a car to monitor the vital signals of the driver. It
is also possible to form a localization and imaging system using several UWB sensors.

Despite of many advantages, many problems with the use of UWB technology are
still needed to be addressed. Due to the large bandwidth, the operation frequency
band of typical UWB systems overlap with many existing wireless systems. Therefore
the power density of UWB systems is limited by spectral masks to prevent interfer-
ence to other systems. The power restriction make UWB systems weak against inter-
ference. It is very likely that the UWB received signal has low signal-to-interference
ratio as well as low signal-to-noise ratio (thermal noise of the receiver) because of
attenuation in the channel. Special techniques have to be applied at the receiver to
cope with these problems. Coping with the noise in the digital signal processing part
is not suitable, because direct analog-to-digital conversion cannot be performed at
reasonable power consumption for signals with several GHz bandwidth like UWB.
Therefore analog signal processing is attractive for UWB systems.

For narrowband communication systems, correlation based techniques are well-
known and widely used. Despite the fact that the correlation based detection can
provide optimal performance, applying these methods to UWB systems is very chal-
lenging. In general, correlation based detection methods require channel estimation
and very precise time synchronization. Detection methods without channel knowl-
edge, which are often referred to as ‘noncoherent’ detection methods, turn out to be
the preferred option for UWB communication systems because they have lower com-
plexity and higher robustness. Methods based on energy detection require little to
no channel knowledge, and they have low complexity, greater robustness to multi-
path propagation as well as high resistance to synchronization errors. The drawbacks
for the energy detection are the performance in the low SNR regime, low multiple access capability, and its weak resistance against narrowband interference. For correlation based detection, these problems can be coped by applying spread spectrum techniques, i.e. several impulses are transmitted for representing one symbol. At the receiver, coherent combination of these impulses are performed in the correlation operation and the performance regarding SNR, multiple access capability and interference is improved. The same solution can not be easily achieved in the energy detection because there is no coherent combination in the process.

In this thesis, we propose novel UWB receiver structures based on a comb filter. The comb filter is a feedback loop with an analog delay element, and it is used to perform a coherent combination to give a SNR improvement and also to suppress interference. The receiver can be used for both communications and ranging because, with proper setting, the output signal of the comb filter is the effective channel impulse response, i.e. UWB impulse convolved with the channel impulse response. For communications, all of the basic detection methods can be directly applied after the comb filter. It can be proved that the solution from the conventional ‘symbol-based’ correlation detection and the ‘chip-based’ correlation detection with comb filter receiver are equivalent under some assumptions. The coherent combination process in the comb filter gives energy detection the benefits that cannot be achieved by applying them directly. In addition to the receiver structures, we also propose several suitable modulation techniques. The results are verified by simulations and compared with conventional approaches.

Using short duration impulse signals, UWB ranging systems can provide high accuracy and very fine resolution. The conventional methods based on analog impulse correlation performs very well in high SNR scenarios. The problem occurs when the SNR is low, because the delay estimation can be largely biased from the ambiguity in the shape of the correlation function, i.e. the estimator tracks the side-lobe of the auto-correlation function instead of the main peak. Moreover, in some applications, super-resolution algorithm might be needed to extract the delays of unresolvable multipath components. We proposed two advanced estimation techniques for UWB ranging systems, i.e. particle filtering and compressed sensing.

Conventional methods based on the tracking of the minimum/maximum correlation value can be seen as a maximum likelihood estimator because it uses only the information from current measurement data. The particle filtering algorithm estimates propagation delays based on a posterior densities, which incorporates the temporal correlation of the change of the estimated parameters (delays). In addition, several multipath components can be modelled and tracked in parallel, which results
in super-resolution. As mentioned before, for UWB impulse signals, analog-to-digital conversion can not be performed directly because it requires high power consumption. Sampling can be view as a scalar product operation between the sampled signal and measurement signals. For conventional sampling method, the measurement signals are time-shifted Dirac delta functions. Compressed sensing is an emerging concept where sampling can be done with different approach and can be performed with sub-Nyquist rate. The underlying assumption is that the signal shall be ‘sparse’ in some domain. Random signals are used as the measurement signals instead of the Dirac delta functions. With this approach, there is always some information about the incoming signal in every sample and the number of samples as well as the sampling rate can be reduced. We propose to use compressed sensing as an alternative method for acquiring UWB signals and as a super-resolution algorithm.

Outline of the Thesis

In Chapter 2, the fundamentals of UWB are discussed. Firstly, a brief history as well as a modern day definition of UWB are introduced. We then look at the regularized spectral masks from different regions and some examples of UWB impulse shapes that conform with the FCC spectral masks. An overview of the UWB transmission model is then discussed. Some basic modulation techniques based on the amplitude and delay of the impulse signals are introduced. Because of the unique characteristics of the UWB signals, different channel models for UWB are discussed. We look at some theoretical channel models for analytical purpose as well as some channel models from IEEE standardizations. In general, UWB signal receiving techniques can be categorized as correlation based detection and methods without channel knowledge (noncoherent methods). Basic UWB receiver structures are introduced, and the basic concept as well as their functionality are addressed. We then introduce the application of spread spectrum techniques, i.e. direct-sequence and time-hopping, in UWB systems. As mentioned above, UWB systems are not only limited to communications but also ranging systems. The basic concept in UWB ranging systems and some performance bounds are discussed. Finally, a practical implementation for the sampling of UWB signals, i.e. equivalent-time sampling, is introduced.

In Chapter 3, we first look at the bit-error rate (BER) performance for the basic receiver structures, i.e. correlation based receivers and energy detection receivers, in several scenarios. After that the basic principle of the comb filter is discussed. The properties of SNR improvement, multiuser capability and interference suppression are addressed in details. The BER performance of the comb filter based receiver for communication systems are compared with the conventional approaches. The main
challenge in the comb filter realization is the analog delay element. The longer the delay, the more difficult is its realization. Shortening of the delay means that the effective channel impulse response is not apparent in the received signal because of the interchip interference. The detailed analysis of the comb filter with shortened delay is presented. It can be shown that the effective channel impulse response can be partially extracted easily with proper setting. This idea forms the basis for an implementation of rake-like comb filter based receiver. This novel receiver structure and its performance is discussed. Finally, we look at a modulation technique called code-reference UWB. The conventional detection method for this type of signal will be introduced and compared with the comb filter based approach.

In Chapter 4, we focus on the UWB ranging systems. Two advanced estimation techniques, i.e. particle filtering and compressed sensing, are discussed. We first introduce the principle of Bayesian filtering. Sampling importance resampling (SIR) particle filtering, which is a sub-optimal Bayesian filter, is considered for this thesis. The basic principle and its application in UWB ranging systems are addressed. The performance of the particle filtering is verified by simulation using measurement data from a set up based on a wireless vital-sign detection. We then discuss the principle of compressed sensing and its application in UWB ranging systems. Finally, we briefly discuss about the application of the comb filter based receiver in UWB ranging systems. In general, all of the ranging algorithms can be used directly after the comb filter.

An overview of this thesis is given in Fig.1.1. Parts of this thesis are published in [16–21]
Figure 1.1: Overview of this thesis.
Chapter 2

Fundamentals of Ultrawideband Systems

In this chapter, we introduce the fundamentals of UWB systems that are used as bases throughout this work. We first look briefly at the history of impulse transmission and then discuss the definition and types of UWB signals. Basic modulation techniques and basic receiver structures are introduced. They are used for performance comparison with our proposed methods in Chapter 3. We also look at different kind of channel models that are typically considered for UWB transmission. Furthermore, we discuss basic concepts for applying UWB signals in ranging applications. These methods are used as benchmark for evaluating the advanced ranging techniques in Chapter 4.
2.1 Brief History of UWB

Despite often being considered as a new technology, transmissions of short impulse signals exist as the first form of wireless transmissions [4, 22]. In 1887, Heinrich Hertz transmitted impulse signals in one of his wireless transmission experiments over a distance of several meters. Guglielmo Marconi later performed a radio transmission across the Atlantic (3500 km) using a similar principle in 1901 [22]. These impulse signals hold many similar characters to modern day UWB impulse signals but the equipments, especially the antennas, are very different. Transmission of short impulses was the simplest method at the time and was the dominant method of wave generations for several years. However, to accommodate the demand for multiuser, multiplexing and bandwidth efficiency, the transmission with narrowband carrier based systems became the main focus. The research on impulse technology was scarce until the early 1960’s. The development of time domain devices, i.e. the sample and hold receivers by the Tektronix Inc. and the sampling oscilloscope by the Hewlett Packard Company, played a major role in giving researchers more understanding about the characteristics of the impulses signals [23]. The transmission of impulse signals was known as a baseband, carrier-free or impulse technology until the term “Ultrawideband” was given by the U.S. department of defense in 1989. The UWB technology was studied for applications such as radar, sensing and military communication and can be used only under special license until the commercial regularization by the FCC in 2002.

2.2 UWB Regulations

UWB systems are usually based on short time sub-nanosecond impulses and occupy bandwidth much larger than the minimum required for delivering particular information. The bandwidth of UWB signals can be in the range of several GHz, which is much larger than typical narrowband signals (kHz) and spread spectrum signals (MHz). Fig. 2.1 illustrates the differences between the spectrum of the narrowband signals, the spread spectrum signals and the UWB signals. The operation bandwidth of UWB signals overlap with many existing systems, and therefore emission power limitation is necessary.

The UWB technology for commercial purposes was at first considered as a transmission of signals with a fractional bandwidth $BW_{frac}$ higher than 0.25 [24]. The fractional bandwidth is the ratio of the 10 dB bandwidth $BW_{10dB}$ to the center frequency $f_c$. It can be calculated as
2.2 UWB Regulations

Narrowband Communications (kHz)

Spread-Spectrum Communications (MHz)

UWB Communications (GHz)

Figure 2.1: Comparison of the general spectrum of different wireless systems.

\[
BW_{frac} = \frac{BW_{10dB}}{f_c} = 2 \frac{f_H - f_L}{(f_H + f_L)},
\]

(2.1)

where \( f_H \) and \( f_L \) are the 10 dB cutoff frequencies. In 2002, FCC refined the definition. The bandwidth of UWB signals was given as the fractional bandwidth \( BW_{frac} \) of larger than 0.2 or an absolute bandwidth \( BW_{abs} \) of at least 500 MHz [6]. Furthermore, spectral masks limiting the frequency region and emission power for both indoor and outdoor were given. The frequency band allocated for UWB is 3.1-10.6 GHz and the maximum mean equivalent isotropically radiated power (EIRP) in this frequency region is under FCC Part 15 rules, i.e. -41.3 dBm/MHz (measured with 1 MHz resolution bandwidth spectrum analyzer). The FCC spectral masks for indoor and outdoor UWB transmissions are shown in Fig. 2.2(a).

The allocated frequency band directly coincides with the IEEE 802.11a wireless local area networks (WLAN), which operate in the 5 GHz region with 20 MHz bandwidth. In general, the UWB systems suffer more disturbances from the WLAN systems than the opposite direction because of the big difference in the maximum limit of EIRP. The frequency region 0.96-1.61 GHz for GPS transmissions is well protected and the maximum EIRP for UWB systems in this band is limited to -75 dBm/MHz. Some studies regarding interference between UWB systems and several narrowband systems such as WLAN, GSM and GPS can be found in [25, 26].

In addition to the mean EIRP limit, the power limit in terms of peak power was also given. The impulse transmissions typically operate with very low duty cycle, and the peak emission level increases proportion to the time between impulses for a fixed average EIRP. At one point the amplitude of the UWB impulse signals shall not be increased even if the duty cycle is reduced further. The peak emission limit is given as 0 dBm EIRP density (measured in a 50 MHz bandwidth). More details on the relationship between Impulse repetition rate and the peak EIRP limit can be found in [27].
After the announcement of the FCC spectral masks, other regions in the world also announced their own masks for UWB transmissions. Most notable spectral masks are from Europe, Japan and South Korea [4,28,29]. The spectral masks from these regions are much stricter than the FCC spectral masks. The European UWB spectral mask and Japanese UWB spectral mask for UWB transmitters without detect-and-avoid (DAA) algorithm are shown in Fig. 2.2(b).

Only the bandwidth and the emission power were given as the definitions for UWB transmissions. As a consequence, there are two types of modern UWB signals. The first one follows the classical approach, i.e. using short impulse signals for transmission (known as Impulse Radio UWB). The second type is a wide-band version of Orthogonal Frequency Division Multiplexing (OFDM).

**Impulse Radio Ultrawideband**

Short-duration impulse signals are used for the transmissions of the impulse radio ultrawideband (IR-UWB) systems. The main difference between the impulse signals for modern day UWB systems and the conventional impulse technology is that both carrier-less baseband signals and carrier-based bandpass signals are considered as UWB signals. Due to the power limitation, the IR-UWB transmissions are well-suited for short range indoor communications, e.g. wireless personal area networks (WPAN).
and wireless body area networks (WBAN). The short duration signals also give advantages for radar, imaging and localization applications. IR-UWB is considered as the physical layer for some IEEE standardizations such as the IEEE 802.15.4a (WPAN low data rate) and also being included as part of IEEE 802.15.6 (WBAN healthcare and medical services). It was one of the candidates for IEEE 802.15.3a (WPAN high data rate). Unfortunately, the task group 3a was disbanded because of the disagreement between two proposals. IR-UWB will be taken as a basis in this thesis and the term UWB shall be depicted as the impulse radio version of UWB.

**Multiband-OFDM**

This type of UWB is based on OFDM modulation with quadrature phase shift keying and dual carrier modulation. The basic waveforms for this type of UWB are not impulsive but they are classified as UWB signals since the bandwidth is larger than 500 MHz. The frequency region from 3.1-10.6 GHz is divided to 14 groups with each group occupying the bandwidth of 528 MHz. Multiple access is performed by frequency hopping (FH) within a subgroup consisting of three frequency bands. The WiMedia alliance was the main developer for this technology, and it was the competing candidate for the IEEE 802.15.3a standard. The flexibility to avoid strong narrowband interference and the potential to transmit more bits per symbol compared to IR-UWB make it a good candidate for high data rate WPAN communications. After cancellation of the task group 3a, this technology made its way into commercial products but they were not so successful. As a result of this, the WiMedia alliance was disbanded in 2008. The technological specifications were then passed on to other industry groups. This type of UWB is not considered in this thesis, and more details about the multiband orthogonal frequency division multiplexing (MB-OFDM) systems with some comparison studies to IR-UWB can be found in [30–33].

**2.3 UWB Transmission Model**

A brief overview of the UWB transmission is discussed in this section. We consider a digital transmission model and assume that the propagation channel is linear time-invariant (LTI). Fig. 2.3 shows a coarse model of the basic digital transmission. The data (bits) sequence $x(k) \in \{0, 1\}$ is sent to the receiver by the transmitter via a propagation channel. The transmitted signal and the received signal are referred to as $s(t)$ and $g(t)$, respectively. The propagation channel is described by the channel impulse response $h(t)$ with additive noise $n(t)$. The received data sequence is given as $\hat{x}(k)$.
In this section, we only look at the interconnection between the main components, i.e. the transmitter, the propagation channel and the receiver, and their basic functionality. Each of them will be explained in more detail in the following sections.

At the transmitter, the data sequence $x(k)$ is mapped to a transmit alphabet $A_e$, which is a set of basic waveform. The size of the transmit alphabet $A_e$ determine the number of bit per transmit symbol $N_b$. Given that $N_A$ is the size of the transmit alphabet $A_e$, we have $A_e = \{e_0(t), e_1(t), ..., e_{N_A-1}(t)\}$ and $N_b = \log_2(N_A)$. The transmitter chooses one of the basic waveforms according to the incoming data sequence and sends it as a transmitted signal $s(t) \in A_e$.

UWB systems are usually operated with low-duty cycle, i.e. the duration of the UWB impulse is much smaller compared to the symbol period $T_s$. The basic waveforms for an UWB system usually consist of the UWB impulse $p(t)$ and a long pause period. The number of impulses per basic waveform and the duration between impulses can be varied depending on the modulation technique. Different type of modulation techniques for UWB transmission will be discussed in Sec. 2.5 and Sec. 2.8.

We consider the propagation channels to be linear time-invariant (LTI) systems and usually assume that they are unchanged between impulses. The received signal $g(t)$ can be expressed as

$$g(t) = s(t) \ast h(t) + n(t),$$

(2.2)

where $\ast$ represents the convolution operation and $n(t)$ is additive white Gaussian noise (AWGN). Several type of channel models with different channel impulse response $h(t)$ are discussed in more detail in Sec. 2.6.

As mentioned above, the transmitted signal $s(t)$ is a series of different basic waveforms. It can also be viewed as a series of modulated UWB impulses $p(t)$ with some periods between them. The result from the convolution between $p(t)$ and $h(t)$ is referred to as the effective channel impulse response $h_p(t) = p(t) \ast h(t)$. Given that

![Block diagram of a digital transmission model.](image)

Figure 2.3: Block diagram of a digital transmission model.
the minimum duration between impulses is $T_p$ and the duration of the channel impulse response is $T_m$, no overlapping of the effective channel impulse responses $h_p(t)$ occurs at the receiver, if the basic waveforms are chosen such that $T_p > T_m$. In this case, the received signal for the modulated UWB impulses $p(t)$ usually consist of a corresponding number of effective channel impulse responses $h_p(t)$ as illustrated in Fig. 2.4. A Dirac delta impulse is used as the UWB impulse shape $p(t)$ for illustration and the AWGN is neglected for clarity of presentation. Based on the received signal $g(t)$, a decision is made at the receiver every symbol period to determine which basic waveform from the set of alphabet $A_e$ has been transmitted. The result is the received data symbol $\hat{x}(k)$. There are many detection methods for UWB transmission, and they are discussed in more detail in Sec. 2.7.

Figure 2.4: Illustration of the UWB signal before and after the channel. $T_p$ is the minimum duration between impulses. The AWGN has been neglected for clarity of presentation.

### 2.4 Impulse Shapes for UWB Systems

The impulse shape (waveform) for UWB transmissions can be chosen freely as long as it follows the regulations. Different shapes give advantages in different ways [34]. The capacity of UWB communication systems can be varied with different impulse shapes [35], and the same applies to the ranging accuracy of UWB radar systems [36]. The key idea is to find the compromise between the spectral mask utilization, ranging capability and implementation complexity. The most common impulse shapes are the derivations of the Gaussian impulse waveform: $p_G^{(0)}(t) = \frac{1}{\sqrt{2\pi\sigma^2}} \cdot \exp\left(-\frac{t^2}{2\sigma^2}\right)$. 

\[
\hat{x}(k) = \begin{cases} 1 & \text{if } x(k) = 1 \\ 0 & \text{otherwise} \end{cases}
\]
The spectral shape of these signals can be controlled by the standard derivation $\sigma$ and the derivative order. Examples of different parameters of impulses based on Gaussian waveforms are shown in [34,35,37]. Notable examples are the 5-th and 7-th derivative of Gaussian waveform because their spectra can fit very well to the FCC spectral masks and easy to implement. The 5-th and 7-th derivative Gaussian impulse can be written as

$$p_G^{(5)}(t) = \frac{A_5}{\sqrt{2\pi}} \cdot \left( -\frac{t^5}{\sigma^{11}} + \frac{10 \cdot t^3}{\sigma^9} - \frac{15 \cdot t}{\sigma^7} \right) \cdot \exp\left( -\frac{t^2}{2\sigma^2} \right), \quad (2.3)$$

$$p_G^{(7)}(t) = \frac{A_7}{\sqrt{2\pi}} \cdot \left( -\frac{t^7}{\sigma^{15}} + \frac{21 \cdot t^5}{\sigma^{13}} - \frac{105 \cdot t^3}{\sigma^{11}} + \frac{105 \cdot t}{\sigma^9} \right) \cdot \exp\left( \frac{t^2}{2\sigma^2} \right), \quad (2.4)$$

where $A_5$ and $A_7$ are normalized constants. The time domain and frequency domain of the 5-th derivative of a Gaussian impulse signal with $\sigma = 51$ ps and FCC indoor spectral mask are shown in Fig. 2.5, and the 7-th derivative Gaussian impulse with $\sigma = 62$ ps together with the FCC outdoor spectral are shown in Fig. 2.6. It can be seen that the spectrum of both Gaussian impulses fits very well to the FCC indoor spectral mask. An example of low complexity impulse generation devices for the 5th, 7th derivative Gaussian impulse signals was presented in [27, 38]. Using similar principles, a tunable impulse generator which can generate impulse signals fit to European, South Korean as well as Japanese spectral masks was introduced in [39].

Figure 2.5: 5th derivative Gaussian impulse with $\sigma = 51$ ps in time domain and frequency domain (with FCC indoor spectral mask).
2.4 Impulse Shapes for UWB Systems

Figure 2.6: 7th derivative Gaussian impulse with $\sigma = 62$ ps in time domain and frequency domain (with FCC outdoor spectral mask).

Impulse signals for modern UWB systems are not limited to carrier-less baseband signal. UWB signals can also be upconverted baseband signals similar to the narrowband transmissions. The baseband impulse shapes such as Gaussian waveform and raised-cosine (RC) waveform are often considered. The original UWB systems are known for their low complexity implementation because no mixer is required. For this type of impulses, there is a need to have a mixer at the transmitter but, unlike narrowband systems, it can be shut-off between the transmissions of impulses. The mixer is turned-on only for short duration during the transmission of each impulse, and therefore the transmitters can still being classified as low complexity devices. For carrier based impulse, we consider here the RC waveform with roll-off factor $\alpha = 1$ as the envelope of the carrier sinusoidal signal. The equation for this impulse shape is then given as

$$p_{RC}(t) = A_{RC} \cdot \left[ \text{sinc} \left( \frac{t}{T} \right) \left( \frac{\cos \left( \frac{\pi t}{T} \right)}{1 - \frac{4t^2}{T^2}} \right) \right] \cdot \cos(2\pi f_0 t), \quad (2.5)$$

where $A_{RC}$ is a normalized constant, $T$ is the width of the waveform that determines the bandwidth and $f_0$ is the carrier frequency. An example of a RC impulse with $T = 0.5$ ns and $f_0 = 4.5$ GHz in time and frequency domain is shown in Fig. 2.7. The parameters are chosen according to the frequency region (2-6 GHz) used in the WBAN channel model developed for IEEE 802.15.4a [40], since the channel model is only valid for this band.
2 Fundamentals of Ultrawideband Systems

Figure 2.7: Raised cosine UWB impulse with $T = 0.5$ ns and $f_o = 4.5$ GHz in time domain and frequency domain.

2.5 Basic UWB Modulation Techniques

UWB systems are normally operated with very low duty cycle. This means the duration of the UWB impulse signals are much smaller than the time between impulses. Unlike conventional narrowband communication system, the UWB impulses together with the gap between impulses are termed as basic waveform. There are numerous modulation techniques for UWB, since most of the modulation techniques found in typical communication systems can be applied to the UWB systems easily. The basic modulation techniques for UWB signals use the amplitude, the delay time (position) or the shape of the impulses (waveforms) to carry the message information (bits) [41]. To prevent intersymbol interference (ISI), an appropriate symbol period $T_s$ for each modulation technique is chosen differently according to the multipath delay spread of the channels. In the following section, the three most common basic modulation methods for UWB are introduced, i.e. pulse amplitude modulation (PAM), pulse position modulation (PPM) and transmitted reference (TR).

2.5.1 Pulse Amplitude Modulation

The classical PAM can be directly applied for the UWB transmissions. The message information is encoded in the amplitude of the impulses. The PAM UWB impulse transmission signal can be written as
2.5 Basic UWB Modulation Techniques

\[ s(t) = \sum_{k=-\infty}^{\infty} b_k p(t - kT_s), \]  

(2.6)

where \( s(t) \) is the transmit signal, and \( b_k \) is the \( k \)-th transmit symbol. The number of amplitude levels depends on the number of transmit bits per symbol. We consider binary transmission, i.e. \( A_e = \{e_0(t), e_1(t)\} \), and therefore one bit is transmitted per symbol. The two widely used modulation techniques are binary pulse amplitude modulation (BPAM) and on-off keying (OOK). The transmit symbols are \( b_k \in \{-1, 1\} \) for BPAM and \( b_k \in \{0, 1\} \) for OOK. That means the data bit ‘1’ is represented by one impulse for both BPAM and OOK, and the BPAM transmit impulse has a negative amplitude while OOK transmit nothing for data bit ‘0’. In other words, the basic waveforms for BPAM are \( e_0(t) = -p(t) \) and \( e_1(t) = p(t) \), while the basic waveforms for OOK are \( e_0(t) = 0 \) and \( e_1(t) = p(t) \). In general, this specific type of BPAM is often referred as binary phase shift keying (BPSK). An example of transmitted signals for BPAM and OOK are shown in Fig. 2.8. For illustration, dirac delta impulse is used as the impulse shape.

![Figure 2.8: UWB basic waveforms for data bit ‘0’ and ‘1’ of (a) BPAM (b) OOK.](image)

The amplitude-based modulation techniques are often considered in practice since the signals are very simple to generate. The received PAM signal is a train of weighted effective channel impulse responses. The symbol period \( T_s \) is in general chosen to be larger than the multipath delay spread \( T_m \) to prevent ISI, i.e. overlapping of the effective channel impulse responses. OOK is very common for UWB communication systems because it is possible to use detection method without channel knowledge such as energy detection.
2.5.2 Pulse Position Modulation

As a consequence of operating with very low duty cycle, the information can be encoded in the position (delay) of the impulses. The transmit signal for PPM can be written as

\[ s(t) = \sum_{k=-\infty}^{\infty} p(t - b_k T_{ppm} - kT_s), \]  

(2.7)

where \( b_k \) is the transmit symbol and \( T_{ppm} \) is the time shift between different transmit basic waveforms. The time shift is usually selected such that the impulse waveforms are not overlapping, resulting in an orthogonal transmission. For binary pulse position modulation (BPPM) transmission, \( b_k \in \{0, 1\} \) and \( T_{ppm} = T_s/2 \) are often considered. This means that the basic waveforms for BPPM are \( e_0(t) = p(t) \) and \( e_1(t) = p(t - T_s/2) \). An example of a transmitted signal for PPM is shown in Fig. 2.9.

![Figure 2.9: UWB basic waveforms for data bit '0' and '1' of BPPM.](image)

For this setting, \( T_s \) has to be chosen to be at least twice of \( T_m \) in order to preserve the orthogonality at the receiving side and prevent ISI. PPM is also very popular in practice because it can be detected with energy detection like OOK.

2.5.3 Transmitted Reference

One of the main challenges for the detection of UWB signals is the channel estimation at the receivers. The main focus of UWB system design is usually on the low complexity implementation but the channel estimation required for the correlation based receivers are always not simple. Therefore transmitted Reference is introduced to avoid the explicit channel estimation process [42]. The basic waveform of TR consists of two impulses. The first impulse is used as a pilot signal for channel estimation, while
2.6 UWB Propagation Channels

the second one is used for encoding the information bits. BPAM with $b_k \in \{-1, 1\}$ is usually considered for the modulation of the information impulses. The transmit signal of basic TR modulation with BPAM is given as

$$s(t) = \sum_{k=-\infty}^{\infty} \left( p(t - kT_s) + b_k p(t - kT_s - T_{TR}) \right),$$

(2.8)

where $T_{TR}$ is the delay between the two impulses which has to be larger than the multipath delay spread $T_m$ to avoid overlap. This means that the basic waveforms for TR are $e_0(t) = p(t) - p(t - T_{TR})$ and $e_1(t) = p(t) + p(t - T_{TR})$. An example of TR transmit signals are shown in Fig. 2.10.

![Figure 2.10: UWB basic waveforms for data bit '0' and '1' of TR modulation.](image)

The detection of TR modulated signals has to be performed with a specific type of receiver, i.e. the autocorrelation receiver. A properly delayed version of the pilot impulse together with the channel impulse response are used as the reference for the correlation process to detect the transmit information. For TR modulation, half of the energy is spent every symbol for the channel estimation. For improvement in this respect, differential phase shift keying (DPSK) can be considered. The concept for the detection of the DPSK signals is similar to TR signal detection. Instead of transmitting pilot impulses, the impulses from the previous symbols can be used for as the reference. Performance comparison between TR and DPSK in different scenarios can be found in [43].

### 2.6 UWB Propagation Channels

The characteristics of the UWB propagation channels can be very different to that of narrowband systems because of the large signal bandwidth. The assumptions that are
used in conventional channel modeling for standard wireless communication systems cannot be applied directly to the UWB cases [44, 45]. For example, the multipath propagation in indoor environment for UWB transmissions is much more resolvable, and therefore Rayleigh fading cannot be assumed like in typical narrowband systems. Numerous measurements for UWB systems were performed, and channel models for different environments were proposed during the last decade. In this section, we review some notable channel models that are widely considered in the literature.

### 2.6.1 AWGN Channel

The AWGN channel is the most basic channel for any system. It is a single path channel with no scaling factor, and therefore the channel impulse response \( h(t) \) in (2.2) is the Dirac function \( \delta(t) \). The receive signal \( g(t) \) for an AWGN channel can be written as

\[
g(t) = s(t) + n(t).
\]

(2.9)

Thermal noise in the receiver is typically the primary source of the additive noise \( n(t) \). In addition, the attenuation (path-loss) is interpreted in the signal-to noise ratio (SNR) of the channel. The channel is modelled as infinite bandwidth and does not include the smearing effect from antennas or other components. The AWGN channel is not expected in any practical environment but it is usually considered as a benchmark for different transmit and receive techniques.

### 2.6.2 Multipath Propagation Channel

The most common propagation channel assumed for UWB is a multipath propagation channel. The multipath could come from unintentional reflections of nearby scattering objects or intentional backscattered signals from complex-shaped objects in ranging applications. As shown in Sec. 2.4, the duration of the UWB impulses is about the inverse of the bandwidth and typically less than nanosecond. This means that the multipath can be resolved down to path delay difference in the order of a nanosecond or less. For the narrowband signals, the same amount of path delay difference in the channel would not be resolvable, and thus resulting in fading. This behaviour is illustrated in Fig. 2.11. The example channel is a simple 2-path channel consisting of a direct path and a second path caused by reflection. A narrowband signal (sinusoidal) and an UWB impulse signal are transmitted through the same channel. The results are significantly different as the narrowband signal has much longer duration
than the delay difference between the two paths. The reflected path is not resolvable resulting in the receive signal being a phase-shifted and amplitude changed replica of the original signal. On the other hand, UWB impulses are so short that individual reflections can be separated. The amplitude of the reflected path can be different depending on the propagation time and also on the properties of the reflecting objects.

![Diagram of 2-path propagation channel and the effect on the output signals for both narrowband systems and UWB systems.](image)

Figure 2.11: An example of a 2-path propagation channel and the effect on the output signals for both narrowband systems and UWB systems.

A simplified model of the reality is often considered for the modeling of multipath propagation channels. The receive signal can be viewed as a weighted sum of time-shifted versions of the transmitted UWB impulses. The multipath channel impulse response \( h(t) \) can be represented using a tapped delay line model as

\[
    h(t) = \sum_{m=0}^{M-1} \alpha_m \delta(t - \tau_m),
\]

(2.10)

where \( \alpha_m \) and \( \tau_m \) are the amplitude and delay of the \( m \)-th path. The maximum number of paths is given by \( M \). The tapped delay line model is commonly used to model wireless communication systems and also forms the basis for many UWB channel models. Similar to the AWGN channel, each path in this model is considered to have infinite bandwidth and the frequency dependency from components as well as distortion due to reflections are not included. In a more advanced model, these effects can be taken into account by linear filtering.
2.6.3 Wireless Personal Area Network Channel Models

Since the announcement of the FCC regulations, there have been a lot of interests for using UWB systems for many fields of applications, especially for short-range wireless communication systems. The potential of providing high data rate and precise delay time estimation (distance) with low complexity devices made UWB systems very popular choice for several standards. It is considered as the physical layer for the IEEE 802.15.4a (WPAN low data rate), and two variants of UWB signal models were the candidates for the IEEE 802.15.3a (WPAN high data rate) before the disband of the task group 3a. Channel models for different scenarios were developed based on several working groups and measurements [46, 47]. The UWB channel models for IEEE 802.15.3a [46] and IEEE 802.15.4a were [47] commonly used in literature. Studies show that clustering phenomena are observed in the UWB indoor propagation channels, i.e. the multipath components tend to arrive in groups (clusters) rather than at random. The main reason is that many resolvable rays diffracting from one object arrive at the receiver as a group. The amplitude of the multipath components decay exponentially according to their propagation time and they can be categorized into two types: inter- and intra-cluster decay. Inter-cluster decay is the decay rate between clusters, while intra-cluster decay (ray decay) is the decay rate of the paths within each cluster. To model the amplitude decays and clustering behaviour, both channel models rely on a modification of the Saleh-Valenzuela (SV) model [48]. The basic SV model describes the multipath propagation channel by dividing it into many groups (clusters) with exponential decay. The channel impulse response according to the basic SV model can be written as

\[ h(t) = \sum_{l=0}^{L} \sum_{m=0}^{M_l} \alpha_{m,l} \delta(t - T_l - \tau_{m,l}), \] (2.11)

where \( T_l \) represents the arrival time of the \( l \)-th cluster. \( \alpha_{m,l} \) and \( \tau_{m,l} \) represent the amplitude and the time delay of the \( m \)-th path in the \( l \)-th cluster. The number of resolvable paths in the \( l \)-th cluster is given as \( M_l \). \( T_l \) and \( \tau_{m,l} \) are modeled as independent Poisson processes with cluster arrival rate \( \Lambda \) and ray arrival rate \( \lambda \) as control parameters. The clusters exponential decay is defined by the cluster decay factor \( \Gamma \), while the rays in every clusters follow the ray decay factor \( \mu \). Fig. 2.12 illustrates the basic principles of the SV channel model [48].

For the UWB channel models, the arrival rates for both clusters and rays are modeled as mixture of Poisson processes instead of a single Poisson process in the classic SV model. Each ‘path’ in the UWB channel model is a combination of many individually unresolvable paths, which are grouped together in resolvable bins, hence the
amplitude factor $a_{m,l}$ for each path is described by the fading statistics. The number of unresolvable paths in each resolvable bin is much less than in a typical narrowband system, and therefore the fading statistics is better, i.e. no deep fade (Rayleigh fading). It was concluded that the log-normal distribution fit best with the measurements for IEEE 802.15.3a [46]. On the other hand, the Nakagami-m distributions was chosen for the IEEE 802.15.4a [47]. The UWB indoor propagation channels are heavily dependent on the distance and surrounding environment, therefore a generalization of channel models is always a challenge. One solution, which was adopted by IEEE 802.15.3a and IEEE 802.15.4a channel models, is dividing them into sub-channel modes. The channel models for IEEE 802.15.3a and IEEE 802.15.4a use flexible parameters, i.e. $\Lambda$, $\lambda$, $\Gamma$ and $\mu$, as basic parameters to fit the channel realizations to different scenarios. The channel models of IEEE 802.15.3a are divided into four different categories, as summarized in Table 2.1. Specific parameters and more details for each modes of the IEEE 802.15.3a channel models can be found in [46].

<table>
<thead>
<tr>
<th>Mode</th>
<th>Distance</th>
<th>Channel</th>
</tr>
</thead>
<tbody>
<tr>
<td>CM-1</td>
<td>0-4 m</td>
<td>Line-of-sight (LOS)</td>
</tr>
<tr>
<td>CM-2</td>
<td>0-4 m</td>
<td>Non-LOS (NLOS)</td>
</tr>
<tr>
<td>CM-3</td>
<td>4-10 m</td>
<td>NLOS</td>
</tr>
<tr>
<td>CM-4</td>
<td>-</td>
<td>Severe NLOS</td>
</tr>
</tbody>
</table>

Table 2.1: Different channel modes for IEEE 802.15.3a WPAN channel model.

The IEEE 802.15.4a channel models focus on low data rate communication systems and they consider larger area. Unlike the IEEE 802.15.3a models, the channel realizations are given in the complex baseband equivalent. The channel models are catego-
rized based on the environment, and the operational frequency regions are not the same for all the scenarios. Different channel modes for IEEE 802.15.4a are listed in Table 2.2. Specific parameters and more details of the IEEE 802.15.4a channel models are summarized in [47].

<table>
<thead>
<tr>
<th>Mode</th>
<th>Distance</th>
<th>Frequency band</th>
<th>Channel</th>
</tr>
</thead>
<tbody>
<tr>
<td>Residential</td>
<td>7-20 m</td>
<td>2-10 GHz</td>
<td>LOS and NLOS</td>
</tr>
<tr>
<td>Indoor office</td>
<td>3-28 m</td>
<td>2-8 GHz</td>
<td>LOS and NLOS</td>
</tr>
<tr>
<td>Outdoor</td>
<td>5-17 m</td>
<td>3-6 GHz</td>
<td>LOS and NLOS</td>
</tr>
<tr>
<td>Open outdoor</td>
<td>-</td>
<td>-</td>
<td>LOS only</td>
</tr>
<tr>
<td>Industrial</td>
<td>2-8 m</td>
<td>-</td>
<td>LOS and NLOS</td>
</tr>
</tbody>
</table>

Table 2.2: Different channel modes for IEEE 802.15.4a WPAN channel model.

The clustering approach is one of many approaches for the modeling of the UWB indoor propagation channels. In addition to these two channel models, there are various other measurements and channel models in literatures [49–52]. A comparison study between different approaches in channel modeling can be found in [53].

2.6.4 Wireless Body Area Network Channel Models

UWB systems are very good candidates for WBAN, since they promise small and compact systems. Devices for WBAN are typically located in very close proximity or even inside the human body. Therefore low complexity and low power consumption is very important. The main focus of WBAN is on medical applications, and these devices are usually connected to sensors that can monitor vital signs such as ECG, temperature, and mobility [54].

The human body is a complex structure and the propagation channel can be drastically different with slight position changes of UWB devices. The human tissue also has different electrical properties which affect the propagation of the electromagnetic wave. The channels can be very dynamic depending on the posture and movement of the human body in different scenarios. These properties make the WBAN channels very different from other environments such as indoor propagation channels. Many UWB measurements performed in close proximity to the human body have been carried out in order to understand the characteristics of the radio propagation channel near a human body at UWB frequencies [55–63]. The early notable channel model for WBAN is the contribution for IEEE 802.15.4a standardization by Fort et al. [47, 55].

finite difference time domain (FDTD) simulations were used for the
analysis of the electromagnetic wave with 2 GHz bandwidth in the 2-6 GHz range. The transmitters/receivers were placed on several positions on the body surface for measurements. The UWB signals either travel along the human body or are reflected in the environment (parts of body, floor and walls). They can not penetrate through the body because of extreme high attenuation. According to the measurements, the propagation channels consist of two groups of multipath. The first one came from the signal diffracting around the body and the second one that arrived much later was the result from the reflection of the ground. Illustration of the measurement set up and an example of a channel impulse response are shown in Fig. 2.13.

The delay difference between two paths is deterministic, since the distance to the ground is known, and therefore can be calculated from the position of the transmitter on the body surface. The channel parameters in this channel model depend on the position of the receiver on the body. Three scenarios for the receiver position are considered in this channel model:

Similar to the WPAN channel models, the ‘Paths’ are bins of many unresolvable multipath components. The bin size is generally chosen to be the resolution of the measurements, which is 0.5 ns in this case. The number of rays within the bin is not

<table>
<thead>
<tr>
<th>Mode</th>
<th>Distance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Front</td>
<td>0.04-0.17 m</td>
</tr>
<tr>
<td>Side</td>
<td>0.17-0.38 m</td>
</tr>
<tr>
<td>Back</td>
<td>0.38-0.64 m</td>
</tr>
</tbody>
</table>

Table 2.3: Different channel modes for IEEE 802.15.4a WBAN channel model.
so large and the amplitude statistics of the bins are modeled by correlated log-normal distributions. The amplitude of the ground reflection depends on the floor materials (metal, concrete, etc.), which are randomly chosen with equal probability. It is not possible to generalize channel models for all WBAN systems, since the propagation characteristics can be drastically different by slight change of transmitter/receiver position on the body. [56, 57, 59] provide measurement results from similar on-body set up with transmitters and receivers located around the body, e.g. chest, waist and hand. The UWB propagation channel around the human head (ear-to-ear) is considered in [58]. The WBAN channel models for IEEE 802.15.4a did not consider the body movement, which could change the behaviour of the channel. These effects were studied in [57, 61]. A good survey on several WBAN channel models is given in [64].

Recently, the channel model subgroup of the IEEE 802.15.6 standard released several channel models that cover many scenarios in a WBAN hospital environment [65, 66]. Two scenarios are covered for UWB transmissions: body surface to body surface (CM3) and body surface to external (CM4). Another recent notable WBAN channel model was developed by the Centre of Wireless Communications (CWC), University of Oulu, Finland [62]. Unlike the channel models for the IEEE 802.15.6, where measurements took place in simulated hospital rooms, the CWC’s channel model are based on measurements in a real hospital [62]. The measurements for both models cover two body positions, i.e. standing and lying down. Comparison between the channel realizations from these two channel models show that the channel impulse response can be very different, although the objective of these two groups was to provide channel model for hospital scenario [67]. The channel realizations from the IEEE 802.15.6 channel model have rather wide multipath delay spread. It was commented by [63, 67] that this channel model is a bit pessimistic regarding this aspect.

2.7 Basic Receiver Concepts

The emphasis for designing UWB receivers is usually on the analog signal processing, because analog to digital conversion (ADC) for UWB signals requires high power consumption and is impractical. The Nyquist-Shannon sampling theorem states that the sampling frequency has to be at least twice of the signal’s bandwidth in order to perfectly recover the signal. This minimum sampling frequency is known as the Nyquist sampling rate. With a bandwidth of several GHz, sampling is impossible for low complexity UWB systems. Similar receiver structures as used in narrowband systems can be adopted but some modifications according to the UWB signal characteristics are required. For UWB communications, the detection of transmit symbols can be done
2.7 Basic Receiver Concepts

with correlation based methods or methods without channel knowledge. Typically, with perfect synchronization, correlation based detections give better performance. In practice, implementing the correlation based detection can be a very challenging task, therefore methods without channel knowledge such as energy detection and autocorrelation detection are very attractive choices for UWB systems.

2.7.1 Correlation Based Receiver

Correlation based detection of the received signal using the transmitted impulse as the template waveform is known to be the optimum method with respect to the bit error rate (BER) for the AWGN channel. In case of multipath propagation channels, the transmit impulse and the channel impulse response together (convolved) must be used as the template waveform for the correlation detection, and in general more complex signal processing is required. Channel estimation and accurate synchronization are needed for such receivers. Correlation based receivers play a major role in the UWB ranging applications, i.e. radar, localization and imaging. In this section, we discuss about correlation based receivers for both, the optimal approach and practical implementations. For received signals with additive noise, channel matched filter receiver maximizes the SNR of the output signal and is normally used for analytic purposes. It is the common benchmark for performance evaluation. Sub-optimum receivers such as impulse correlation receiver or rake receiver are usually considered in practical implementations.

Channel Matched Filter Receiver

The channel matched filter receiver is a basic detection technique that maximizes the SNR of the wanted signals that have been added by noise. The basic idea is to correlate the incoming signal with a template waveform and sample at sub-Nyquist rate. Both the transmit signal and the channel impulse response are considered as the template waveform for the matching with the incoming signals. This template waveform is chosen based on the convolution product $h_p(t) = p(t) \ast h(t)$, where $p(t)$ is the transmit impulse and $h(t)$ is the channel impulse response. $h_p(t)$ can be referred to as an effective channel impulse response or an effective basic waveform. For communications, the correlation function between the effective basic waveform $h_p(t)$ and the incoming signal $g(t)$ is sampled and used for deciding on the transmit information (bits) with the decision device, i.e. threshold decision. The sampling processes are performed on a symbol basis, and therefore the complexity for ADC is reduced. This method maximize the signal to noise ratio (SNR), hence it is the optimum method.
with respect to the additive noise.

It is common to construct the channel matched filter receiver using correlation filter as the main component. The block diagram of such a receiver is shown in Fig. 2.14. Notice that the impulse response of the correlation filter is $h_p(-t)$, which is the time-reversed version of the effective basic waveform $h_p(t)$.

$$y(t) = g(t) * h_p(-t)$$

$$= [h_p(t) + n(t)] * h_p(-t)$$

$$= \varphi_{h_p h_p}(t) + n_{h_p}(t),$$

(2.12)

where $n_{h_p}(t) = n(t) * h_p(-t)$ is the filtered noise and $\varphi_{h_p h_p}(t)$ represents the autocorrelation function of $h_p(t)$. The decision is then performed by the sample of $y(t)$. In the noise-free case, the sample value is the correlation between the template waveform and the transmit signal including the channel impulse response. The SNR is maximized after the channel matched filter, since the spectral bandwidth of the noise is filtered by the shape of the spectrum of the template waveform.

Realization of linear filter with specific impulse response $h_p(-t)$ can be difficult, and therefore another method to construct the channel matched filter receiver using a correlator is often considered. The receiver consists of a multiplier fed by the template waveform $h_p(t)$, an integrator, a sampler and a decision device. The block diagram for this type of channel matched filter implementation is shown in Fig. 2.15

The implementation of the channel matched filter in practice is very challenging and rather unrealistic, since an analog implementation of an adaptable correlation
2.7 Basic Receiver Concepts

Figure 2.15: Block diagram of the matched receiver constructed by a correlator for UWB systems.

filter or a signal source for $h_p(t)$ is necessary. Full channel knowledge and accurate synchronization are also required and this can be a big challenge for the low complexity approaches.

**Impulse Correlation Receiver**

The transmit impulse $p(t)$ can be used as the template waveform for correlation in the case where the channel impulse response is not fully known. This type of receiver is called impulse correlation receiver. It is considered as a special case of the channel matched filter receiver, and therefore it is an optimum detection method for the AWGN channel. The channel matched filter receiver principles and structures from Fig. 2.14 and Fig. 2.15 maintain but $p(t)$ is used instead of $h_p(t)$ as the template waveform. The impulse correlator receiver is not only used for communications but also very commonly used for ranging applications [27,68]. The impulse correlation output on symbol basis is given as

$$y(t) = [h_p(t) + n(t)] * p(t) = \phi_{pp}(t) * h(t) + n(t) * p(t),$$

(2.13)

where $\phi_{pp}(t)$ is the autocorrelation function of $p(t)$. The output of the correlator is the convolution between $\phi_{pp}(t)$ and $h(t)$ added by noise. The autocorrelation functions of UWB signals have extremely short duration, and therefore they can be used for the estimation of the channel impulse response $h(t)$. As a result, very fine resolution and high accuracy of the channel estimations are promised. An example of the autocorrelation function $\phi_{pp}(t)$ of a 5-th derivative Gaussian impulse shape with $\sigma=51$ ps is shown in Fig. 2.16. The main lobe of the autocorrelation function is very narrow.
(70 ps) and could result in a delay estimation with very high accuracy. On the other hand, the timing synchronization has to be very precise when using this receiver for communication systems. For this impulse shape, mistiming in sampling time by 35 ps could mean missing all of the impulse energy, and a large degradation in the bit error rate performance is expected.

![Autocorrelation function of the 5th derivative Gaussian impulse](image)

Figure 2.16: The autocorrelation function of the 5th derivative Gaussian impulse with $\sigma = 51\text{ps}$.

### Rake Receiver

A rake receiver is a sub-optimum receiver that is constructed by using several impulse correlators in parallel. The impulse correlators are called ‘branch’, and they are designed to match the effects of multipath propagation. Each branch independently collects contribution from a single multipath component, and they are weighted differently according to the power delay profile of the channel before combining for the decision. The structure of the basic rake receiver is illustrated in Fig. 2.17.

There are several types of rake receiver. The basic variants of rake receiver are ‘all rake’ (A-rake), ‘partial rake’ (P-rake) and ‘selective rake’ (S-rake) [69]. The A-rake receiver considers all of the multipath components for the detection, and as a result it can be considered optimum. However, there are some practical limitations, and only P-rake and S-rake are used in practice. Both P-rake receiver and S-rake receiver consider a small fixed number of branches $L$. The P-rake receivers capture the energy for the first $L$ multipath components that arrive at the receiver, while the S-rake receiver collects the energy from the strongest $L$ paths of the channel. The disadvantage of the S-rake receiver is that it still needs full knowledge of the channel state information,
while P-rake needs to know only the first part of the channel. The weighting factors for each branch can be calculated with different methods, e.g. maximal ratio combining (MRC), minimal mean squared error (MMSE) and optimal combining (OC) [69].

### 2.7.2 Energy Detector

Although correlation based detection delivers superior performance compared to methods without channel knowledge under perfect assumptions, the latter have been attracting a lot of popularity in UWB communication systems because of its low implementation complexity [5]. The performance of correlation based detectors can be severely degraded by just some slight deviation in the synchronization. Energy detector, if applied in a proper way, does not require any knowledge about the channel impulse response and are very robust against synchronization inaccuracy. The energy detector is designed for the detection of the PPM, OOK modulations.

In its basic form, the energy detector consists of a squaring device, an integrator, a sampler and a decision device. As its name implies, the receiver uses the squaring device and the integrator to gather the energy of the receiving signal in a certain interval for the decision. PPM and OOK modulation techniques combined with the energy detector are typically used for UWB communications. The energy detector cannot be used for the detection of signals that are sign-based modulated, such as BPSK. The performance is expected to be worse than correlation based receivers, since the noise is also squared. The integrator in combination with the sampler is often known as ‘integrate and dump’. The integrator collects the incoming energy and immediately reset after sampling. The block diagram of the basic energy detector is shown in Fig. 2.18.
To make energy detection for OOK modulated signals, the sampling is typically performed at the end of every symbol period. The sample value is then used for the comparison with a threshold at the decision device to determine the transmit bit. However, the sampling for PPM detection is performed twice within one symbol period. The decision for PPM modulation is easier to perform since comparing the signal energy from two different intervals is enough. An example of the OOK ($T_s = 4\text{ns}$) and PPM ($T_s = 8\text{ns}$) modulated input signals with additive noise and the output signal of the integrate and dump circuit are shown in Fig. 2.19.

Determining the optimum threshold for the OOK detection is not straight-forward because a probability density function (PDF) of the noise at the output of the squaring device is Chi-square distribution. Many factors are needed for the threshold optimization. This includes the noise variance, received signal energy, integration interval, synchronization point, and the bandwidth of the receiver [70]. There is no close-form expression and searches over possible threshold values are needed to find the optimal threshold. It is suggested in [71,72] that, according to the central limit theorem, the Chi-square distribution can be approximated by the Gaussian distribution, given that the integration period is long enough. The decision threshold according to the Gaussian approximation method for OOK detection can be calculated as

$$\gamma_{Gau} = MN_0 + \frac{E_{T_i} \sqrt{MN_0}}{\sqrt{MN_0^2 + 2E_{T_i}N_0 + \sqrt{MN_0^2}}}$$  \hspace{1cm} (2.14)

where $M$ is half of the degree of freedom, and can be calculated as $M = BT_i + 0.5$, while $B$ is the bandwidth of the receiver and $T_i$ is the integration time. $E_{T_i}$ is the collected signal energy without noise for $T_i$ integration period when ‘1’ is sent. $N_0$ is the noise power spectral density. The Gaussian approximation method is not very accurate in some situations but it can be calculated easily [71]. From Fig. 2.19, we can see that the integrator collect some energy from the area where only noise is presence.
2.7 Basic Receiver Concepts

Figure 2.19: Comparison between the squaring device input signal and the integrator output signal for (a) OOK ($T_s = 4$ ns) (b) PPM ($T_s = 8$ ns).

Performance of the energy detector can be improved with a proper choice of the integration interval [72]. The same principle used in the rake receiver can also be applied to the energy detector as well. The receiver can be constructed by several energy detectors with small integration interval. The output from these energy detectors are combined with different weights similar to the rake receiver [70]. The energy detector can also be used for ranging applications but the accuracy and resolution are as good as correlation based methods [73].
## 2.7.3 Autocorrelation Receiver

Autocorrelation receiver is specifically used for the detection of the TR modulation. For the transmitted reference modulation technique, two impulses are used for representing one basic waveform. Only the second impulse carries the information, while the first impulse is used as a reference signal.

The basic assumption is that the channel does not change during the symbol period. The detection of TR signals can be done by delaying the reference impulse (which includes the channel information) to perform correlation with the information impulse. The delay is $T_{TR}$ as in (2.8). The autocorrelation receiver is designed specifically for this operation. It consists of an analog delay element, a multiplier, an integrator, a sampler and a decision device. The block diagram of the autocorrelation receiver is shown in Fig. 2.20.

![Block diagram of the autocorrelation receiver.](image)

The autocorrelation receiver avoid the extra effort for the channel estimation but the noise and interference are included in the reference signal for the correlation process. The performance can be much worse than the correlation based detection when the SNR is bad or interference is strong. Some variants of autocorrelation receivers deal with this problem by iteratively smoothen the reference signal [74]. The integration interval also plays some role regarding the performance, similar to the energy detector. This issue is studied in [72].
2.8 Spread Spectrum Techniques in UWB

Spread spectrum techniques have been widely used in communication systems for the purpose of improvement in performance regarding to narrowband interference and other users during the last decades [75,76]. Almost every UWB communication system in recent time apply some sort of spread spectrum techniques [55]. Several impulses with spreading code are grouped together to form a transmit symbol basic waveform. The primary reason for using the spread spectrum techniques in UWB is to allow multiple access. The most common spread spectrum techniques used in UWB is direct sequence (DS) and time hopping (TH). Early UWB system designs usually based on TH-UWB [77,78] before the DS-UWB systems became increasingly popular in recent years [79–81].

2.8.1 Direct Sequence - UWB

The direct sequence - UWB (DS-UWB) transmit signal consists of a train of so-called chips, where the chips are represented by an UWB impulse \( p(t) \) follow by an constant time interval, which is typically longer than the duration of the multipath delay spread \( T_m \) of the channel. Many chips (impulses) are grouped together to form a DS basic waveform. The individual UWB impulses in the basic waveform are weighted by +1 or -1 according to spreading sequences. The spreading sequences are pseudo-random and each transmitter (user) is assigned to different sequences. A DS basic waveform \( q_i(t) \) for the \( i \)-th user can be written as

\[
q_i(t) = \sum_{n=0}^{N-1} c_{i,n} p(t - nT_c),
\]

where \( p(t) \) is the UWB impulse and \( c_{i,n} \in \{-1, 1\} \) are the spreading sequences with length \( N \) for \( i \)-th user. \( T_c \) is the period between two UWB impulses or 'chip period' and \( T_s = NT_c \) is the symbol period for communications or measurement period for radar/localization applications. For communications, the basic waveform \( q_i(t) \) can be modulated by simply apply the basic modulation techniques in Sec. 2.5.

We first consider DS-UWB for binary transmissions based on the OOK and PPM modulation, i.e. \( A_e = \{e_0(t), e_1(t)\} \). For DS-OOK, transmitting the DS-UWB basic waveform represents the data ‘1’, while not sending anything means ‘0’. On the other hand, the two basic waveforms for the DS-PPM are different by time shifting \( T_{PPM} \). The transmit signals for DS-OOK and DS-PPM are given as
s_{DS-\text{OOK},i}(t) = \sum_{k=-\infty}^{\infty} b_k q_i(t - kT_s), \quad (2.16)

s_{DS-\text{PPM},i}(t) = \sum_{k=-\infty}^{\infty} q_i(t - b_k T_{\text{PPM}} - kT_s), \quad (2.17)

where \( b_k \in \{0, 1\} \) for DS-OOK and binary DS-PPM. This means the basic waveform for DS-OOK of the \( i \)th user are \( e_0(t) = 0 \) and \( e_1(t) = q_i(t) \), and the basic waveform for binary DS-PPM of the \( i \)th user are \( e_0(t) = q_i(t) \) and \( e_1(t) = q_i(t - T_{\text{PPM}}) \).

In addition to the amplitude-based and delay-based modulation, there is also a possibility to use the spreading sequences themselves as means to carry the information. This modulation technique is called DS-code shift keying (DS-CSK), and the transmit data bits are used for the selection of the spreading sequences of the modulated transmit waveforms. The transmit signal for DS-CSK can be written as

\[
s_{DS-\text{CSK},i}(t) = \sum_{k=-\infty}^{\infty} q_{i b_k}(t - kT_s). \quad (2.18)
\]

The transmit bit \( b_k \) determine index of the spreading sequences \( c_{ib_k,n} \in \{-1, 1\} \) used for the transmissions. For binary transmission, the \( i \)th user is assigned with a code set \( C_i = \{c_{i0}, c_{i1}\} \). At least two spreading sequences are assigned to one user, and therefore the number of possible supported users can be less than half of DS-OOK and DS-PPM. This means the basic waveform for DS-CSK of the \( i \)th user are \( e_0(t) = q_{i0}(t) \) and \( e_1(t) = q_{i1}(t) \). The basic waveforms for different DS-UWB modulation techniques are illustrated in Fig. 2.21. For illustration, dirac delta impulse is used as the impulse shape.

In general, the detection techniques for DS-UWB are the correlation based detections \([79, 80]\) because squaring device in energy detectors eliminate the uniqueness of different spreading sequences. Another interesting variant of DS-PPM where impulses in the basic waveform are grouped closer to each other can be found in \([81]\).
2.8 Spread Spectrum Techniques in UWB

Figure 2.21: Transmit basic waveforms for data bit ‘0’ or ‘1’ of three basic DS-UWB transmissions (a) DS-OOK (b) DS-PPM (c) DS-CSK.

2.8.2 Time Hopping - UWB

Time hopping is a spread spectrum technique where spreading sequences are used for randomizing the duration between impulses in the basic waveform. This approach in combination with the PPM modulation is considered as the primary approach for the implementation of UWB communication systems [77,78]. For TH-PPM, the impulse position in each chip is randomized by the index given by the spreading sequences,
and the delay is added for the PPM modulation. The example of TH-PPM basic waveforms are shown in Fig. 2.22.

![TH-PPM basic waveforms](image)

Figure 2.22: UWB transmit basic waveform for data bit ‘0’ or ‘1’ for TH-PPM.

This approach allows the use of energy detection although it does not have the advantage of SNR gain because the impulses together with noise are squared before summing up. All sort of basic modulation, i.e. BPSK, OOK or CSK, can be applied for TH-UWB. This type of spreading spectrum is not the focus in this thesis and more details of this concept and performance comparison to DS-UWB can be found in [77, 78, 82–85].

### 2.9 UWB Systems for Ranging Applications

Apart from communications, UWB systems can be used for ranging applications. The extreme short duration of transmitted impulse can provide precise accuracy as well as very fine resolution, since most of the multipath are usually resolvable. Ranging applications cover both estimating the distance between transmitter/receiver and the distance of the UWB transceiver to some objects. The estimated distance can be used for many purposes such as movement tracking, localization and imaging. UWB signals can also penetrate effectively through different materials (wall, ground).

The emission limits make UWB systems less suitable for estimation of long distances, i.e. global positioning system (GPS) but they are very good candidates for future short-range indoor ranging systems. The UWB ranging based systems show promising results in many areas, e.g. medicine, military, rescue operation, sport and
entertainment [7–15]. The possibility of implementing less complexity devices with low power consumption makes them an attractive choice for using in the WBAN systems. UWB ranging for medical applications have become a main focus for researchers in the last few years. Many kind of applications have been proposed, e.g. tracking of vital signs (breathing rate, heart rate) [7, 13], imaging for breast tumors [8, 12], localization of interventional devices [10, 11].

There are several techniques for estimating the range and the position. The time-based, signal strength-based and angle-based are some of them [73]. The most common method for impulse signals is the time-of-arrival (TOA) based ranging technique. We consider two types of TOA technique namely one-way TOA and two-way TOA. Fig. 2.23 show an illustration of the basic principles of radar and localization with UWB for both one-way and two-way TOA.

Figure 2.23: Examples of ranging applications for (left) UWB radar and tracking (right) UWB imaging and localization.
In the one-way TOA systems, the goal is to find the distance between the transmitter and the receiver. At least one of them can be moving, and the movement tracking of one another can be achieved by continuously estimate the distance. On the other hand, the distance from a transceiver to some dynamic or static object is calculated for the two-way TOA systems. This method is usually used for tracking the movement of the object. For one-way TOA, the propagation delay \( \tau \) is used for the calculation of the distance \( d = \tau \cdot c \), where \( c = 3 \cdot 10^8 \text{m/s} \) is the speed of electromagnetic waves in space. The distance to the reflected object for the two-way TOA is calculated by \( d/2 \).

Several distance estimations with two-way TOA from different directions can be used for finding the location or the shape of some object. It is possible to find a location of a small transmitter inside some object (implantable devices) using one-way TOA.

Some of the challenges in time-based ranging are coping with the noise, multipath components, obstacles, interference and clock drift [73]. The estimation of the TOA is usually performed by the impulse correlation receiver, since it maximizes the SNR of the propagation path. The energy detector can also be used for a low complexity alternative approach but the accuracy and the resolution are expected to be worse [86–88].

### 2.9.1 Performance Bounds

To get a general overview of the achievable accuracy of the UWB ranging systems, the common method is to find a performance lower bound. Many performance bounds have been proposed for different scenarios and assumptions. The bounds are usually calculated for the impulse correlation receiver, since it maximizes the SNR. The Cramer Rao bound (CRB) is a well-known and widely used bound for the prediction of the mean square error (MSE) of unbiased estimators. For both AWGN channel and multipath propagation channel, the CRB can provide closed-form solutions [73]. This bound is a function of SNR and the effective bandwidth of the signal. For derivative Gaussian impulses, the effective bandwidth depends on the derivation order \( n \) and the standard deviation \( \sigma \). The CRB for ranging estimation of the \( n \)-th derivative Gaussian impulses for the AWGN channel is given as

\[
\text{CRB} = \frac{\sigma^2}{(2n + 1)\text{SNR}}. \tag{2.19}
\]

The CRB for the root mean square errors (RMSE) of the distance estimation for the 5-th derivative Gaussian impulse with \( \sigma = 51 \text{ ps} \) in AWGN channel is shown in Fig. 2.24. The CRB is easy to calculate but it is well-known that the CRB is valid only
2.9 UWB Systems for Ranging Applications

in high SNR region (> 15 dB). The bound is said to be too optimistic in the middle (0 - 15 dB) and low (< 0 dB) SNR regions because the ambiguity effect is not included in the calculation. The ambiguity effect is related to the shape of the impulse. As we can see in Fig. 2.16, the autocorrelation function of the Gaussian impulse consists of a main peak and two other side-peaks. For High SNR case, the estimation will always be able to find the main peak. On the other hand, the estimator can pick the entirely wrong peak for the lower SNR case resulting in large amount of biased errors. This effect was not considered for the CRB bound calculation, and therefore it is too optimistic in this SNR region. In other words, the CRB only considers ‘Local errors’, and does not take into account the ‘Global errors’. It is shown in [73,89] that the Ziv-Zakai bound (ZZB) [90] can provide more accurate lower bound for the low and medium SNR regions. To calculate this bound, it is assumed that the propagation delay $\tau$ is randomly distributed in the interval $[0,T_a)$. In summary, the ZZB is calculated by transforming the estimation problem into a binary detection problem. More details on the derivations can be found in [73, 89]. The ZZB for the AWGN channel can be calculated as

$$ZZB = \frac{1}{T_a} \int_0^{T_a} z(T_a - t)P_{\text{min}}(t)dt,$$  \hspace{1cm} (2.20)

$$P_{\text{min}}(t) = Q\left(\sqrt{\frac{\text{SNR}}{E_p}} \cdot \left(1 - \frac{\varphi_{pp}(t)}{E_p}\right)\right),$$  \hspace{1cm} (2.21)

where $P_{\text{min}}(t)$ is the minimum attainable probability of error, $Q(.)$ is the Gaussian Q-function, $\varphi_{pp}(t)$ is the autocorrelation of the UWB impulse and $E_p$ is the impulse energy. The ZZB for $T_a = 10$ ns (3 m) $T_a = 50$ ns (15 m) for the 5-th derivative Gaussian impulse with $\sigma = 51$ ps in AWGN channel are compared with the CRB in Fig. 2.24.

We can see that the CRB is very different to the ZZB in the low SNR region. The ZZB can provide tighter performance bound compared to the CRB but it is much more complicated to calculate. There are no close-form expressions for the ZZB and the calculation has to be done by numerical integrations or Monte Carlo simulations. More performance bounds for several multipath channels (WPAN and WBAN) can be found in [73,91,92]
2.9.2 Sampling of UWB signals

Due to the large bandwidth of the UWB signals, the minimum required sampling rate is high and impractical. This represents the main challenge in implementing the correlation based receivers for ranging applications. Many authors consider the less complex alternative approach using the energy detector [86–88]. In some situations, the accuracy and the resolution of the energy detector approaches can not match the demands of the systems. In many cases, the whole knowledge of the channel impulse response is needed for the estimation of the distance for localization and imaging. For movement tracking of a target signal (path), the impulse correlation receiver can be used for the tracking of the slope of the impulse autocorrelation function [27]. A Delay-Lock-Loop implementation with two impulse correlators is also possible [93]. The main problem for these methods is that finding the initial tracking point is also complicated for UWB signals. The support range of operation depends on the impulse width which can be very small. More importantly, these methods do not work when multipath channels are considered.

One of the widely used techniques for acquiring UWB signals is the equivalent-time sampling, which is the technique employed in the sampling oscilloscope. This
technique requires a repetitive input signal. The equivalent-time sampling can be performed with sequential approach or random approach. We consider the sequential approach since it can provide greater resolution. The basic principle of the sequential equivalent-time sampling with UWB periodic signals is illustrated in Fig. 2.25.

The input signal is sampled only once per period, and a small delay is added to the sampling points after each sample. At the end, the output signal is the combination of several samples across the target waveform in equivalent-time. The output signal can be used for signal processing such as correlation-based technique or some more advance techniques realized with digital signal processing. This approach fits well with the characteristics of the UWB receive signals even when the channel impulse response is included. The duration between UWB impulses is typically in the range of nanoseconds and the channel normally stay unchanged for much longer time, and therefore the receive signal should be repetitive.

Using a commercial sampling oscilloscope for gathering the UWB signals and transferring them to other devices for signal processing purposes might be not so fast and flexible. It is possible to perform the sequential equivalent-time sampling by using the impulse correlator [27]. Assuming that the train of UWB signals is transmitted with frequency $f_1$, the impulse correlation receiver is triggered with frequency $f_2$.
\[ f_2 = f_1 + \Delta f. \] The frequency offset \( \Delta f \) results in accumulated time-shift between transmit and receive impulses over the periods. This method is called sweeping-impulse correlation and it uses the UWB impulses as the sampling signal instead of using a short-duration input impulses (approximating Dirac delta functions). The illustration of impulse sweeping technique is shown in Fig. 2.26. The SNR is maximized when the impulse shape at the receiver matched to the incoming impulses. The drawback of this technique is that the correlation process makes the received signals broader in time domain, and therefore the achievable resolution is reduced. Other sampling methods, e.g. frequency-domain sampling and time-interleaved sampling, can be found in [94].

Figure 2.26: Principle of equivalent-time sampling with the sweeping-impulse correlator.
UWB communication systems are well-known for their potential of achieving high data rate transmissions while low complexity and low power consumption devices can be used. In this chapter, we look at the bit error rate (BER) performance of UWB communication systems with different modulation techniques and receiver structures. Firstly, the BER results from the basic modulation and detection techniques introduced in the last chapter are presented and the general challenges and limitations will be addressed. To cope with these problems like multiuser capability, multipath propagation, low SNR regime and strong interference, a novel receiver structure based on a comb filter is proposed. The comb filter based receiver is designed for the
3 Transmission with Impulse Radio Ultrawideband

DS-UWB signals and it can be used for both communications and ranging applications. All of the basic UWB detection methods can be applied in this receiver concept. It also allows the energy detector to gain the benefits from the DS-UWB transmissions, which are not possible with the conventional concept.

3.1 Performance of Basic UWB Receivers

We first look at the BER performance of the UWB binary transmission using the OOK, PPM and TR modulation techniques from Sec. 2.5. The impulse correlation receiver and the energy detector are considered for the OOK and PPM detection, while the autocorrelation receiver is used for the detection of the TR signals. The 5-th derivative of Gaussian impulse signals with $\sigma = 51$ ps, as shown in Fig. 2.5, is used. The symbol period $T_s$ is 4 ns for the OOK modulation, and 8 ns for the PPM and TR modulation. The AWGN channel is considered and the synchronization is assumed to be perfect. Multiple access is not yet included. The template waveform for the impulse correlation receiver is matched to the transmit impulse shape. The integration period for the energy detector and the autocorrelation receiver are 4 ns, which is the whole information impulse period. The decision threshold for the OOK modulation is half of the energy per bit $E_b$ for the correlation detection. For the energy detector, the Gaussian approximation method from (2.14) is used for the approximation of the optimal decision threshold. The decision of the PPM signals is performed by comparing the energy in two different intervals collected by the impulse correlators or the energy detectors. Sign decision is used for the TR signal detection with the autocorrelation receiver. BER curves with respect to $E_b/N_0$ (the energy per bit to noise power spectral density ratio) for all the settings are shown in Fig. 3.1.

In the perfect synchronisation scenario, the correlation receiver is better than both the energy detector and the autocorrelation receiver as expected. The BER performance from the OOK modulation is slightly better than the PPM modulation when the energy detector is considered, while the same performance is shown for the correlation receiver. We also see that the BER performance from the PPM detection using the energy detection is the same as the TR signal detection using the autocorrelation receiver, although the TR modulation uses only $E_b/2$ for the transmission of the information impulse compared to $E_b$ for the PPM modulation. The Euclidean distance between two symbols in the TR constellation is smaller than the PPM constellation but the noise term involves the product of two independent processes in the TR detection, i.e. the noise from two different intervals, whereas the quadratic noise terms $n^2(t)$ are considered for the PPM detection with the energy detector. In the following
3.1 Performance of Basic UWB Receivers

Figure 3.1: BER performance of PPM/OOK/TR modulation with different basic receivers for the AWGN channel.

part, the PPM and OOK modulation will be taken as the basis. The TR modulation can be neglected since the performance is similar to the PPM modulation, and the energy detector for the PPM detection is less complex than the autocorrelation receiver for the TR detection.

As mentioned in Sec. 2.7.2, the performance of the energy detector can be improved by adjusting an integration interval. The previous BER results cover the whole integration interval of 4 ns. The duration of the UWB impulse signal considered here is only about 500 ps, and therefore the energy detector collects only the noise energy for most of the time. We consider the same settings as in the previous part with the OOK and PPM transmissions in the AWGN channel. The integration periods for the energy detector are 1 ns and 4 ns. The decision threshold for the OOK detection is a function of the integration period and has to be calculated for every setting. The BER performances with respect to $\frac{E_b}{N_0}$ for the energy detector with different integration periods are also shown in Fig. 3.2.

The improvement from reducing the integration period can clearly be seen. The interesting part is that the performance of the OOK modulation tends to be worse for
the small integration period at high $E_b/N_0$. The threshold calculated with the Gaussian approximation method is known to be inaccurate when the degree of freedom is low [72]. Determining the optimal integration interval is not a simple task because more knowledge about the channel is required. For simplicity, we consider only the full integration period with the common knowledge that the results can be improved if more complex algorithms are implemented.

For OOK signals, the decision threshold is always needed for the energy detector to determine the information bits. There is no close-form expression to calculate the optimal threshold, and therefore the Gaussian approximation method is usually considered in practice. We have seen from the previous results that this method can be inaccurate in some situations. In this part, we consider the BER performance from different threshold levels based on the Gaussian approximation threshold $\gamma_{Gau}$. The AWGN channel is considered and the integration period is 4 ns. The BER performances of the OOK detection from different threshold levels are shown in Fig. 3.3.

It is clear that the BER performance become worse when the threshold is lower than $\gamma_{Gau}$. Interestingly, the Gaussian approximation method seems to underestimate the threshold value in the high SNR region, and the BER performance can be improved
3.1 Performance of Basic UWB Receivers

Figure 3.3: BER performance of OOK modulation with the energy detector for different level of decision thresholds.

by increasing the threshold in this situation. The threshold calculation is the main drawback for the detection of the OOK signals with the energy detector. It can become even more complicated when multiuser and narrowband interference are included into consideration, and therefore the PPM modulation is preferred in many situations.

We have seen that the correlation detection performs better than the energy detector in the perfect scenario. The main challenge in the implementation of this type of receiver is the synchronization. The UWB impulse signals and their autocorrelation function have extremely short time duration, and therefore the synchronization has to be very precise. We now look at the BER performance of the UWB receivers when the synchronization is not perfect. Different levels of synchronization inaccuracy (perfect, ±20 ps, and ±40 ps) in the AWGN channel are considered. The errors in the synchronization inaccuracy are uniformly distributed. The 5-th derivative Gaussian impulse with $\sigma = 51$ ps is considered and its autocorrelation function can be seen in Fig. 2.16. It can be seen that mistiming by 35 ps could result in missing all of the impulse energy. The BER performance for different synchronization levels can be seen in Fig. 3.4. Another issue investigated here is the multipath propagation channel. As discussed in Sec. 2.7.1, the channel impulse response has to be included for the optimal detection
of the UWB signal with the correlation methods. We look at the performance loss in the case where the impulse correlation receiver is used on the multipath propagation channel. The multipath delay spread is less than 4 ns, and it is assumed that the impulse correlator is locked to the strongest multipath component. The BER performances for the impulse correlation receiver and the energy detector in the multipath propagation channel are shown in Fig. 3.4.

![Figure 3.4: BER performance of OOK/PPM modulation for the AWGN channel with different synchronization levels and for the multipath propagation channel.](image)

The performance of the correlation receiver suffers from the synchronization uncertainty and the multipath propagation, while no changes in the performance occur in the energy detector. The degradation is higher in the OOK detection compared to the PPM detection because the decision threshold has to be adjusted according to the mean of the received symbol energy. We can conclude that the result from the energy detection is not affected by the channel if the integration interval is greater than the duration of the channel impulse response. Moreover, the synchronization accuracy is much more relaxed compared to the correlation detection.
3.2 Comb Filter Based System Concept for UWB Transmissions

The BER performances from the last section show that the energy detector can be much more robust in the multipath propagation channel and against the synchronization inaccuracy in comparison to the correlation detection. The drawbacks of the energy detector are the performance in the low SNR regime, the low multiple access capability, and its weak resistance against narrowband interference. In applications where the attenuation and the interference are strong, it is important to find a way to improve the SNR of the received signals. Increasing the transmit power is not an option because the emission power of the UWB signals is limited by the spectral masks. Typically, the spread spectrum techniques are adopted for coping with these problems. The energy detector can support multiple access when the TH-UWB is considered but the SNR gain is not achieved. The key idea in achieving the SNR gain is the coherent combination of the incoming impulses, but this process is not performed if the energy detector is used directly. The issue with the strong narrowband interference is also unsolved in the TH-UWB case.

We propose a comb filter based receiver for the DS-UWB detection. This receiver structure allows the use of the energy detector in the multiple access scenarios with the DS-UWB modulated signals. It gives the energy detector access to the SNR gain and is also able to suppress narrowband interference without any explicit modification.

The comb filter receiver can also be used for ranging. This aspect will be discussed in more detail in Chapter 4. In the following sections, the basic concept and more details on the receiver structure as well as the BER performance will be addressed.

3.2.1 Basic Concept of Comb Filter

The comb filter is a feedback loop with an analog delay element, and it can be considered as a high-gain resonant circuit for wide band signals. We first consider ideal components where there is no attenuation or distortion (frequency dependent) in the analog delay element. The ideal loop gain $G_c$ of the comb filter is one. The period of the incoming impulses should be matched to the analog delay element. The comb filter is designed to sum up the signals with a period being the same as the analog delay time and other signals that do not have the same period as the comb filter are suppressed. After some periods, the last impulse period at the output is used for further process. The SNR of the comb filter output signal can be significantly improved, since the signal power grows quadratically, while the noise power grows only linearly with the number of summed up operation. The comb filter shall be reset after the last
impulse period to avoid instability (oscillation). The block diagram of the comb filter and the illustration of the comb filter accumulation process is shown in Fig. 3.5. The comb filter is reset after 4 iterations in this example.

In Fig. 3.6, an example of the UWB input and output signals of the comb filter without resetting are shown. The input signal is a train of UWB impulse with the period of 4 ns. The SNR of the input signal is -6 dB, and we can see that the UWB impulses cannot be distinguished from the noise. The SNR is measured in the bandwidth of the UWB signal for the impulse period. The SNR improvement in the comb filter output signal can be seen clearly as the impulses become visible after few iterations.

Given that $N$ is the number of iterations, the UWB signal is algebraically summed up, and therefore the signal energy is increased by a factor of $N^2$. On the other hand, the noise contributions in each period are added in power, and therefore the noise energy at the output is increased only by a factor of $N$. The comb filter SNR gain $G_p$ (SNR improvement) can be calculated as

$$G_p = 10 \cdot \log_{10}(N) \text{ [dB]}.$$ (3.1)

The values of $G_c$ shall not be larger than one in practical systems, because then the comb filter become unstable and an oscillation occurs. $G_c$ is designed to be one but, for real components, an attenuation in the comb filter loop is possible. If $G_c$ is less than one, the signals are attenuated and can be vanished after a few iterations in the comb filter. For example, the weighting factor from going through the comb filter with $G_c = 0.8$ for 10 times is 0.1. Using the same input signal from Fig. 3.6, the output

![Figure 3.5: Basic principle of the comb filter.](image-url)
3.2 Comb Filter Based System Concept for UWB Transmissions

![Comb filter input signal](image1)

![Comb filter output signal: Gc=1](image2)

Figure 3.6: Comparison between the UWB input signal (upper) and the UWB output signal (lower) of the comb filter for Gc=1 without resetting.

![Comb filter output signal: Gc=0.8](image3)

Figure 3.7: The UWB output signal of the comb filter with Gc=0.8.

We can see that the output signal becomes saturated after some iterations because only the contribution from the recent impulses are included. The achievable comb filter SNR gain Gp in this case is obviously smaller than 10 \log_{10}(N) \text{ dB}. The comb filter SNR gain Gp can be calculated as a function of the gain Gc of the comb filter and the number of iterations N as
3 Transmission with Impulse Radio Ultrawideband

\[ G_p = 10 \cdot \log_{10} \left( \frac{\left( \sum_{n=0}^{N-1} G_c^n \right)^2}{\sum_{n=0}^{N-1} G_c^{2n}} \right) \text{[dB].} \] (3.2)

The relationship between \( G_p \), \( G_c \) and \( N \) are shown in Fig. 3.8.

![Graph showing the relationship between \( G_p \), \( G_c \), and \( N \).](image)

Figure 3.8: Relationship between the SNR gain \( G_p \), the comb filter loop gain \( G_c \), and the number of iterations \( N \).

The number of iterations shall be limited, if there is a known loss in the comb filter loop. Because the SNR improvement cannot be increased after some iterations. We can also see that the comb filter loop gain has to be controlled more precisely if a higher number of iteration is considered. The other challenges for the practical implementation of the comb filter such as time jitter in transmit impulses and the effect of the group delay variation of the analog delay element can be found in [16,18].

### 3.2.2 Comb Filter Receiver Structure

The comb filter will be used as the basis for our proposed receiver structure for DS-UWB detection. The DS-UWB symbol waveform consists of impulses with constant
3.2 Comb Filter Based System Concept for UWB Transmissions

The impulse period weighted by the spreading sequence. The combination of the UWB impulse $p(t)$ and the period between two impulses is depicted as a ‘chip’. The basic assumptions are that the channel is time invariant within the symbol period $T_s$ and the chip period $T_c$ is longer than the multipath delay spread to prevent interchip/intersymbol interference (ICI/ISI). The received signal $g(t)$ consists of a corresponding number of the convolution between the channel impulse response $h(t)$ and the UWB impulses $p(t)$ with the weighting factor according to the spreading sequence. The convolution result, $h_p(t) = h(t) * p(t)$, is also known as the effective channel impulse response. In order to use the comb filter for the DS-UWB detection, a multiplier has to be placed in front of the comb filter to ‘despread’ the incoming signal. We first look at the relationship between the input signal of the multiplier and the output signal of the comb filter. The incoming signal is multiplied with a spreading sequence waveform $d(t)$ (i.e. a train of rectangular waveforms weighted by spreading sequence). If the spreading sequences of the incoming signal and the spreading sequence waveform are the same, the output of the multiplier $u(t)$ is a periodically repeated effective channel impulse responses with period $T_c$. The signal is then summed up at the comb filter and only the last chip period $v(t)$ of the output signal is taken for further signal processing. $v(t)$ is expected to be the effective channel impulse response amplified by the number of chip per symbol $N$. The process of the spreading sequence waveform multiplication and the comb filter accumulation are illustrated in Fig. 3.9.

![Figure 3.9: Illustration of the signals at the multiplier and the comb filter.](image)
The comb filter based receiver consists of an antenna, a low noise amplifier (LNA), the multiplier, the comb filter, the energy detector for communications and the impulse correlator for radar/localization applications. The receiver structure and the overview of the communication systems are illustrated in Fig. 3.10. In general there are many transmitters with different corresponding spreading sequences, and the sequences are selected such that the mutual cross-correlation values are as small as possible. This guarantees that many transmitters can be used at the same time in the same area, e.g., several implants for digital transmission. The signals from all transmitters are assumed to be transmitted in parallel with synchronization in a certain time window. The spreading sequence waveform fed to the multiplier at the receiver is matched to the target user. Interference from different UWB transmitters and other systems are eliminated at the comb filter.

![Figure 3.10: Block diagram of the comb filter based receiver and the overview of the UWB transmission system.](image)

We now look at the signals at the comb filter receiver in more details. Assuming no ICI/ISI, the signal can be analyzed separately on a symbol basis. For simplicity, we can consider the unmodulated DS-UWB as the transmitted signal and also neglect the additive noise at the receiver. The data modulation such as OOK or PPM can be easily included at the end, and the noise can be considered separately. The transmitted
signal for the \( i \)-th user for one symbol is given as

\[
s_i(t) = \sum_{n=0}^{N-1} c_{i,n} p(t - nT_c),
\]

where \( p(t) \) is the UWB impulse and \( c_{i,n} \) is the spreading sequence assigned for the \( i \)-th user. \( N \) is the number of chip per symbol. The received signal from the \( i \)-th user without the additive noise can be written as

\[
g_i(t) = \sum_{n=0}^{N-1} c_{i,n} h_p(t - nT_c),
\]

where \( h_p(t) = p(t) \ast h(t) \) is the effective channel impulse response. \( g_i(t) \) is then multiplied with the spreading sequence waveform \( d_j(t) \), which is a train of rectangular waveforms weighted by the spreading sequence \( c_{j,n} \). The spreading sequence waveform \( d_j(t) \) is given as

\[
d_j(t) = \sum_{n=0}^{N-1} c_{j,n} \text{rect} \left( \frac{t - nT_c - (T_c/2)}{T_c} \right).
\]

The multiplier output signal/comb filter input signal can be expressed as

\[
u_{ij}(t) = g_i(t) \cdot d_j(t)
= \sum_{n=0}^{N-1} c_{i,n} c_{j,n} h_p(t - nT_c) \cdot \text{rect} \left( \frac{t - nT_c - (T_c/2)}{T_c} \right)
= \sum_{n=0}^{N-1} c_{i,n} c_{j,n} h_p(t - nT_c).
\]

The comb filter input signal consists of the ‘remodulated’ effective channel impulse responses. These waveforms are feedback delayed and iteratively summed up at the comb filter. Each of the comb filter output chip interval is the summation of the current incoming chip with all the previous chips. Therefore the last chip period of the comb filter output signal is the sum of all the chip intervals of the input signal, and it can be written as

\[
v_{ij}(t) = \sum_{n=0}^{N-1} c_{i,n} c_{j,n} h_p(t),
\]
where $v_{ij}(t)$ is the last chip period at the output of the comb filter, and $c_{i,n}$ and $c_{j,n}$ are the spreading sequences of the transmitter and the receiver. By representing the signals in a block of chip interval, the comb filter accumulation process is illustrated in Fig. 3.11.

For the comb filter with matched sequence ($i=j$), the comb filter output results $v_{ii}(t) = \sum_{n=0}^{N-1} c_{i,n} c_{i,n} h_p(t) = Nh_p(t)$. We can see that $v_{ii}(t)$ is a result from the coherent combination of the incoming effective channel impulse responses $h_p(t)$, and therefore the energy increased $N^2$ times. For the noise which is uncorrelated, the multiplication does not change the result. The summation of uncorrelated noise still result in $N$ times increased in the noise power. The basic modulation of the DS-OOK and DS-PPM can be simply added to the $v_{ij}(t)$ because the amplitude deviation or time-shift occurs within the chip period when no ICI/ISI is considered. It has to be noted that the comb filter itself is a linear time-invariant system but the windowing of the last chip period from the output signal make the whole process a time-variant system. The channel impulse response is available at the output of the comb filter and all
of the basic receiver principles can be used here. The important thing is that the SNR gain from the spread spectrum technique is already achieved at this point. Therefore the energy detector can get access to this benefit unlike the conventional approaches. Assuming that the channel impulse response remains unchanged within the symbol period, the correlation detection with the effective channel impulse response \( h_p(t) \) as the template waveform would result in the optimal detection similar to the conventional channel matched filter receiver approach. This comparison will be discussed in more details in Sec. 3.2.3. The suppression of the multiuser and the narrowband interference occurs at the comb filter and will be addressed in the following sections.

**Multiuser Interference Suppression**

The multiplier and the comb filter are the crucial parts for the multiuser interference (MUI) suppression. As shown in Fig. 3.9, the output of the multiplier is a periodical repeat of the effective channel impulse response \( h_p(t) \) when the transmit and receive sequences are matched. If they are not the same, the weighting factors of the \( h_p(t) \) are the scrambled version between two sequences as in (3.6). After the comb filter, \( h_p(t) \) is weighted by the cross-correlation value between the two sequences \( \sum_{n=0}^{N-1} c_i,n c_j,n \), as shown in (3.7). The illustration of the multiplication and the comb filter accumulation of the two received signals with orthogonal sequences is shown in Fig. 3.12.

![Figure 3.12: Illustration of the multiuser interference suppression at the comb filter.](image)

The spreading sequence set has to be properly chosen in order to have low cross-
correlation value. The first spreading sequence set we consider is the maximum-length sequence (m-sequence). The m-sequences are widely considered in practice because they have an overall low cross-correlation and are very simple to generate. The m-sequences are generated by linear feedback shift registers of length \( m \), and the sequence of length \( N \) is determined by \( N = 2^m - 1 \), where \( m \) is positive integer. The periodic autocorrelation function \( \phi_{c_i,c_i}(k) \) of the m-sequences has the following characteristic:

\[
\phi_{c_i,c_i}(k) = \sum_{n=0}^{N-1} c_{i,n} c_{i,n-k} = \begin{cases} N & \text{for } k = 0, \\ -1 & \text{else.} \end{cases} \tag{3.8}
\]

The other member \( c_j \) in the m-sequence set can be generated by shifting the original sequence \( c_i \) cyclically. The cross-correlation function of the m-sequence has value -1 except at one particular shift that make the two sequences identical. The periodic autocorrelation and cross-correlation function of the m-sequences are illustrated in Fig. 3.13. It has to be noted that the index \( n \) of the spreading sequence belongs to a cyclic group of modulo \( N \), e.g. \( c_{i,N} = c_{i,0} \) and \( c_{i,-1} = c_{i,N-1} \).

Alternatively, binary zero-correlation-zone (ZCZ) sequence [95] can also be considered. Unlike m-sequences, these sequences have a cross-correlation of zero within a small window but the drawback is a smaller number of sequences in one set. Given a ZCZ sequence set with family size \( N_s \), each sequence is of length \( N \), and \( Z \) is the maximum shift. The sequences have the following characteristic:

\[
\phi_{c_i,c_j}(k) = \sum_{n=0}^{N-1} c_{i,n} c_{j,n-k} = \begin{cases} N & \text{for } k = 0, \ i = j, \\ 0 & \text{for } k = 0, \ i \neq j, \\ 0 & \text{for } 0 < |k| \leq Z. \end{cases} \tag{3.9}
\]

For binary ZCZ sequences, the relationship between the family size \( N_s \), the sequence length \( N \) and the maximum zero shift \( Z \) is given as \( N = 2N_s \cdot Z \). This means that we have to make a compromise between these parameters. The bigger the size of the zero correlation zone the smaller the family size. Example of periodic autocorrelation and cross-correlation function of the ZCZ sequence set with \( N = 128 \), \( Z = 4 \) are illustrated in Fig. 3.13. The main advantage of using the ZCZ sequence set is that the transmit waveforms are orthogonal and the MUI can be completely eliminated at the comb filter, while the drawback is the limited number of supportable users due to the small family size. Of course, if low interference can be tolerated, low correlation zone (LCZ) sequences could be used as well [96], with the result of increasing the number of supportable users.
3.2 Comb Filter Based System Concept for UWB Transmissions

![Figure 3.13: Autocorrelation and cross-correlation of the sequence set for (a) m-sequence ($N=127$) (b) ZCZ sequence ($N=128, Z=4$).](image)

Narrowband Interference Suppression

Since UWB signals cover very large bandwidth, strong interference within the band is possible and can cause problems at the receiver. Without additional effort, the comb filter in combination with the spreading sequence waveform multiplication can suppress narrowband interference very well. The comb filter transfer function $H(f)$ is given as follows:

$$H(f) = \sum_{k=-\infty}^{\infty} T_s \cdot \text{sinc} \left( \frac{f - \frac{k}{T_c}}{T_s} \right) \cdot e^{-j\pi f T_s}. \quad (3.10)$$

We can see that the transfer function of the comb filter consists of several peaks. The peaks could be seen as tunnels that allow only signals with specific frequencies to pass. Only a periodic signal that has a period which equals to one or multiples of the comb filter delay can go through the comb filter without distortion. Of course, the comb filter alone is weak against any interference that fall directly in those peaks. The inclusion of the multiplier in front of the comb filter improves this aspect. After the multiplication with the spreading sequence waveform, the spectrum of the UWB signal has a shape matched to the transfer function of the comb filter (signal with period $T_c$). On the other hand, the narrowband interferer is spread by this multipli-
ulation and only some frequency components could go through the comb filter. The width of each peak depends on the number of chips per symbol $N$. It gets smaller as the number of summation steps in the comb filter increases and as a result more interference is suppressed. After the summation, the process of taking only the last chip period, which is a multiplication with a time-shifted rectangular waveform with duration $T_c$, smoothen the UWB spectrum. The narrowband interference suppression process from the input of the multiplier to the output of the comb filter in the frequency domain is illustrated in Fig. 3.14.

![Illustration of the narrowband suppression in the comb filter.](image)

The improvement of the signal-to-interference ratio (SIR) of the UWB signal is demonstrated in Fig. 3.15. The signals at the input of the multiplier are the UWB signal and a narrowband interference, which is the IEEE 802.11a OFDM WLAN signal with a bandwidth of 16.66 MHz and a center frequency of 5.2 GHz. In this example, the input SIR of -15 dB is improved by 10 dB for $N = 63$. We can see that the interference was suppressed very well and only some residual frequency left at the comb filter output.

### 3.2.3 Comparison to Conventional Correlation Detection

The comb filter is designed to perform the coherent combination which is the crucial part of the conventional correlation detection. The correlations in the conventional DS-UWB detection method are performed on symbol basis. The optimum detection with respect to the additive noise can be achieved by the channel matched filter re-
3.2 Comb Filter Based System Concept for UWB Transmissions

Figure 3.15: Example of the UWB input signal with narrowband interference (upper) and the comb filter output signal (lower).

receiver as mentioned in Sec 2.7.1. The template waveform for the correlation process of the channel matched filter receiver is given as

\[ w_j(t) = \sum_{n=0}^{N-1} c_{j,n} h_t(t - nT_c), \]  

(3.11)

where \( w_j(t) \) is the template waveform with \( c_{j,n} \) as the spreading sequence, and \( h_t(t) \) is the estimated channel impulse response or the template chip waveform. If the channel estimation is perfect and the transmit/receive sequence matched, we have \( h_t(t) = h_p(t) \) and \( c_{j,n} = c_{i,n} \). Assuming perfect synchronization, the output of the channel matched filter receiver can be expressed as the scalar product of the incoming signal and the template waveform, which can be written as

\[ y_{ij} = (g_i(t), w_j(t)) = \left( \sum_{n=0}^{N-1} c_{i,n} h_p(t - nT_c) \right) \left( \sum_{n=0}^{N-1} c_{j,n} h_t(t - nT_c) \right). \]  

(3.12)

The scalar product operation can be expressed in the integration form, and (3.12) can be rewritten as
\[ y_{ij} = \int_{-\infty}^{\infty} \sum_{n=0}^{N-1} c_{i,n} c_{j,n} h_p(t - nT_c) h_l(t - nT_c) dt. \] (3.13)

Since the channel remain unchanged during the symbol period, it is obvious that the scalar product term \( \int_{-\infty}^{\infty} h_p(t - nT_c) h_l(t - nT_c) dt \) give the same result for \( n = [0, 1, 2, ..., N - 1] \). Therefore this term can be represented by \( \int_{-\infty}^{\infty} h_p(t) h_l(t) dt \), and (3.13) can be rewritten as

\[ y_{ij} = \int_{-\infty}^{\infty} \sum_{n=0}^{N-1} c_{i,n} c_{j,n} h_p(t) h_l(t) dt \] (3.14)

\[ = ( \sum_{n=0}^{N-1} c_{i,n} c_{j,n} h_p(t), h_l(t) ). \]

The first term of the scalar product in (3.14) is the output of the comb filter \( v_{ij}(t) \) as shown in (3.7). Therefore we can conclude that the correlation process between the template chip waveform and the comb filter output signal is equivalent to the conventional correlation detection method. This relation is illustrated in Fig. 3.16.

### 3.2.4 Bit Error Rate Performance of Comb Filter Receiver

The SNR gain from the comb filter coherent combination can be demonstrated by the improvement in BER performance with respect to SNR. The modulation techniques considered here are OOK \((N = 1)\), PPM \((N = 1)\), DS-OOK \((N = 63)\) and DS-PPM \((N = 63)\) with m-sequence. The impulse correlation receiver and the energy detector are considered after the comb filter. The AWGN channel is used and the synchronization is assumed to be perfect. With the assumption of no ICI/ISI, the results from the AWGN channel is sufficient, since the BER performance from the energy detector remains unchanged under multipath propagation channels as shown in Fig. 3.4. The analog delay element in the comb filter is ideal, i.e. \( G_c = 1 \) and no group delay variation. The chip period \( T_c \) is 4 ns for DS-OOK and 8 ns for DS-PPM, and the symbol period \( T_s \) is \( N T_c \). The decision threshold of the energy detector for the OOK and DS-OOK are calculated using the Gaussian approximation method. Only one user is considered and no narrowband interference is presented. The BER performance with respect to SNR for DS-PPM and DS-OOK with \( N = 1 \) and \( N = 63 \) using m-sequence are shown in Fig. 3.17.
3.2 Comb Filter Based System Concept for UWB Transmissions

Both methods give the same result

\[ w(t) = \sum_{n=0}^{N-1} c_{i,n} h_{f}(t-nT_{c}) \]

Correlation with template symbol waveform

\[ v_{i}(t) = Nh_{p}(t) \]

\[ h_{i}(t) = h_{p}(t) \]

\[ g_{i}(t) \]

\[ u_{i,i}(t) \]

\[ \text{Delay and sum up} \]

\[ \text{Multiply with spreading sequence} \]

\[ \text{Correlation with template chip waveform} \]

Figure 3.16: Comparison between the conventional method for the DS-PPM signal detection and the comb filter based method.

The SNR improvement of \(10\log(63) = 18\text{dB}\), as calculated in (3.1), can be clearly seen from the BER performance. We can see that the SNR gain is achievable for the energy detector in the same way as the correlation detection. This is not possible with the conventional energy detection method. It has to be noted that using several chips per symbol gives a performance gain with respect to SNR but not to \(E_{b}/N_{0}\) due to the difference in the data rate. For UWB transmissions, the SNR cannot be improved by increasing the transmit power because of the spectral mask limitation. In general, a trade-off between the data rate and the SNR improvement at the receiving side has to be made.

we now look at the BER performance under the influence of a strong narrowband interference. The simulations in this section consider AWGN channels with and without additional narrowband interferer. The narrowband interferer is the WLAN signal and has the same setting as in Fig. 3.14 with an average SIR of -15 dB at the input of the comb filter. The number of chips per symbol \(N\) is 3, 15, and 63 for both DS-OOK and DS-PPM. Only the energy detector is considered after the comb filter. The receiver for DS-PPM does not require any extra modification for the inclusion of the
strong narrowband interference. However, the decision threshold calculation for the DS-OOK method becomes more difficult. The mean of the interferer energy at the output of the comb filter has to be estimated and included in the calculation. The BER performance of the DS-PPM and DS-OOK with $N=3, 15, 63$ under the influence of narrowband interference (SIR $= -15$ dB) are shown in Fig. 3.18. The BER performance for $N=1$ without the narrowband interference are also included as the benchmarks.

The BER performance for both methods is improved with increasing number of chips per symbol. The degradation of the performance due to the narrowband interference for DS-PPM is much less than that for DS-OOK. As we can see from the Fig. 3.14, the residual frequency left over is sinusoidal. The narrowband interferer gives a contribution to both integrator outputs for DS-PPM, and because the outputs are compared, the influence is reduced. For the DS-OOK the influence remains.

Now we look at the influence of the spreading sequence choice for the multiple access. As shown in Fig. 3.13, the m-sequence is not orthogonal but easy to generate, while ZCZ sequence is an orthogonal sequence set but potentially support less num-
3.2 Comb Filter Based System Concept for UWB Transmissions

Figure 3.18: BER performance of DS-OOK/DS-PPM modulation ($N = 3, 15, 63$) for the AWGN channel with strong narrowband interference (SIR = -15dB).

The BER performance of the DS-PPM with eight users are considered. The sequence considered is the m-sequence $N = 127$ and ZCZ sequence $N = 128$, $Z = 4$. The channel is AWGN channel and the users are synchronized. To simulate a near-far scenario, the average received power of the wanted user signal compared to each of other users (near-far ratio) is 0 dB and -10 dB for the m-sequence and -10 dB for the ZCZ sequence. The BER performance for all the settings are shown in Fig. 3.19.

The BER performance from the m-sequence is worse than the ZCZ sequence, because the interference are not completely eliminated due to the imperfect correlation property. The performances from the ZCZ sequence remain the same even with many users transmit in parallel. We could also see that the difference in the received signal strength does not affect the performance in case the ZCZ sequence is used, whereas the m-sequence could suffer from this.
3 Transmission with Impulse Radio Ultrawideband

3.3 Shortened Delay Comb Filter Receiver Structure

3.3.1 Problem Statement

The assumption we have so far is that the chip period $T_c$ is sufficiently longer than the multipath delay spread of the channel $T_m$, i.e. $T_c > T_m$ for DS-OOK and $\frac{T_c}{2} > T_m$ for DS-PPM. The main challenge for implementing the comb filter based receiver is to realize the wideband analog delay element. The longer the delay, the more difficult is its realization. The attenuation in the comb filter loop as well as the group delay variation have to be controlled. Shortening the delay means that the assumption from above does not hold any more. The chip period is shorter and overlapping of the channel impulse responses occurs at the receiver. An example of such a situation is illustrated in Fig. 3.20. In this example, we look at the two possible received signals of the DS-PPM modulated signal. The duration of the two-path channel is longer than half of the chip period. For illustration, dirac delta impulse is used as the impulse shape.
3.3 Shortened Delay Comb Filter Receiver Structure

The influence from the interchip interference in the output signals after the comb filter is obvious. The DS-PPM transmission is designed such that the signal after the comb filter exists only either in the first part (‘0’ is sent) or in the second part (‘1’ is sent). Because of the overlapping, the signal can be spread over the two intervals. Not only the energy collected in the intended interval is reduced but the energy from the other interval is also increased, and this disturbs the detection process. The BER performance of the DS-PPM can be severely degraded because of this. In this section, we present a novel concept for the comb filter based UWB receiver. The delay of the

Figure 3.20: Illustration of the interchip interference after the comb filter when the channel impulse response is too long. The transmitted signal is DS-PPM, and the duration of the two-path channel is longer than half of the chip period.
analog delay element can be shortened while the performance remains.

### 3.3.2 Signal Analysis

An extension of the DS-CSK modulation (see Sec. 2.8) is considered here. The basic concept of the DS-CSK modulation is to use the spreading sequences as means for the transmission of data bits. In addition to the basic DS-CSK principle, some impulses are added at the beginning of each transmit symbol as a cyclic prefix similar to OFDM transmission. The purpose of the cyclic prefix is to have a predictable intersymbol interference, and the number of cyclic prefix impulses depends on the length of the channel impulse response. Assuming that the channel impulse response is limited to a number $M$ of chip intervals $T_c$, the number of the cyclic prefix impulses would be $M - 1$. The cyclic prefix impulses are weighted by the cyclic shifted spreading sequence. The transmitted signal $s_i(t)$ of the extended DS-CSK for the $i$-th user with the spreading sequence $c_{i,n}$ can be written as

$$s_i(t) = \left( p(t) * \left[ \sum_{n=-(M-1)}^{N-1} c_{i,n} \delta(t - nT_c) \right] \right) * \left( \sum_{k=-\infty}^{\infty} \delta(t - kT_s) \right), \quad (3.15)$$

where $p(t)$ is the UWB impulse used at the transmit side, $\delta(t)$ is a dirac delta impulse, and '$*$' means convolution. $T_s$ is the symbol interval, and $T_c$ is the 'chip' interval. It has to be noted again that the index $n$ of the spreading sequence belongs to a cyclic group of modulo $N$, e.g. $c_{i_N,N} = c_{i_N,0}$ and $c_{i_{N-1},N-1} = c_{i_{N-1},N-1}$. The extended DS-CSK symbol waveform consists of $M + N - 1$ impulses in which the first $(M - 1)$ impulses are the cyclic prefix impulses and $N$ impulses are used for transmitting the information, and therefore $T_s = (M + N - 1) \cdot T_c$. The sum at the right hand side of (3.15) describes an infinite transmission of DS-CSK waveforms. For binary transmission, each user is assigned with a code set $C_i = [c_{i_0}, c_{i_1}]$. Different users use different pairs of sequences for their binary transmissions. Illustration of the transmit symbol for the extended DS-CSK modulation with $N = 4$, $M = 3$, $c_{i_0} = [1, 1, -1, -1]$, and $c_{i_1} = [1, -1, -1, 1]$ is shown in Fig. 3.21. It has to be noted that these parameters are chosen for illustration purposes, and $N \gg M$ is usually considered in practical situations.

The basic comb filter based receiver for the DS-CSK modulation is shown in Fig. 3.22. It consists of two parallel comb filters with despreading (multiplication) followed by the energy detectors. The multipliers are fed with different spreading sequences. The energies from the two branches are then compared for the decision of the transmitted
information bits. The advantage of this modulation technique is that no threshold calculation is required at the receiver.

We now look at the signals at the comb filter receiver in more detail. For simplicity, we assume perfect synchronization between the transmitter and the receiver. We look at one transmit symbol only, and therefore the index for the spreading sequence is $i$. The channel is assumed to be time invariant within the symbol interval. With the cyclic prefix being long enough, we can consider each transmitted symbol independently and we can use the periodic or cyclic convolution property similarly as in OFDM. After cutting out the cyclic prefix in the received signal the following results

$$g_i(t) = h_p(t) \ast_{cyc} \left[ \sum_{n=0}^{N-1} c_{i,n} \delta(t-nT_c) \right], \quad (3.16)$$

where $h_p(t)$ is the effective channel impulse response, which is the convolution between the transmit impulse $p(t)$ and the channel impulse response $h(t)$. '\( \ast_{cyc} \)' means a cyclic convolution. If the effective channel impulse response is too long ($M > 1$), the resulting interchip interference is included in (3.16).
Figure 3.22: Comb filter based receiver with the energy detectors for the DS-CSK modulation.

To get a clear view of the received signal, it is better to represent the effective channel impulse response in a ‘chip-based’ form, i.e. dividing it into $T_c$ intervals. The effective channel impulse response $h_p(t)$ is of length $MT_c$ and it can be represented in the chip-based form as

$$
h_p(t) = \sum_{m=0}^{M-1} h_p(t) \cdot \text{rect} \left( \frac{t - mT_c - (T_c/2)}{T_c} \right)$$

(3.17)

$$
= \sum_{m=0}^{M-1} \hat{h}_p^{(m)}(t - mT_c).
$$

(3.18)

where,

- $h_p^{(m)}(t)$ is the effective channel impulse response $h_p(t)$ in the $[mT_c, (m + 1)T_c]$ interval. It can also be written as

$$
h_p^{(m)}(t) = h_p(t) \cdot \text{rect} \left( \frac{t - mT_c - (T_c/2)}{T_c} \right).
$$

(3.19)

- $\hat{h}_p^{(m)}(t)$ is the time-shifted version of the $h_p^{(m)}(t)$. This function has non-zero value only for the $[0, T_c]$ interval. It can be expressed as

$$
\hat{h}_p^{(m)}(t) = h_p^{(m)}(t + mT_c).
$$

(3.20)

The relationship between $h_p^{(m)}(t)$, $\hat{h}_p^{(m)}(t)$ and $h_p(t)$ is illustrated in Fig. 3.23.
3.3 Shortened Delay Comb Filter Receiver Structure

Figure 3.23: Illustration of the relation between \( h_p(t) \), \( \hat{h}_p^c(t) \) and \( \hat{h}_p^{(m)}(t) \).

Using this chip-based approach, it can be proved, (see Appendix A.), that the received signal \( g_i(t) \) in (3.16) can be rewritten as

\[
g_i(t) = \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} c_{i,n-m} \hat{h}_p^{(m)}(t - nT_c).
\]  

(3.21)

Similar to the basic comb filter receiver concept, \( g_i(t) \) is then multiplied with the spreading sequence waveform \( d_j(t) \) from (3.5). The spreading sequence used in the receiver is assumed for now \( c_{j,n} \). The output of the multiplier can be expressed as

\[
u_{ij}(t) = g_i(t) \cdot d_j(t) = \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} c_{i,n-m} c_{j,n} \hat{h}_p^{(m)}(t - nT_c).
\]  

(3.22)

As we can see from (3.22), the comb filter input signal \( u_{ij}(t) \) in each chip interval \( T_c \) is the overlay of \( M \) signal parts. As an example, we look at the time interval \([T_c, 2T_c]\) of \( u_{ij}(t) \) with \( M = 3 \). The signal in this interval is

\[c_{i,1}c_{j,1}\hat{h}_p^{(0)}(t - T_c) + c_{i,0}c_{j,1}\hat{h}_p^{(1)}(t - T_c) + c_{i,N-1}c_{j,1}\hat{h}_p^{(2)}(t - T_c)\].

The first term is the intended signal that was sent in this period and the second and third term are the interchip interference from the previous chips. It has to be noted that the last term is the result from the cyclic prefix. If the cyclic prefix is not included in the transmitted signal, this term would be the result from the intersymbol interference, and therefore would be unpredictable. At the comb filter, the chips are then delayed and iteratively summed up. The last chip period of the output signal is chosen for further processing similar to the basic concept. The comb filter accumulation process for \( N = 4 \), \( M = 2 \) is illustrated in Fig. 3.24 using the chip-based approach. The last chip period of the comb filter output signal \( v_{ij}(t) \) can be written as
$$v_{ij}(t) = \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} c_{i,n-m} c_{j,n} \hat{h}_p^{(m)}(t). \quad (3.23)$$

For visualization purpose, $v_{ij}(t)$ can also be expressed in another form as

$$v_{ij}(t) = \left( \sum_{n=0}^{N-1} c_{i,n} c_{j,n} \right) \cdot \hat{h}_p^{(0)}(t) + \left( \sum_{n=0}^{N-1} c_{i,n-1} c_{j,n} \right) \cdot \hat{h}_p^{(1)}(t) + \ldots \quad (3.24)$$

$$\ldots + \left( \sum_{n=0}^{N-1} c_{i,n-(M-1)} c_{j,n} \right) \cdot \hat{h}_p^{(M-1)}(t).$$

We can see that different parts of the effective channel impulse response $h_p(t)$ are weighted differently. The choice of the spreading sequences and their correlation properties play an important role here. Different parts of the channel impulse response can be selected by the choice of the receive sequence $c_{j,n}$. In general, the detection of the signal from the $i$-th user can be done by selecting $j = i$. By using $c_{i,n}$ as the receiving sequence, the output signal is the combination of $N\hat{h}_p^{(0)}(t)$ and interference from the other parts of $h_p(t)$ that are weighted by the shifted autocorrelation values. If the shifted autocorrelations are zero, we can suppress the unwanted parts perfectly. This process is illustrated in Fig. 3.25. The other parts of the $h_p(t)$ can be selected by using the cyclic shifted version of $c_{i,n}$ at the receiver. For example, $c_{i,n-1}$ can be used for extracting the $\hat{h}_p^{(1)}(t)$. This process is illustrated in Fig. 3.26. Multiuser interference can be considered in the case where $j \neq i$. In this case the effective channel impulse responses are all weighted by the cross-correlation function instead. In the scenario where perfect synchronization is not assumed, the timing error can be easily considered as an additional delay to the channel impulse response $h_p(t)$. 
3.3 Shortened Delay Comb Filter Receiver Structure

\[ v_{ij}(t) = \sum_{n=0}^{3} \sum_{m=0}^{1} c_{i,n-m} c_{j,n} \hat{h}_{p}^{(m)}(t) = \]

Figure 3.24: Illustration of the comb filter accumulation process with \( N = 4, M = 2 \).
Receiving Signal $g_i(t)$: 
$$\sum_{n=0}^{N-1} c_{i,n} \hat{h}_p^{(0)}(t-nT_c) + c_{i,n-1} \hat{h}_p^{(1)}(t-nT_c)$$

Despreading $d_i(t)$: Matched sequence 
$$\sum_{n=0}^{N-1} c_{i,n} \text{rect}(t-nT_c)$$

Signal after multiplication $u_i(t)$: 
$$\sum_{n=0}^{N-1} c_{i,n} c_{i,n} \hat{h}_p^{(0)}(t-nT_c) + c_{i,n} c_{i,n-1} \hat{h}_p^{(1)}(t-nT_c)$$

Signal after comb filter $v_i(t)$:
$$[8(1)\hat{h}_p^{(0)}(t) + [4(1)+4(-1)]]\hat{h}_p^{(1)}(t)$$

Figure 3.25: Illustration of the channel extraction with shortened delay comb filter for $N=8, M=2$. The transmit and receive sequences are matched.
3.3 Shortened Delay Comb Filter Receiver Structure

**Receiving Signal** $g_i(t) : \sum_{n=0}^{N-1} c_{i,n} \hat{h}_p^{(0)}(t-nT_c) + c_{i,n-1} \hat{h}_p^{(1)}(t-nT_c)$

**Despreading** $d_i(t) : \text{Cyclic shifted sequence } \sum_{n=0}^{N-1} c_{i,n-1} \text{rect}(t-nT_c)$

**Signal after multiplication** $u_{i,i}(t) : \sum_{n=0}^{N-1} c_{i,n-1} c_{i,n} \hat{h}_p^{(0)}(t-nT_c) + c_{i,n-1} c_{i,n-1} \hat{h}_p^{(1)}(t-nT_c)$

**Signal after comb filter** $v_{i,i}(t)$:

$\hat{h}_p^{(0)}(t) + \hat{h}_p^{(1)}(t)$

Figure 3.26: Illustration of the channel extraction with shortened delay comb filter for $N = 8, M = 2$. The receive sequence is the shifted version of the transmit sequence.
3.3.3 Rake-like Comb Filter Based Receiver

The property of being able to extract different parts of the channel impulse response gives an opportunity to construct a receiver by using the rake receiver concept from Sec. 2.7.1. This means for each part of the effective channel impulse response with interval $T_c$, we have one rake branch for collecting its energy. For binary DS-CSK, two parallel set of rake branches with different corresponding spreading sequence sets are needed. The spreading sequences for each set of the rake branches are cyclic shifted version of one single sequence. The energies of the rake branches in the set are summed up and compared with the energy sum of the other branches set. The comb filter in every branch is reset at the end of every symbol like in the basic concept. The block diagram of the rake-like comb filer based receiver for DS-CSK is shown in Fig. 3.27.

![Block diagram of the rake-like comb filter based receiver for DS-CSK transmission.](image)

In comparison to the basic concept described before, the delay of the analog delay element can be much shorter. If the delay is shortened, for example, from 12 ns to 2 ns, this is much more realistic with regard to realization, i.e. size, attenuation, frequency dependency (group delay variation). Moreover, the data rate is higher because of the shorter chip period.
3.3 Shortened Delay Comb Filter Receiver Structure

We now look at the BER performance of the rake-like comb filter receiver compared to the basic concept. A deterministic two-path channel similar to the one that was used for the illustration of the interchip interference in Fig. 3.20 is considered. In this setting, the energy of the two multipath components is the same, therefore the interchip interference is even stronger than in the example of Fig. 3.20. The 5-th derivative Gaussian impulse with $\sigma = 51$ ps is considered, and the ZCZ sequence with $N = 128$, $Z = 4$ is used. Only one user is considered to focus on the effect of the interchip interference. The first path delay is 1 ns and the second path comes at 6 ns. In Fig. 3.28, the BER performance from the basic comb filter receiver for the DS-PPM modulation with $T_c = 8$ ns, and the DS-CSK modulation with $T_c = 4$ ns, 8 ns are compared with the performance of the rake-like comb filter receiver for the DS-CSK modulation with $T_c = 4$ ns.

![Figure 3.28: BER performance of DS-CSK modulation with the rake-like comb filer based receiver for the 2-path deterministic channel.](image)

We can clearly see that the DS-PPM detection does not work under strong interchip interference. The DS-PPM modulation could provide good performance if the chip period is selected large enough, however with a data rate decrease and more difficulty in realization. The performance for the DS-CSK with the basic comb filter receiver with $T_c = 4$ ns suffers from the delay shortening because it cannot collect all of the...
energy from the channel impulse response. The performance from the rake-like comb filter receiver with $T_c = 4 \text{ ns}$ is the same as the basic method with $T_c = 8 \text{ ns}$. The performance remains with the shortening of the analog delay element for the rake-like comb filter receiver. It has to be noted that the total delay is still the same. The individual analog delay element is shortened to $4 \text{ ns}$ but we need two rake branches to cover the channel impulse response of $8 \text{ ns}$. It is more beneficial in practice to have several short analog delay elements than one long delay element because of the smaller physical size, less attenuation and a more constant group delay.

We now look at a more practical channel model for the evaluation of our proposed receiver structure. In the following, the WBAN channel model from [40], which was introduced in Sec. 2.6.4, will be considered. The UWB impulse shape is the RC waveform with $T = 0.5 \text{ ns}$ and $f_0 = 4.5 \text{ GHz}$ as shown in Fig. 2.7. Note, that this impulse shape is selected due to the limitation of the channel model specification. The proposed receiver concept supports any UWB impulse shapes. Each channel realization consists of two groups of multipath components with a lognormal fading statistic for each group. We used 4000 channel realizations for the BER performance evaluation. The total propagation time of the channels is $12 \text{ ns}$. The parameters are selected such that the ratio between the energy of first path to second path is $6 \text{ dB}$ on average. It has to be noted that in some of the channel realizations the second path was stronger than the first path. Eight users with the same average receive energy are considered. We consider a DS-CSK transmission with $T_c = 2 \text{ ns}$, which corresponds to $M = 6$. The spreading sequences were m-sequences with $N = 127$. An example of a received signal at the input of the comb filter is shown in the upper part of Fig. 3.29. It is normalized to the amplitude of the target signal (range $\pm 1$). Additive noise is not considered here to focus only on the ICI and MUI suppression. We can see that both, ICI and MUI are very strong here. The target signal cannot be distinguished from the interference at all. The SIR in this example is $-18 \text{ dB}$. In the lower part of Fig. 3.29, the original channel impulse response (black) is compared to the results taken from six different rake branches with $T_c = 2 \text{ ns}$. From the results we can see that the interference is suppressed very well. Only some residual interference can be seen which is due to the m-sequences which have no perfect cross and autocorrelation functions. The interference can be totally eliminated by using appropriate ZCZ sequences.

There are two possible ways to implement the rake-like comb filter receiver. The first method is called 'parallel' approach. In this one, the transmission is rather straightforward. The number of rake branches in one set is $M$. The spreading sequence for each branch is selected such that the total integration area cover the whole channel impulse response. The second method is called 'serial' approach. For this
3.3 Shortened Delay Comb Filter Receiver Structure

Figure 3.29: Input signal of the comb filter (upper). Comparison between the actual channel impulse response and the output signal of the rake branches (lower).

method, the number of rake branches in one set is less than $M$. The transmission of one information bit is repeated over several symbols depends on the number of rake branches per set. The spreading sequences are cyclically shifted over the symbol period to collect all of the signal energy. For example, the channel impulse response that cover $M = 6$ chip interval can be detected with 3 rake branches per set over 2 symbols. The receiver collect the energies from $h_p^{(0)}(t)$, $h_p^{(1)}(t)$ and $h_p^{(2)}(t)$ in the first symbol, and $h_p^{(3)}(t)$, $h_p^{(4)}(t)$ and $h_p^{(5)}(t)$ in the second. The total length of the analog delay in the receiver is reduced but also the data rate. There is certainly a loss with respect to $E_b/N_0$ because of the data rate difference but the performance with respect to the SNR remains. A trade-off between the complexity of the analog delay element realization and the data rate has to be made.

We now look at the BER performance of these two types of rake-like comb filter receiver in the WBAN channel. For the original basic comb filter concept, $T_c = 12$ ns and 6 ns are considered. We label them as ‘Basic 1’ and ‘Basic 2’, respectively. For the rake-like receiver, we label the ‘parallel’ approach, i.e. $T_c = 2$ ns with 6 rake branches,
as ‘Rake-like 1’. This receiver yields equivalent integration time of 12 ns in one symbol. For ‘Rake like 2’, one data bit is transmitted over two symbol period. The number of rake branches per set is 3, and the equivalent integration time of 6 ns per symbol is achieved. The BER performance for the four receivers are shown in Fig. 3.30.

Figure 3.30: BER performance of DS-CSK modulation with the basic comb filer based receiver and the rake-like comb filer based receiver with the WBAN channel.

We can see that the performance of our original concept got worse if the delay is shortened. There is a loss of about 4 dB at the BER for $10^{-4}$. The results for ‘Rake-like 1’ is comparable to ‘Basic 1’. The difference comes from the energy lost by the cyclic prefix and the residual interference due to the m-sequences. The ‘Rake-like 2’ is comparable to the ‘Basic 2’ at high $E_b / N_0$. The results show that we can achieve very similar performance to the original concept with much shorter analog delay element. The new concept also adds more flexibility in the implementation of the receiver. We have considered only equal gain combining of the signal energy from different rake branches. Given that more channel knowledge is available at the receiver, improvement in the performance can be expected similarly done in the optimization method for the basic energy detector in [70].
3.4 A Novel Detection Method for Code-Reference UWB Transmission

In this part, we look at a novel detection method for code-reference (CR) modulated UWB signals. The CR modulation technique is closely related to the transmitted reference (TR) modulation technique introduced in Sec. 2.5.3. The basic idea of the TR modulation is to transmit an additional pilot (reference) impulse within the transmitted symbol for the channel estimation purpose. For TR, the pilot impulse and the information impulse are separated in time, and the pilot impulse including the channel impulse response is delayed to be used as a template reference for the correlation detection as discussed in Sec. 2.7.3. Recently, this idea has been expanded from the time domain pilot impulse separation in TR to the frequency domain and the code domain, i.e. frequency-reference (FR) modulation and the CR modulation, respectively [97–99]. The CR modulation technique and the FR modulation technique transmit the information impulses and pilot impulses simultaneously, and they are separated in their respective domain. There are several names for the CR modulation technique in literature, i.e. code-multiplexed transmitted-reference [97], code-shifted reference [98], code-orthogonalized transmitted reference [99]. There are some minor differences between them but they all share the same basic principle, i.e. using code for the pilot/information separation, and they also share similar receiver concepts.

In general, each $i$-th user is assigned two spreading sequences (codes), i.e. $c_i$ for the information and $c_{ri}$ for the pilot (reference). In this work, the cyclic shifted guard period introduced in the last section for DS-CSK is also included in the CR transmitted signal model for later analysis with the comb filter based receiver. The transmit signal of the CR modulation for the $i$-th user is given as

$$s_{CR,i}(t) = \sum_{k=-\infty}^{\infty} \sum_{n=-(M-1)}^{N-1} \left[ b_k c_{i,n} p(t - nT_c - kT_s) + c_{ri,n} p(t - nT_c - kT_s) \right],$$

where $p(t)$ is the UWB impulse, $T_s$ and $T_c$ are the symbol period and chip period. The channel impulse response duration is expected to be $MT_c$, and therefore $M - 1$ impulses are added as the cyclic-shifted guard period. $N$ is the number of information impulses (chips) per symbol, i.e. $T_s = NT_c + (M - 1)T_c$, and $b_k$ is the transmit information symbol. We consider binary transmission with BPSK for the information encoding, and therefore $b_k \in \{-1, 1\}$. The cross-correlation between the spreading sequences of the information $c_i$ and the reference $c_{ri}$ shall be low (ideally zero).
In [97,98], more than two sequences are assigned for one transmitter. Several information symbols with different information sequences are transmitted simultaneously along with the pilot, hence the name multiplexing and code-shifted.

### 3.4.1 State of The Art

The main focus of the conventional CR receiver design is to get rid of the analog delay element, which is the essential part of the autocorrelation receiver for the TR detection as shown in Fig. 2.20. Two receiver structures for CR have been reported so far, and they are shown in Fig. 3.31. \( d_{ir}(t) \) is a train of rectangular impulses weighted by the scrambled version between \( c_i \) and \( c_{ri} \), i.e.

\[
d_{ir}(t) = \sum_{n=0}^{N-1} c_i c_{ri} \text{rect}(t-nT - \frac{T_c}{2}).
\]

The decision device for both receiver structures is performed based on a sign decision.

![Figure 3.31: Block diagram of the conventional CR-UWB receivers.](image)

It has to be noted that these two receivers are actually the same type of receiver with different orientation. The implementation with squaring device (Fig. 3.31(a)) is simpler and more popular. Power splitter and power combiner are not needed, so it is easier to implement. Interestingly, these receiver structures were adopted from the receiver for the FR modulation technique. As being pointed out in [97,100], FR and CR are closely related. The difference can be narrowed down to the elementary shape of the carrier signal, i.e. half-cosine for FR and rectangular for CR. FR can be seen as a special case of CR, in which the codes are picked from the Walsh-Hadamard sequence set and the elementary shape of the carrier signal is sinusoidal instead of square wave. In [101], it was shown that the optimal selection of the CR codes from the Walsh-Hadamard sequence set for the multiuser case resembles the carrier frequencies in the FR modulation.

The conventional detection method relies on the fact that the transmit signals \( s_{CR,i}(t) \) are pruned because of the combination between the information and the pilot sequences. The transmit signal for single-user CR can be regarded as a burst-mode
PPM modulation, as being pointed out in [100]. For example, we have a CR transmission with $c_i = [1, -1, 1, -1]$, $c_{ri} = [1, 1, -1, -1]$ and $b_k \in \{-1, 1\}$. The effective transmit sequences are the summation of these two sequences, which are $[2, 0, 0, -2]$ for $b_k = 1$ and $[0, 2, -2, 0]$ for $b_k = -1$. We can see that the two different basic waveforms occupy different time slots in the symbol similar to the burst-mode PPM modulation. We consider the received signal with no noise, and therefore the receive sequences after the squaring device are $[4, 0, 0, 4]$ for $b_k = 1$ and $[0, 4, 4, 0]$ for $b_k = -1$. The key idea is to use the scrambled sequence between $c_i$ and $c_{ri}$ as the selector. In this example, the scramble sequence $c_{ir} = c_i c_{ri} = [1, -1, -1, 1]$. After the multiplication, the received sequences are $[4, 0, 0, 4]$ for $b_k = 1$, and $[0, -4, -4, 0]$ for $b_k = -1$. The integrator collects the energy over the symbol period and the decision can then be performed by sign decision.

The key assumption for this detection method is that the chip period $T_c$ shall be large enough to avoid channel impulse response overlapping, i.e. $M = 1$. The overlapping of the received signal could cause large BER performance degradation similar to the DS-PPM as shown in Fig. 3.28. One critical drawback for the conventional detection method is that the SNR gain from transmitting several impulses per symbol is not achievable, because the received signal is squared before being summed up. In general, the number of chips per symbol $N$ cannot be so high because the performance with respect to $E_b/N_0$ would get worse with the increasing $N$. The multiuser interference as well as the narrowband interference are not suppressed before the squaring device, and this could result in a large BER performance degradation. Moreover, it is not easy to increase the data rate because the receiver is only well-suited for BPSK modulated information impulses. After the squaring device, the noise is squared, and therefore the distribution is Chi-square. The decision thresholds for multi-level modulation technique, such as 4PAM, are very difficult to calculate with the Chi-square distribution (similar to the basic energy detector). The data rate can be increased by multiplexing as shown in [97, 98] but the family size of the sequence set is very limited, especially for small $N$. In summary, the advantage of the conventional receiver is that no analog delay element is needed, but there are still many other aspects needed to be improved.

### 3.4.2 Comb Filter Based Receiver for Code-Reference UWB

The key idea of our proposal is to separate the pilot impulses from the information impulses at the receiver. The pilot impulses including the channel impulse response shall be used for the correlation detection. The main objectives are to achieve the SNR gain and to suppress the interference (multiuser interference, inter-chip interference,
narrowband interference) at the receiver. As shown in the previous sections, the comb filter based receiver is designed to perform exactly all these tasks. The assumption on the length of the chip period $T_c$ can also be relaxed, since the comb filter based receiver allow overlapping of the channel impulse responses as shown in Sec.3.3. We can see that the CR transmitted signal in (3.25) holds some similarity to the DS-CSK transmitted signal in (3.15). The comb filter based CR receiver can be constructed in a similar way as the comb filter based DS-CSK receiver in Fig. 3.22, or using the rake-like concept as in Fig. 3.27. For DS-CSK, the energy of the branches is compared to determine the branches that contain the UWB signal. The difference is that, for CR, one set of branch is used for extracting the reference signal while the other set is assigned for the information signal. The ‘clean’ chip-based reference signal is then used as the template for the correlation detection of the ‘clean’ chip-based information signal. The decision is based on sign. The rake-like comb filter based CR receiver structure is shown in Fig.3.32

![Figure 3.32: Block diagram of the rake-like comb filter based receiver for CR-UWB transmission.](image)

We now look at the comb filter output in more details. The CR received signal can be seen as a combination of two received signals from (3.21) in parallel. One received signal with sequence $c_i$ is modulated by $b_k$, and the other with $c_r$ is unmodulated. Considering one branch of the comb filter which has $c_{j,n}$ as the multiplication
sequence, according to (3.21)-(3.23), the output of the comb filter can be written as

\[ v_{ij}(t) = \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} b_k c_{i,n-m} c_{j,n} \hat{h}_p^{(m)}(t) + \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} c_{r_i,n-m} c_{j,n} \hat{h}_p^{(m)}(t), \]  

where \( \hat{h}_p^{(m)}(t) \) is one part of the effective channel impulse response as illustrated in Fig. 3.23. We can see that the reference part and the information part are weighted differently. The correlation property of the sequences plays a crucial role here. For the reference branches, we select the receiver sequence \( c_{j,n} \) such that the reference part is amplified, while the information part is suppressed. The similar idea goes for the information branches. The SNR is improved and the interference are suppressed as explained in Sec. 3.2. we can say that the reference signal and the information signal are ‘cleaned’, which is an improvement compared to the conventional detection method. With the comb filter based receiver, the SNR gain is achievable for CR-UWB transmission. No explicit channel estimation is needed. The synchronization is relaxed compared to the conventional correlation based receivers because the reference impulses are always synchronized to the information impulses. The required synchronization accuracy is on chip-level. Only simple adjustment is required from the DS-CSK comb filter receiver, i.e. no additional analog delay element or complicated devices.

In general, the BER performance of the CR transmissions is expected to be the same as DS-CSK for the same chip period \( T_{c,CSK} = T_{c,CR} \). Similar to the relationship between TR and PPM, discussed in Sec. 3.1, the Euclidean distance between two symbols in the CR constellation is smaller than the DS-CSK constellation because half of the transmitted power is given to the reference signal. However, the noise term for CR involves the product of two independent processes, i.e. the noise term from two comb filter outputs, whereas the quadratic noise terms are considered for the DS-CSK.

The advantage of the CR detection with the comb filter based receiver over the conventional detection method and the DS-CSK transmissions is the flexibility. For the DS-CSK and conventional CR detection, the data rate is limited by the family size of the sequence set. More sequences are needed to increase the data rate. The complexity of the receiver is also increased because more parallel branches are needed for the corresponding sequences. For comb filter based CR receiver, there is no such problem. The detection is based on the correlation detection, therefore the decision threshold is very simple to calculated. The multi-level modulation such as 4-ASK or 8-ASK can be easily used in place of BPSK, and the receiver structure remains the same.
i.e. no additional branches are needed. The only change is that the decision device is a multi-level threshold decision instead of sign. The BER performance degradation with respect to $E_b/N_0$ for increasing the data rate is similar to the classical M-ASK transmission.

Moreover, the performance of the comb filter based CR receiver can be further improved. In general, the comb filters are reset every symbol period because the incoming waveforms over different symbols are not the same. Unlike the information branches, the reference branches sum up the pilot signals which are unmodulated, and therefore the input signal of the comb filter is expected to be the same as long as the channel remains unchanged. The comb filter for the reference branches can be kept for longer than one symbol period without resetting. Given that the comb filter sum up the pilot signal over $M_s$ symbols, the SNR improvement of the reference template in the ideal case is $10 \cdot \log_{10}(M_sN)$ [dB]. If the channel remains unchanged and $M_s$ is large enough, the performance of the CR-UWB detection with the comb filter based receiver can reach the matched filter bound for the CR-UWB correlation detection, i.e. 3dB worse than the matched filter bound for the BPSK correlation detection because of the pilot transmitting power.

### 3.4.3 Simulation Results

In the following, we look at the performance of the comb filter based CR receiver in different scenarios. It has to be noted that the comb filter modifications for improvement/implementation are done on the reference branches only, i.e the information branches are always ideal and reset every symbol. First, we look at the BER performance in an ideal case where the comb filters of the reference branches have a memory over $M_s = 1, 2, 10, 100, 1000$ periods, i.e. the output of the comb filter is the sum over the latest $M_s$ symbols. The BER performance for the comb filter without reset is also included. The channel is assumed to be unchanged within these periods. A deterministic two path channel with strong interchip interference is considered, which is similar to the scenario for Fig. 3.28. The effective channel impulse response cover 8 ns, and the chip period is $T_c = 4$ ns, i.e. $M = 2$. The number of rake branches per set is two, and the resulting effective integration period cover 8 ns. There are eight users transmitting in parallel, and the spreading sequence set are the ZCZ sequences with $N = 128, Z = 4$. The correlation properties of the spreading sequence set are illustrated in Fig. 3.13 (b). The BER performances from this scenario can be regarded as the benchmarks for later practical implementation. The conventional detection method, from Fig. 3.31, with the same setting as well as with the one user case in the AWGN channel are included for comparison. The BER performances are shown in Fig. 3.33.
3.4 A Novel Detection Method for Code-Reference UWB Transmission

Figure 3.33: BER performance of CR detection with $M_s = 1, 2, 10, 100, 1000$, and ‘no reset’ comb filter based receiver for a deterministic 2-path channel. For comparison, the BER performance for the conventional method in the 2-path channel and AWGN channel are included.

We can see that the BER performances from the comb filter based CR receiver are far superior to the conventional detection method. The BER performance for the comb filter with no reset reach the matched filter bound for the OOK, PPM correlation detection (3 dB worse than BPSK) shown in Fig. 3.1. The performance for $M_s = 1$ is the same as the DS-CSK in Fig. 3.28. The performances for the comb filter receiver with memory fall between these two cases. The BER performance can be improved with increasing $M_s$, and we can see that the performance is reaching the matched filter bound for $M_s = 1000$. It has to be noted that the performance of the conventional method can be improved with decreasing $N$, but it would still be worse than the comb filter receiver with $M_s = 1$.

As shown in (3.26), the correlation properties of the sequence set are the main key for the interference suppression. The previous BER performances were ideal because the selected ZCZ sequence can eliminate all the interference. In this section, we look at the BER performance for the case where the correlation properties are not perfect, but still maintain the low cross-correlation values. The ratio between the length of the se-
sequence $N$ and the cross-correlation value plays an important role on the performance degradation. In this part, the ZCZ sequence with $N = 128$, $Z = 4$ and m-sequence with $N = 31$, 127 are considered. The channel is the same deterministic 2-path channel with strong interchip interference, and eight users are transmitting in parallel with equal average received energy (near-far ratio = 0 dB). The comb filter with $M_s = 1, 100$ and without reset are considered. The BER performances are shown in Fig. 3.34. Some performance degradation can be seen but we can see that the receiver can still give good results for non-ideal sequence set.

![BER performance of CR detection with the comb filter based receiver with no reset and $M_s = 1, 100$. Three spreading sequence sets are considered, i.e. m-sequence with $N = 31, 127$ and ZCZ sequence with $N=128$, $Z = 4$.](image)

We now look at the practical implementation aspect for the comb filter based CR receiver. The comb filter with memory, which give results in Fig. 3.33, can be easily implemented in the digital domain. However, the challenge occurs when the analog implementation of the comb filter is considered. We propose two methods for the analog implementation of the comb filter based CR receiver. The first method is to reset the comb filter of the reference branches after some fixed number of iteration $M_r$. The SNR improvement of the reference signal reaches the peak just before the reset, and it has to be built up again afterwards. The BER performance from this type of implementation shall be in between the performance from $M_s = 1$ and $M_s = M_r$. We
consider the same scenario as in Fig. 3.33, i.e. eight users, 2-path deterministic channel, ZCZ sequence with $N = 128$, $Z = 4$. The BER performance for the comb filter based CR receiver with $M_r = 1, 2, 10, 100, 1000$ are shown in Fig. 3.35. The BER performance for the comb filter without reset is also included as a benchmark.

![Figure 3.35: BER performance of CR detection with $M_r = 1, 2, 10, 100, 1000$, and 'no reset' comb filter based receiver for a deterministic 2-path channel.](image)

Alternatively, the attenuation in the analog comb filter loop gain $G_c$ can be seen as a memory. In the ideal case, we have $G_c = 1$ which means that the memory is perfect. In Fig. 3.7, it was shown that for $G_c < 1$, the comb filter output signal saturated at some point. This is because the memory in the comb filter is not perfect and the information of the signal is lost after going through the comb filter several times. We can implement the reference branches by attenuated comb filter without reset. For this type of implementation, the exact number of the iteration in the comb filter is very important. The number of chips per symbol is limited because the SNR gain $G_p$ of the comb filter $G_c < 1$ has an upper bound as shown in (3.2), and illustrated in Fig. 3.8. For this scenario, we consider 1 user with the AWGN channel, i.e. $M = 1$, and Walsh-Hadamard sequences set with $N = 8$ and 16. The comb filter for the reference branches have $G_c = 1, 0.99, 0.95, 0.9, 0.85$, while $G_c = 1$ is considered for the information branches. The BER performance for the comb filter based CR receiver for different $G_c$ are shown in Fig. 3.36. The BER performance for the comb filter for
$G_c = 1$ with $M_r = 1$ is also included as a benchmark. The improvement in the BER performance from the basic implementation, i.e. $G_c = 1$ and $M_r = 1$, can be seen in almost all the settings. One particular setting that give worse performance is $N=16$ and $G_c = 0.85$. This is because the maximum achievable SNR gain $G_p$ for $G_c = 0.85$ is 8.24 dB, as calculated in (3.2), is significantly smaller than the ideal comb filter gain for $N = 16$, which is 12 dB as calculated in (3.1). In other words, the early reference impulses vanished before the end of the symbol period.

![Figure 3.36: BER performance of CR detection with the comb filter based receiver with $G_c = 1, 0.99, 0.95, 0.9, 0.85$ for 1 user in the AWGN channel.](image)

In summary, we have shown that the performance of the comb filter based CR receiver performs much better than the conventional receiver. It has to be noted that the main objective of the conventional CR receiver is to eliminate the analog delay element, which is found in the TR-UWB detection. Our proposed receiver concept contains analog delay elements in the comb filters, but the required length of these analog delays is much smaller than those needed for the TR detection. The delay can be shortened as demonstrated by the rake-like comb filter receiver concept. We have shown that the performance of the comb filter based receiver can reach the optimum matched filter bound under certain conditions.
The extreme short duration of the UWB impulse signals make them well-suited for both communications and ranging applications. As mentioned in Sec. 2.9, the estimated distance from the propagation delay can be used in many applications, e.g. tracking of moving object, imaging of unknown object, as illustrated in Fig. 2.23. The conventional delay estimation method is a time based approach, which can be performed with the impulse correlator receiver. The propagation delay can be determined by searching for the maximum/minimum correlation value between the received signal and the template impulse. This method works well if the SNR is high enough. There is a certain SNR threshold where the performance could become sig-
significantly worse as demonstrated by the performance bounds in Fig. 2.24. The problem occurs if the main peak of the UWB impulse correlation signal cannot be easily distinguished from its side lobes of the autocorrelation function due to the noise. The resolution provided by UWB is very good compare to other systems, because the multipath components are usually resolvable. However, in some applications, the channel can be a highly dense multipath propagation. The performance of the conventional method can be strongly degraded because of the bias from additional un-resolvable multipath components. Super-resolution algorithms are needed to extract these multipath components.

In this chapter, we want to address an algorithm for delay estimation and movement tracking, which can be used for the UWB ranging problems. The conventional method can be classified as a maximum-likelihood estimation, since it does not use any prior information for the estimation. More advance techniques involving a-priori information could be used for improving the performance in the lower SNR case. Particle filtering is a known technique used in localization applications and tracking in dynamic scenarios [102–105]. It implements a sequential Bayesian estimation by using Monte-Carlo methods. The estimation is based on a posterior density, and it uses a movement model to incorporate the temporal correlation of the change of the estimated parameters.

Another major challenge for the UWB ranging is the analog to digital conversion. Sampling of signals with such large bandwidth might be impractical due to power consumption. The problem of the conventional sampling method is that it can be very wasteful when applying to the UWB signals. Sampling can be view as a scalar product operation between the sampled signal and measurement signals. For conventional sampling method, the measurement signals are time-shifted Dirac delta functions. UWB systems usually operate with low duty cycle, and therefore the samples are mostly noise. Compressed sensing is an emerging concept that acquiring signal (sample) can be done with different approach. The underlying assumption is that the signal shall be ‘sparse’ in some domain. Random signals are used as the measurement signals instead of the Dirac delta function. With this approach, there is always some information about the incoming signal in every sample. This sampling technique is well-suited for ‘sparse’ signals, and UWB signals with low duty cycle are relatively sparse in time domain. In this work, the compressed sensing is considered for two purposes. The first is to use it as an alternative method for acquiring UWB signals, and the second is to use it as the super-resolution radar algorithm.

The comb filter based receiver can be used for improving the performance of the UWB ranging systems. As shown in Sec. 3.2, the channel impulse response with
improved SNR is available at the output of the comb filter receiver. The conventional method as well as the two advanced techniques, i.e. particle filtering and compressed sensing, can be included in the comb filter based receiver structure.

4.1 Particle Filtering

The estimation of unknown parameters of a system of interest from a set of noisy observable measurement is a problem that can be found in many situations, e.g. estimating the propagation delay and the amplitude of the multipath components from the UWB received signal. This problem can be regarded as a stochastic filtering process, and the Bayesian filtering is a well-known method for solving this problem via Bayes’ theorem. Implementing the optimal Bayesian filter can be difficult because it involves complex high-dimensional integrals. Particle filtering is a sub-optimum Bayesian filtering algorithm, which can achieve optimum solution under some restrictions.

In general, the tracked systems are dynamic and their underlined model can be non-linear and non-Gaussian. Dynamical systems are usually modeled using a state-space (time-based) approach with discrete-time formulation, since the measurements usually arrive in certain intervals. Dynamical systems in this sense can be characterized by a state vector $x_k$ and a measurement vector $z_k$. Two models describing their relation and the evolution of the dynamical systems have to be defined. The first model is the system model (state transition equation), which describes the evolution of state vector $x_k$ from time instant $k-1$ to time instant $k$. The second model is a measurement model (measurement equation), which is a model describing the relation between the state vector $x_k$ and the measurement vector $z_k$ at time instant $k$. Given that $f_k(.)$ and $h_k(.)$ are known (possibly non-linear) functions, the state transition equation and the measurement equation can be described as

$$x_k = f_k(x_{k-1}, v_k), \quad (4.1)$$

$$z_k = h_k(x_k, n_k), \quad (4.2)$$

where $v_k$ and $n_k$ are the vector of transition noise and the vector of the measurement noise, respectively. The state transition equation and the measurement equation can be represented in a probabilistic form as a transition prior (movement model) $p(x_k|x_{k-1})$ and a likelihood $p(z_k|x_k)$, respectively. It can be seen from (4.1) and (4.2) that a state $x_k$ is only a function of the previous state $x_{k-1}$ with some transition noise,
and the measurement \( z_k \) is only a function of \( x_k \) with additional measurement noise. Therefore the system model together with the measurement model form a first order Markov process, as shown in Fig. 4.1. Notice that the state vector \( x_k \) is hidden and the objective of the stochastic filtering is to estimate it from the available measurement \( z_k \).

![Figure 4.1: A first order Markov model for a dynamic system.](image)

### 4.1.1 Recursive Bayesian Filtering Algorithm

The objective of the Bayesian filtering is to obtain the posterior density \( p(x_{1:k} | z_{1:k}) \) from a set of measurements \( z_{1:k} \) to estimate the current state vector \( x_k \). Roughly speaking, the posterior density \( p(x_{1:k} | z_{1:k}) \) is the probability density that the state sequence of the dynamical system is \( [x_1, x_2, x_3, ..., x_k] \) given that the history of measurements is \( [z_1, z_2, z_3, ..., z_k] \). The Bayesian filtering can provide the optimal solution in the sense of computing the posterior density [106]. The posterior density is regarded as the complete solution to the estimation problems, because all of the available statistical information are included in it [107]. An initial density \( p(x_0) \), the movement model \( p(x_k | x_{k-1}) \), and the likelihood \( p(z_k | x_k) \) are the tools for the posterior density estimation. Typically, the estimation of \( x_k \) is required at every time step when a new measurement \( z_k \) is received. The calculation of \( p(x_{1:k} | z_{1:k}) \) at every time step \( k \) can result in increased computation complexity and high memory requirement, since all of the measurements up to that point are reprocessed and have to be kept. To overcome this problem, a recursive approach is a common and convenient method. The esti-
4.1 Particle Filtering

Information for each step is performed sequentially and based only on the solution from the previous step \( p(x_{1:k-1}|z_{1:k-1}) \) and the new measurement data \( z_k \). As a result, the complete history of the measurement data is not needed. In this case, the posterior density \( p(x_{1:k}|z_{1:k}) \) can also be represented as \( p(x_k|z_{1:k}) \), and the state vector \( x_k \) can be easily estimated at every time step. The recursive Bayesian filtering can be divided into two stages: prediction and update.

**Prediction**

The goal of the prediction stage is to obtain the prior density \( p(x_k|z_{1:k-1}) \), which is the probability density of \( x_k \) given that only the measurement data up to time step \( k-1 \) are available. The Chapman–Kolmogorov equation (law of total probability) and the assumption that \( x_k \) depends only on \( x_{k-1} \) are the main keys in obtaining the prior density. The prediction equation can be written as

\[
p(x_k|z_{1:k-1}) = \int p(x_k|x_{k-1})p(x_{k-1}|z_{1:k-1})dx_{k-1}.
\]

(4.3)

We can see that the prior density \( p(x_k|z_{1:k-1}) \) can be found by using a combination of the movement model \( p(x_k|x_{k-1}) \) and the posterior \( p(x_{k-1}|z_{1:k-1}) \) from the previous time instant \( k-1 \). Notice that the initial density \( p(x_0) \) is used as the prior density for the first time step.

**Update**

In order to obtain the posterior density \( p(x_k|z_{1:k}) \), the latest measurement \( z_k \) is used for updating the prior \( p(x_k|z_{1:k-1}) \) from (4.3) via Bayes’ theorem. The update equation can be written as

\[
p(x_k|z_{1:k}) = \frac{p(z_k|x_k)p(x_k|z_{1:k-1})}{p(z_k|z_{1:k-1})},
\]

(4.4)

where \( p(z_k|z_{1:k-1}) \) is called an evidence probability density. For the estimation of \( x_k \), this term can be neglected or expressed as a constant value because it is independent from the state vector \( x_k \).

Fig. 4.2 is an illustration of the connection between the prediction and update processes of the recursive Bayesian filtering. In summary, the prior density \( p(x_k|z_{1:k-1}) \) is constructed in the prediction process from the movement model \( p(x_k|x_{k-1}) \) and the posterior density in the previous time step \( p(x_{k-1}|z_{1:k-1}) \). It is then combined with
the likelihood \( p(z_k|\mathbf{x}_k) \), which can be obtained after a new measurement \( z_k \) at time instant \( k \) is available, to estimate the current posterior density \( p(x_k|z_{1:k}) \).

![Block diagram of update and prediction process of the recursive Bayesian filter.](image)

There are several criterion to estimate the state vector \( \mathbf{x}_k \) from the posterior density. Two common methods are the minimum mean-square error (MMSE) estimate, which is the conditional expectation of the state \( \mathbf{x}_k \) with respect to measurements \( z_{1:k} \), and the maximum a posteriori (MAP) estimate, which searches for the maximum value of the estimated posterior density. These two solutions can be expressed as

\[
x_k^{\text{MMSE}} = E \{ \mathbf{x}_k | z_{1:k} \} = \int \mathbf{x}_k \cdot p(\mathbf{x}_k | z_{1:k}) d\mathbf{x}_k, \tag{4.5}
\]

\[
x_k^{\text{MAP}} = \arg \max_{\mathbf{x}_k} p(\mathbf{x}_k | z_{1:k}). \tag{4.6}
\]

The MAP estimate has lower complexity but suffers some drawbacks especially in a high-dimensional space. High probability density does not always guarantee a good
solution. The high probability density could be a result from a narrow peak, and it is possible that the actual state belongs to the smaller but broader density mass.

Unfortunately, the Bayesian filtering can only provide a conceptual solution, as it can not be determined analytically in general. The evaluation of complex high-dimensional integrals is required for the computation of the probability densities in the Bayesian filtering algorithm. In practice, the optimal Bayesian filtering can only be implemented under strict restrictions. Two well-known optimal recursive Bayesian filtering algorithms are Kalman filter and grid-based filter. The basic assumptions for the Kalman filter is that the dynamical system equations, i.e. (4.1) and (4.2), are linear and the posterior density at every time step is Gaussian. The grid-based filter represents the posterior density in a discrete state space. The complexity of this method grows exponentially with the number of dimensions. Therefore, it is only well-suited for low-dimensional estimation problems. There are two sub-optimal algorithms which were derived from these two optimal methods: extended Kalman filter and approximated grid-based filter. The extended Kalman filter can handle non-linear dynamic system equations but still assume the posterior density to be Gaussian, while the approximated grid-based filter uses cells instead of discrete points in the state space. More details on these four methods can be found in [107].

Particle filtering is one of the emerging concepts that implement the sub-optimal recursive Bayesian estimation. The advantage of this algorithm is that the dynamic systems can be described by nonlinear functions and the posterior density is not restricted to Gaussian. There are many variant of particle filters. The most common one is the sampling importance resampling (SIR) particle filtering, which will be described in more details in the following.

### 4.1.2 Sampling Importance Resampling Particle Filtering

Particle filtering performs suboptimum non-linear filtering with the Monte Carlo sampling principle for implementing recursive Bayesian filter [107]. The idea of this algorithm is to represent the posterior density \( p(x_k|z_{1:k}) \) by a set of random samples (particles) with associated weights. The state vector \( x_k \) are estimated based on these samples and weights. The posterior density is represented in a discrete form similar to the grid-based method. Unlike the fixed points in the grid-based method, the position of the particles in the state space change from one time step to another. Using particles with associated weights, the posterior density \( p(x_k|z_{1:k}) \) can be represented as
\[ p(x_k|z_{1:k}) \approx \sum_{n=1}^{N_s} w_k^{[n]} \delta(x_k - x_k^{[n]}), \]  

(4.7)

where \( x_k^{[n]} \) is the position of the \( n^{th} \) particle in the state vector space. \( w_k^{[n]} \) is the weight of \( n^{th} \) particle. \( N_s \) is the number of particles. The approximation of the posterior density in (4.7) approaches the true posterior density, if the number of particles \( N_s \) is sufficiently large. In other words, the particle filtering can be regarded as the optimal Bayesian filtering given that the number of particles is large enough.

As the name implies, the two important elements of the SIR particle filtering are the importance sampling principle and the resampling algorithm. The classical Mote Carlo sampling draws the samples via the posterior density, and this can be difficult for the practical implementation [107]. On the other hand, the importance sampling principle draws the samples using another proposal distribution and weights the samples according to how they fit to the posterior density. In practice, it is very common to choose the transitional prior \( p(x_k|x_k^{[n]}|_{k-1}) \) as the importance density. This selection is proven to be both effective and simple as shown in [107]. The resampling algorithm is performed every time step \( k \) to eliminate the particles with low weight. If the resampling is not performed, a problem called degeneracy occurs. The degeneracy problem describes the situation where most of the particles wander around the state space without any restrictions. Therefore, it is very likely that the total particle weight concentrates only on a few particles that falls in the high density area. Most of the contributions from the other particles do not count because their weight are too small. The resampling algorithm redraws the particles according to their weight. The small particles are eliminated and re-spawn from the larger ones. The number of the duplicate samples from the large particles depends on their relative weight to the total weight sum \( \sum_{n=1}^{N_s} w_k^{[n]} \). After the resampling process, the total number of the particles remain the same, and the weight of all particles is reset to \( 1/N_s \).

We look now at the prediction and update processes at time step \( k \) for the SIR particle filtering. The samples are drawn from the transitional prior density \( p(x_k|x_k^{[n]}|_{k-1}) \) or the initial density \( p(x_0) \) in the first time step. The new measurement \( z_k \) becomes available and the importance weights can then be calculated. Compared to other type of particle filters, the importance weights for the SIR particle filtering are much simpler to calculate. In general, the weight of the particles shall be carried from one step to the next, but the SIR particle filtering always resets the weights every time step because of the resampling process. Therefore, the weight is directly related to the likelihood and the relation is given as
4.1 Particle Filtering

\[
\tilde{w}_k^{[n]} \propto p(z_k|x_k^{[n]})
\] (4.8)

After the weight calculation, the approximation of the posterior density can be drawn according to (4.7). The weight sum \( \sum_{n=1}^{N_s} \tilde{w}_k^{[n]} \) is then normalized to represent the true probability density. The result can be estimated by MMSE or MAP as in (4.5) and (4.6), respectively. After the estimation, the resampling process starts and then the prediction process, according to the movement model \( p(x_{k+1}|x_k^{[n]}) \), is performed. The randomness in the movement model gives some diversity to the particles that spawn from the same (large) particle in the resampling process. The new measurement becomes available and the processes repeated. The illustration of one cycle of SIR particle filtering is shown in Fig. 4.3.

Simply drawing the samples from the movement model in the prediction step and calculating the weights directly from the likelihood in the update step are the main advantages of the SIR particle filtering. One drawback is that the movement model \( p(x_k|x_k^{[n]}|_{k-1}) \) is independent from the measurements \( z_k \). As a result, the particles will explore the state space without making use of the knowledge from the observations. Moreover, the resampling algorithm is performed at every time step and this can lead to another problem in the state space exploring aspect. It is possible that the diversity among the particles is very low because most of the particles originate from the same particle after some iterations. Partially redraws some fixed number of particles after the resampling or perform the resampling process once every few iterations could be helpful in dealing with this problem. It should be noted that particle filtering is a method well-suited for systems with noisy measurements. Using a particle filtering in a high SNR scenario is not entirely appropriate because the likelihood density can be too narrow [106]. Moreover, the particle filters cannot outperform the Kalman filters or the grid-based method if their strict assumptions are true.

4.1.3 Particle Filtering for UWB Radar

To demonstrate the use of particle filtering in UWB ranging systems, a setup consisting of a bistatic UWB transceiver and a moving metal plate is used. Measurements of the reflected signal are used for the distance estimation and the movement tracking of the metal plate. The background application behind this setup is the tracking of the chest movement for the vital sign detection (breathing/heart rate) for biomedical diagnostics. The model is used as a rough approximation for later tests with human bodies. A schematic block diagram of the setup and an example of a receiving signal after correlation with a target 30 cm away is shown in Fig. 4.4.
The 5th derivative Gaussian impulse fitting to the FCC mask is used and the repetition rate is 200 MHz (i.e. $T_s = 5$ ns). The corresponding distance for two way wave propagation of 5 ns is 75 cm. The metal plate moves periodically within 5 mm range. The receiver is a cross-correlation receiver, and the analog-to-digital conversion (ADC) is performed by the equivalent time sampling method using impulse template as illustrated in Fig. 2.26. The parameters are selected such that the equivalent sampling frequency is approximately 270 GHz. For a conventional maximum tracking method, an accuracy of 0.5 mm can be achieved. The received signal consists of two main contributions which can be seen in each period, corresponding to two-path.
propagation on the channel. The first path is the direct path between the transmit and the receive antennas (direct coupling signal). This signal has very strong visible ringing due to signal reflection from the impedance mismatch. The second signal is a signal reflected from the moving metal plate. The transmit signal is a train of unweighted UWB impulse and can be written as

\[ s(t) = \sum_{k=-\infty}^{\infty} p(t - kT_s), \quad (4.9) \]
where \( p(t) \) is an UWB impulse with a spectrum fitting with given regulation masks. (4.9) means that an infinite number of periods are transmitted. As \( p(t) \) will be considered here as analogue of a symbol waveform for a digital transmission, the period \( T_s \) is also called ‘symbol period’. It is straightforward then to consider the transmission path from transmitter via the reflector to the receiver as ‘channel’. We use a tapped delay line to model this (multipath) channel. The channel we considered is slow time-varying. The amplitude and the delay time do not change within a symbol period \( T_s \).

The channel impulse response at the \( k \)-th symbol period is then given as

\[
h_k(t) = \sum_{m=0}^{M-1} \alpha_{m,k} \delta(t - \tau_{m,k}), \tag{4.10}\]

where \( \delta(t) \) is a dirac delta impulse, \( \alpha_{m,k} \) and \( \tau_{m,k} \) are the time-variant amplitude and propagation delay of the \( m \)-th path at \( k \)-th symbol, respectively. The total number of paths for the multipath propagation is \( M \). We assume no band limitation for this channel impulse response model. To model the physical system, the received impulse \( \tilde{p}(t) \) now represents the transmitted impulse \( p(t) \) as well as all remaining linear filtering \( r_m(t) \) in the transmit-receive chain of the \( m \)-th path, i.e. \( \tilde{p}_m(t) = p(t) * r_m(t) \). The received signal can be written as

\[
g(t) = \sum_{k=-\infty}^{\infty} \sum_{m=0}^{M-1} \alpha_{m,k} \tilde{p}_m(t - \tau_{m,k} - kT_s) + n(t). \tag{4.11}\]

The additive white Gaussian noise \( n(t) \) shall model the noise of the low-noise amplifier at the receiver. As shown in Fig. 4.4, we have \( M = 2 \) for this measurement setup. The first path is the direct path between the transmit and the receive antennas (direct coupling signal). This signal has very strong visible ringing due to signal reflection from impedance mismatch. The second signal is a signal reflected from the moving metal plate. The signal after the correlation can be represented as

\[
z(t) = \sum_{k=-\infty}^{\infty} \sum_{m=0}^{1} \alpha_{m,k} \varphi_{pp_m}(t - \tau_{m,k} - kT_s) + n_p(t), \tag{4.12}\]

where \( \varphi_{pp_m} \) is the cross-correlation of the received impulse and the template impulse for \( m \)-th path. The two paths are slightly different in shape because of the band limitation and different reflections of each propagation paths as seen in Fig. 4.4. The signal in (4.12) is then sampled by the impulse correlator with the equivalent-time sampling method. \( L \) samples at times \( (n + kL)T_s \), \( n = 0, \ldots, L - 1 \), can be grouped together.
to form a vector $z_k$. This leads to a symbol-based discrete time model, which can be expressed as

$$z_k = \Phi(\tau_k)\alpha_k + n_k,$$  \hspace{1cm} (4.13)

where $\Phi(\tau_k)$ is a $L \times M$ signal matrix which has UWB cross-correlation signal vectors as columns, i.e. $\Phi(\tau_k) = [\phi_0(\tau_{0,k}), \phi_1(\tau_{1,k})]$, and $\phi_m(\tau_{m,k})$ is a $L \times 1$ column vector representing the cross-correlation impulse $\varphi_{p\hat{p}}(t - \tau_{m,k})$. $\tau_k = [\tau_{0,k}, \tau_{1,k}]^T$ and $\alpha_k = [a_{0,k}, a_{1,k}]^T$ are $M \times 1$ column vectors containing the delay and amplitude of each path at time $k$. $n_k$ represents samples of the additive Gaussian noise process.

We can now see that the interested unknown vectors $x_k$ for the particle filtering framework in this setup are the amplitude $\alpha_k$ and delay $\tau_k$. The measurement signal vector $z_k$ is directly the received signal vector from (4.13). The dimension of $x_k$ can be reduced because $\alpha_k$ can be estimated from $z_k$ and $\tau_k$ using simple geometry mapping. The estimation of the amplitude vector is given by

$$\hat{\alpha}_k = (\Phi(\tau_k)^H \Phi(\tau_k))^{-1} \Phi(\tau_k)^H z_k.$$ \hspace{1cm} (4.14)

According to (4.14), the estimated amplitude vector $\hat{\alpha}_k$ and the signal matrix $\Phi(\tau_k)$ are used for describing the likelihood function as

$$p(z_k|\tau_k) = (2\pi \sigma^2)^{-1} \exp \left[-\frac{(z_k - \Phi(\tau_k)\hat{\alpha}_k)^H(z_k - \Phi(\tau_k)\hat{\alpha}_k)}{2\sigma^2} \right].$$ \hspace{1cm} (4.15)

The likelihood function is used for the calculation of the particle weights according to (4.8). The movement model for the particle filtering prediction process can be constructed by a basic first order Markov chain. This model suggests that the propagation delay evolve slowly in a similar way as the previous step with some additional noise. The movement model can be described by

$$\tau_k = \tau_{k-1} + \Delta_{k-1} + n_m,$$ \hspace{1cm} (4.16)

where $\Delta_{k-1} = \tau_{k-1} - \tau_{k-2}$ is the temporal change of the channel delay vector and $n_m$ is an artificial noise vector which adds randomness to the movement model. Each particle has a delay vector $\tau_k^{[n]}$ (state vector), i.e. its own equations (4.14)-(4.15) for the update and the prediction process. The result from every time step is the posterior density $p(\tau_k|z_{1:k})$ as given in (4.7). The delay can be estimated from the posterior density with MMSE method from (4.5).
4.1.4 Simulation Results

Particle filtering with a 2-path model is used for the propagation delays tracking. In the following, tracking results for a moving metal plate with distances of approximately 90 cm and 120 cm are discussed. The metal plate move periodically back and forth within 5 mm range. The symbol period is 5 ns, and therefore the distance of ambiguity for this setup is 75 cm. For the estimations, we use the a-priori knowledge that the target is in the 75-150 cm range. This is sufficiently large for our target application. The reflected signal appears one period after the original impulse was transmitted. Particle filtering with 1000 particles is considered and the results are compared with a conventional maximum tracking method. The initialization of the state vector for each particle covers the area of 30 cm range (2 ns) from the target with uniform distribution. The movement of the first path (direct coupling) and the second path (metal plate) are tracked simultaneously. We are only interested in tracking the moving metal plate. The tracking of the direct coupling path is used for suppressing the bias in the scenario where the two paths are coincided. The shape of the direct coupling signal $\varphi_{p0}(t)$ is measured and used at the receiver. The information about the exact shape of the reflected signal from the moving metal plate $\varphi_{p1}(t)$ is unknown. For tracking this signal, we approximate the $\varphi_{p1}(t)$ by the ideal cross-correlation of the 5-th derivative Gaussian impulse $\varphi_{pp}(t)$.

**Target Distance 120 cm**

We first consider a setup with the moving target at approximately 120 cm. An example for one period of the received signal is shown in Fig. 4.5 (upper). The reflected signal is located at around 8.8 ns. In this example, the reflected signal can be still recognized easily. Fig. 4.5 (lower), shows the tracking results of the moving metal plate from both methods (particle filtering and maximum tracking). The tracking results fit well with each other and the small movement of 5 mm was estimated correctly. We can see that the particle filtering is more robust. This improvement comes from the fact that the movement model incorporates the temporal correlation of the change of the channel delays in different time steps. The conventional method does not use this information and the results can change rapidly. The particle filtering needs some iterations to converge to the correct estimate.
4.1 Particle Filtering

Figure 4.5: Received signal with target distance $\approx 120\,\text{cm}$ and tracking result for target distance $\approx 120\,\text{cm}$ from conventional maximum tracking and particle filtering.

**Target Distance 120 cm with Additional Noise**

We consider the case where the noise is strong and the peak of the signal cannot be easily identified. To reduce the SNR of the signal, Gaussian noise was added to the measurement data of the previous part, so that the SNR was approximately $0\,\text{dB}$. An example for one period of the received signal $z_k$ is shown in Fig. 4.6 (upper). The target signal is not clearly visible any more and the peak value is disturbed strongly by noise. The tracking results are shown in Fig. 4.6 (lower). The conventional method does not work because the main peak of the cross-correlation is now comparable to the secondary peaks. The tracking results from the conventional method rapidly jump from one peak of correlation function to the other. The particle filtering still gives good estimates, because it does not consider only the maximum point in the target signal but the waveform as a whole. The movement model also plays a role in this improvement because the estimated delay cannot be changed too rapidly.
Figure 4.6: Received signal with target distance \( \approx 120 \text{ cm} \) with additional noise and tracking result for target signal \( \approx 120 \text{ cm} \) with additional noise from conventional maximum tracking and particle filtering.

**Target Distance 90 cm**

Now we consider the tracking of the reflected signal for the moving metal plate at a distance of 90 cm. An example of a received signal is shown in Fig. 4.7 (upper). We can see that the reflected signal is coincided with the ringing of the direct coupling signal. In this case, the amplitudes of the target signal and the ringing are comparable. It is not easy to distinguish between these two signals any more. This is the same situation as in radar where we have cluttering. It can cause a bias to the estimation. A comparison of the tracking results from maximum tracking and particle filtering is shown in Fig. 4.7 (lower). We can see that the maximum tracking performs very badly because of the bias. The tracking results from particle filtering are very good. The use of the multipath propagation model eliminates the error bias given by the clutter (direct coupling).
4.1 Particle Filtering

Figure 4.7: Received signal with target distance \(\approx 90\) cm and tracking result for target distance \(\approx 90\) cm from conventional maximum tracking and particle filtering.

**Additional Remarks**

The drawback of the particle filtering is mainly its complexity. Our system model is relatively simple and this drawback is not so serious. For vital sign detection or small-scale localization, the model given in this paper is sufficient. Using particle filtering in parallel with conventional methods and exchanging information between them could also help reducing the complexity. The complexity of the method can be adjusted by the constraints given to the model. With more complexity, we could improve the results for the delay tracking especially for low SNR. The amplitude vector was estimated directly from the received signal. The approximation of the \(a_k\) in (4.14) is likely to be inaccurate when the measurement vector \(z_k\) is noisy. It is also possible to keep this amplitude vector as an additional unknown part in the state vector \(x_k\).

The system model in this work considers a fixed 2-path channel model. The algo-
Advanced Concepts for UWB Ranging Systems

An algorithm can also cope with the case of more multipath components and more dynamic scenarios with changing in the number of paths as in [108]. Moreover, the example of cluttering here was stationary, but the method can also work with dynamic cluttering without additional modification.

Additionally, we would like to thank Dr. Bernd Schleicher and Dayang Lin from Institute of Electron Devices and Circuits, University of Ulm and Dr. Mario Leib from Institute of Microwave Techniques, University of Ulm for providing us the measurement setup for the experiments in this section.

4.2 Compressed Sensing

One of the major challenges for the UWB impulse technology is to bring (sample) the analog UWB signals into the digital domain. The Nyquist-Shannon sampling theorem states that the sampling frequency has to be twice of the cut-off frequency or the signal bandwidth in order to perfectly reconstruct the analog signal [109]. Simple analog-to-digital conversion (ADC) is not feasible for UWB systems because of their large bandwidth. The power consumption for such high sampling frequency is too demanding for any practical realizations. Therefore, digital signal processing techniques such as noise averaging is not easy to perform. A big part of the total signal processing shall be done in the analog domain before doing ADC with lower sampling rates. A practical solution to acquire the UWB signals is to perform the equivalent-time samples, which was introduced in Sec. 2.9.2. The samples are collected over several repetitive UWB signals to combine as one period of UWB signal in the equivalent-time domain. Since UWB systems are usually operated with low duty cycle, the signal exists only in a short period of time. In other words, the UWB signals are relatively ‘sparse’ in time domain. We can say that the conventional sampling approach is very wasteful because most of the samples are just noise.

In recent years, many interests were drawn to compressed sensing [110]. It is a concept where unknown signal can be acquired with less measurements (samples) than the sampling theorem requires. The main conditions are that the unknown signal must have a ‘sparse’ representation in some domain and that the set of signals used for measuring is ‘incoherent’ with respect to the unknown signal. We can see that this fits quite well to the UWB systems with low duty cycle.

For conventional sampling, the measurements (samples) were performed in time domain. The sampling process can be generalized as scalar products between the unknown signal and measurement signals. Time-shifted Dirac-delta impulse signals are used as the measurement signals for the conventional sampling method. As men-
tioned above, for this approach, most of the samples give no additional information when the unknown signal is sparse in time domain. For compressed sensing, the measurement signals are random signals, e.g. Gaussian noise and Walsh-Hadamard functions. Every measurement (sample) contains some information about the unknown signal. The reconstruction process is more complicated for compressed sensing but the number of samples can be much less than the conventional approach.

There have been some studies about applying compressed sensing to UWB systems for several purposes, e.g. channel estimation [111,112] and communication [113,114]. In this work, compressed sensing will be used in the scope of channel estimation. Two scenarios are considered. The first one is to use it for acquiring (sampling) signal. The second is to apply it in the post processing to achieve super-resolution. We first look at the performance in simulated scenarios, i.e. ideal channel, AWGN channel and multipath propagation channel. The algorithm is then verified by two different measurement setups, which aim to perform a localization of an active device inside a lossy medium and a high resolution imaging of an unknown object. The main objective is to estimate the propagation delay of multipath components from highly attenuated and strongly interfered UWB received signals. The attenuation is caused by the wave propagation through a lossy medium and the interference can caused by multi-scattering of an object with complex-shape. Applying compressed sensing directly to these types of signals is a challenging task because both signal and noise are reconstructed at the same time. Our results show that with a proper setting, we can cope with these problems to some degree.

4.2.1 Fundamentals

Sampling, as we know, is to take a measurement of an analog signal at one time instant. The process can be explained mathematically as a scalar product between the analog signal and a dirac impulse signal. The dirac impulse signal is considered as the sampling function. It is obvious that this method does not suitable for signals which are sparse in time domain. The idea of compressed sensing is to choose a more suitable sampling function for the sparse signal case. As a generalization of the conventional sampling, the acquisition of an unknown signal $z(t)$ can be described by taking measurements with more general sampling functions $a_k(t)$. This means to calculate the following scalar product:

$$y_k = \int_{-\infty}^{\infty} a_k(t)z(t)dt,$$  \hspace{1cm} (4.17)
where \( y_k \) are the samples, and the scalar product will also be termed 'measurement'. In general, \( a_k(t) \) span a subspace of the signal space containing \( z(t) \).

For conventional sampling, the \( a_k(t) \) is a time-shifted dirac impulse signal \( \delta_k(t) \). Several samples are combined and the analog signal \( z(t) \) is 'reconstructed'. Interpolation is very simple and sufficient for reconstructing the signal. For compressed sensing, the measurement is done in a different way. A simple yet most effective approach is by using random signals, such as noise or predefined PN sequence, as measurement signals \( a_k(t) \). Unlike conventional sampling, the samples do not resemble the original signal at all. Every sample contains some information about the original signal in contrast to the conventional case where no useful information in samples is possible.

Compressed sensing can lead to a much less number of samples but required more complex reconstruction operator to extract the information from the samples. Roughly speaking, there is a trade off between the number of samples and the complexity in the signal reconstruction. The reconstruction techniques for compressed sensing will be discussed in more details later in the next section. An illustration of conventional sampling and compressed sensing is illustrated in Fig. 4.8.

In the following, we consider a discrete-time representation of (4.17). By taking \( K \) measurements, we can write the whole sampling process as

\[
y = Az,
\]

where \( y = [y_1, y_2, \ldots, y_K]^T \) is a Kx1 vector containing the samples and \( A \) is a KxN measurement matrix with a discrete-time representation of \( a_k(t) \) in its rows \( a_k \). \( z \) is a Nx1 vector which represents \( z(t) \) with \( N \) samples. For comparison, \( N \) is the amount of samples required to satisfy the Nyquist-Shannon sampling theorem of \( z(t) \). In order to acquire full knowledge of \( z \) from \( y \) and \( A \), \( K \geq N \) is required. If \( K < N \), the system of equations is underdetermined and the solution for \( z \) is not unique. An illustration of the discrete-time representation in (4.18) for the conventional sampling and compressed sensing is shown in Fig. 4.9. The measurement matrix \( A \) for the conventional sampling is an identity matrix that represent the time-shifted dirac functions.
4.2 Compressed Sensing

Figure 4.8: Comparison between the conventional sampling and the compressed sensing reconstruction.
Figure 4.9: Illustration of the discrete-time signal model of the conventional sampling (upper) and the compressed sensing (lower).
4.2 Compressed Sensing

Dictionary of Basis

One important thing in compressed sensing is that the sparsity of the considered signals $\mathbf{z}$ is not limited only to the time domain. It is sufficient for the sparse recovery that the signal $\mathbf{z}$ can be represented in some domain that is sparse. Given that $\mathbf{z} = \mathbf{B}\mathbf{x}$ we can rewrite the system equation in (4.18) as

$$\mathbf{y} = \mathbf{A}\mathbf{z} = \mathbf{AB}\mathbf{x} = \mathbf{D}\mathbf{x}, \quad (4.19)$$

where $\mathbf{x}$ is a vector that can represent $\mathbf{z}$ in a sparse domain and $\mathbf{B}$ is a $N \times N$ matrix so called 'dictionary of basis' which represents a linear transformation between $\mathbf{z}$ and $\mathbf{x}$. $\mathbf{D} = \mathbf{AB}$ is called an effective measurement matrix. The dictionary can be either achieved through machine learning or predefined, e.g. a Fourier transform, Walsh-Hadamard transform or convolution matrix. If $\mathbf{z}$ is already in the sparse domain, the dictionary of basis $\mathbf{B}$ can be simply represented by an identity matrix. The recovery of $\mathbf{x}$ with the knowledge of $\mathbf{y}$, $\mathbf{A}$ and $\mathbf{B}$ would lead to the solution of $\mathbf{z}$. In Fig. 4.10, a linear transformation with Walsh-Hadamard transformation matrix is illustrated. We can see that $\mathbf{z}$, which is not sparse at all in time domain, can be represent by a sparse vector $\mathbf{x}$ through the Walsh-Hadamard transformation.

![Diagram](Figure 4.10: Matrix representation of the Walsh-Hadamard dictionary of basis.)
An example of compressed sensing reconstruction through the Walsh-Hadamard dictionary is shown in Fig. 4.11. We consider a signal $z$, which is ‘dense’ in time domain. Assuming that the number of required samples in time domain for this signal is $N = 256$, and it can be represented in Walsh-Hadamard transform domain with four coefficients. The measurements are performed by randomly sampling the signal 30 times ($K = 30$) which is less than the required samples for conventional sampling. In other words, the measurement matrix $A$ is formed by randomly selecting 30 rows from an identity matrix with size $N \times N$. As a result, the effective measurement matrix $D$ is constructed by the corresponding rows of $B$. The original signal in Walsh-Hadamard domain can be reconstructed perfectly and the time domain signal can be recovered with simple inverse Walsh-Hadamard transformation.

Figure 4.11: Example of the sparse reconstruction through the Walsh-Hadamard dictionary of basis. The time domain signal is randomly sampled (top), the signal is first recovered in the sparse domain (middle). The reconstructed time domain signal (bottom) can be calculated through the inverse Walsh-Hadamard transformation.
4.2 Compressed Sensing

Quality of Measurement Matrix for Sparse Recovery

In addition to the basic requirement that the unknown signal shall be sparse in some domain, the measurement functions in the matrix $A$ shall also be ‘incoherent’ to the dictionary of basis $B$ of the sparse domain. The mutual coherence between the measurement matrix $A$ and the dictionary of basis $B$ is a parameter widely used for identifying the quality of the measurement matrix $A$ for sparse recovery of the signal $x$. The mutual coherence between $A$ and $B$ can be calculated as

$$
\mu(A, B) = \max_{1 \leq k, j \leq N} \frac{|(a_k^T, b_j)|}{\|a_k^T\|_2 \|b_j\|_2}
$$

(4.20)

where $a_k$ represents the $k$-th row of $A$, and $b_j$ is the $j$-th column of $B$. $\|\cdot\|_2$ is the 2-norm. The mutual coherence is the maximum absolute value of the cross-correlations between the rows of $A$ and the columns of $B$. Low mutual coherence means that the sample functions are dense in the sparse domain. This ensures that there is always some information about the sparse signal $x$ in every sample. In general, random sampling functions, such as Gaussian matrices and Bernoulli matrices ($\pm 1$ with an equal probability), have low mutual coherence to any fixed basis with high probability [110]. Therefore, they are good sample functions for sparse signal reconstruction. On the other end, an example of the high mutual coherence case is for the conventional sampling matrix and time-domain sparse signals. $A$ is part of an identity matrix, and the mutual coherence between $A$ and $B$, which is an identity matrix, is maximized. As a result, it is clear that the conventional sampling is not well-suited for time-domain sparse signals.

4.2.2 Reconstruction Algorithms

In general, the most common approach to solve the system equation in (4.19) is to use the method of frame (also known as $L_2$ minimization) [115]. It is the simplest method but not well-suited for the sparse signal recovery since the recovered signal would almost never be sparse. We now look at the sparse signal reconstruction methods in compressed sensing. The optimal solution for the sparse signal recovery in (4.19) shall be achieved through the so-called "$L_0$-minimization", which can be written as

$$
\min_x \|x\|_0 \text{ subject to } y = Dx,
$$

(4.21)

where $\|\cdot\|_0$ is 0-norm or the number of non-zero element in the vector. The fundamental problem of the $L_0$-minimization is that it is a NP-hard problem, therefore it is not
straight-forward to find the solution [110]. In general, there are two common methods for coping with this problem. The first one is called convex relaxation, e.g. basis pursuit (BP) proposed in [116]. The basic idea is to substitute the $L_0$-minimization problem by convex $L_1$-minimization. Another method is to use greedy algorithms, e.g. matching pursuit (MP) proposed in [117, 118]. They are iterative algorithms that build a sparse solution by selecting non-zero elements (atoms) in a greedy way one at a time or in groups. The two methods determine the sparse solution in a different way. We can say that BP solves the problem in a top-down manner, while the MP constructs the solution bottom-up. The initial solution vector for BP is at least $M$-sparse ($M$ non-zero elements), while OMP starts with an empty solution vector. The solution from BP can be regards as the global solution of the convex relaxation, while this could not be guaranteed by MP [116]. The advantage of the algorithms based on the MP is their lower computation complexity. In general, a trade-off between the complexity and the performance has to be made.

**Basis Pursuit**

The principle idea of the basis pursuit is to use the $L_1$-minimization instead of the $L_0$-minimization to find the sparse solution of underdetermined systems. The solution for the $L_1$-minimization is the same as $L_0$-minimization under certain conditions, but $L_1$-minimization is a convex problem and can be solved by simple linear programming [116]. The $L_1$-minimization can be expressed as

$$\min_x \|x\|_1 \text{ subject to } y = Dx$$

(4.22)

where $\|x\|_1 = \sum_{n=1}^{N} |x_n|$. A geometrical visualization of the $L_2$-minimization and $L_1$-minimization for a two-dimensional problem is shown in Fig. 4.12. There exist many solutions for the underdetermined system ($K < N$), and they can be represented by a line in the two-dimensional plane. The solution for the $L_2$-minimization is the point on the line that has the smallest distance from the origin, and the process can be visualized by a circle expansion. The solution of the $L_2$-minimization is the point $(x_1,x_2)$ where the circle intersects with the line. On the other hand, an expansion of a diamond shape is considered for the $L_1$-minimization. We can see that the solution of the $L_1$-minimization would always include zero, i.e. $(x_1,0)$ or $(0,x_2)$, as the intersection is always at the corner of the diamond.

There are many criterions describing the condition for the perfect sparse recovery with $L_1$-minimization, e.g. restricted isometry property (RIP), exact reconstruction principle (ERP) and uniform uncertainty principle (UUP) [119–122]. The basic idea is
that the columns in $\mathbf{D}$ shall be almost orthogonal to each others. The system model in (4.19) suggests that a $N$-dimensional vector is mapped (projected) into a smaller $K$-dimensional vector. We can also say that the $n$-th element of $\mathbf{x}$ is mapped into a subspace spanned by the corresponding column of $\mathbf{D}$. Each element shall be mapped into different subspaces in order to be separated again in the reconstruction process. If the subspaces are highly correlated, we can say that the geometry of the new vector space is bad for the sparse reconstruction. Conveniently, it is well-known that random matrices, such as Gaussian matrices and Bernoulli matrices, can guarantee the successful recovery with high probability if the number of measurement $K$ is large enough [121, 122].

We now look at the case where $\mathbf{y}$ is noisy, i.e. $\mathbf{y} = \mathbf{Dx} + \mathbf{n}$, where $\mathbf{n}$ is a $Kx1$ noise vector. The direct application of basis pursuit to this noisy signal would give a problem in sparse signal reconstruction, since the algorithm would try to reconstruct both the signal and the noise together. Some constraints have to be added in the recovery process to suppress the noise. An extension of BP to deal with this problem is called basis pursuit denoise (BPDN), which can be described as

$$\min_{\mathbf{x}} \frac{1}{2} \| \mathbf{y} - \mathbf{Dx} \|_2^2 + \lambda \| \mathbf{x} \|_1,$$

(4.23)

where $\lambda$ is regularization parameter that control the balance between the sparsity and the noise matching of the solution vector. Small value of $\lambda$ would lead to a solution with more non-zero entries, but the difference between $\mathbf{Dx}$ and $\mathbf{y}$ is smaller. The solution from larger value of $\lambda$ is more sparse but less fit to $\mathbf{y}$, which is the wanted

Figure 4.12: Illustration of a 2-dimensional underdetermined system with the solutions from the $L_2$-minimization (left) and the $L_1$-minimization (right)
signal plus noise. In general, the value of $\lambda$ shall be selected according to the SNR. In [116], it was suggested that the $\lambda$ value can be calculated as $\lambda_p = 2\log(p)\sigma$, where $p$ is the cardinality of a normalized dictionary $D$ and $\sigma$ is the standard deviation of the noise.

**Orthogonal Matching Pursuit**

Greedy algorithms based on matching pursuit (MP) are widely considered for the compressed sensing reconstruction because of their low complexity. The MP was initially proposed for a signal decomposition purpose in [117]. The basic assumption of the MP method is that the columns of the effective measurement matrix $D$ are incoherent to each other. We can see from Fig. 4.9 (lower) that if the signal vector $z$ is sparse, $y$ is actually a summation of some column vectors from $A$ with the non-zero elements from $z$ as their weighting factors. Notice that $z$ is already in the sparse domain for this example, i.e. $D = A$ and $x = z$. We consider (4.19) as the basic system model for consistency. Given that only $x_2$, $x_3$ are non-zero elements in $x$. We have $y = x_2\hat{d}_2 + x_3\hat{d}_3$, where $\hat{d}_n$ is the $n$-th column of $D$. This characteristic is the key idea in the MP algorithm to construct the sparse solution. The MP algorithm is an iterative process. It starts the process by introducing two vectors, i.e. a solution vector $\hat{x}_0$ and a residual vector $r_0$. The first iteration of the MP algorithm is illustrated in Fig.4.13.

In the first iteration, the solution vector $\hat{x}_0$ is empty, i.e. all elements are zero, and the residual vector $r_0$ is $y$. The algorithm searches for the column that has the highest coherence to the current residual vector $r_0$. The index of this column is then used for adding a new element to the solution vector $\hat{x}_0$. The scalar product between that column and the current residual $r_0$ is used as the coefficient for the new element. The solution vector is updated with the new element, and it is now $\hat{x}_1$. The residual vector $r_0$ is then updated to $r_1$ by subtracting the column with highest coherence. The process is then iteratively repeated and the number of non-zero elements in the solution vector depends on the number of iterations. Orthogonal matching pursuit (OMP) is the most popular variant of MP. The main difference to the basic MP is that all of the coefficients in the solution vector are updated in every iteration by solving the least-squares problem.
Figure 4.13: Illustration for the first iteration of the matching pursuit algorithm.
4.2.3 Compressed Sensing for UWB Ranging Systems

In this work, compressed sensing is considered for two purposes. The first one is to use it for the analog-to-digital conversion (compressive sampling) at the receiver, and the second is to use it in the post-processing as a super-resolution radar algorithm to extract multipath components in dense multipath propagation channels. The UWB transmit signal \( s(t) \) is the periodic repeated UWB impulse signal \( p(t) \) as in (4.9). The UWB transmit signal \( s(t) \) is considered as analogue of symbol waveforms for a digital transmission, the period \( T_s \) is also called the symbol period. The channel impulse response \( h_k(t) \) is a tapped delay line multipath channel model for \( k \)-th symbol as in (4.10). The received signal \( g(t) \) is then given as

\[
g(t) = \sum_{k=-\infty}^{\infty} g_k(t - kT_s) = \sum_{k=-\infty}^{\infty} h_{p,k}(t - kT_s) + n(t),
\]

where \( h_{p,k}(t) \) is the effective channel impulse response, which is a convolution between the \( k \)-th symbol transmitted impulse and the channel impulse response, i.e. \( h_{p,k}(t) = p(t - kT_s) \ast h_k(t) \). The additive white Gaussian noise \( n(t) \) shall model the noise of the low noise amplifier (LNA) in the receiver. \( g_k(t) \) is a symbol-based received signal. A schematic block diagram of the proposed UWB receiver for signal acquisition is shown in Fig. 4.14.

\[\begin{array}{ccc}
\int & a_k(t) \times g_k(t) & \int \\
LNA & kT_s & \text{Signal} \\
\text{Processor} & y_k
\end{array}\]

Figure 4.14: Basic receiver structure for signal acquisition with compressed sensing.

\( a_k(t) \) is a sequence of rectangular impulses weighted by Bernoulli matrices (±1 with equal probability), and total duration \( T_s \). This measurement function is different in every interval \( T_s \). The width of the rectangular impulses determines resolution of the acquisition. The use of this \( a_k(t) \) can lead to low complexity for the implementation of the receiver. Because the weighting factor is either 1 or -1, the signal can be generated by a 1-bit digital-to-analog converter together with shift register circuit generating the
sequence of binary weights. Every symbol interval we get one measurement value \( y_k \) by integrate and dump, which forms the scalar product between \( g_k(t) \) and the sample functions:

\[
y_k = (a_k(t), g_k(t)).
\]

(4.25)

Every \( K \) symbol interval, the signal processor performs one signal reconstruction. The effective channel impulse response \( h_{p,k}(t) \) is assumed to be unchanged within these intervals. The measurement is performed serially rather than parallel leading to lower power consumption, and it can be represented by \( h_p(t) \). The noise in each sample is different, and this will give advantage later in noisy cases. The reconstruction model for the interval of duration \( KT_s \) can be written in discrete form as

\[
y = Ag = Ah_p + n_A,
\]

(4.26)

where \( y = [y_1, y_2, \ldots, y_K]^T \) is a \( K \times 1 \) vector. \( A \) is a \( K \times N \) matrix with \( a_k \) as rows being a discrete-time representation of \( a_k(t) \). \( h_p \) is a \( N \times 1 \) vector which represents \( h_p(t) \) in discrete-time with \( N \) samples. \( n_A = [n_1, n_2, \ldots, n_K]^T \) is the noise vector where \( n_k = (a_k(t), n_k(t)) \). Given that the width of the rectangular impulses in \( a_k(t) \) is \( T_r \), we have \( N = T_s / T_r \). We can clearly see the similarity between our signal model (4.26) and the compressed sensing system model in (4.19). For the super-resolution radar algorithm purpose, we assume that \( g \) is acquired by the equivalent-time sampling method and (4.26) can be directly performed in the digital domain.

To improve the sparsity of our signal model, we can introduce a dictionary matrix \( P \) which has the UWB impulse shape as the basis. This is similar to 'signal reconstruction using multipath diversity' introduced in [111]. We can rewrite our system equation as

\[
y = APh + n_A,
\]

(4.27)

where \( P \) is a Toeplitz matrix used for representing the convolution of \( p(t) \ast h(t) \) in discrete-time. It consists of shifted versions of samples of \( p(t) \). \( h \) is a \( N \times 1 \) vector that is a discrete-time representation of \( h(t) \) and \( h_p = Ph \). Fig. 4.15 gives an illustration of (4.26) and (4.27) for an ideal channel. The compressed sensing theory is used at the receiver for calculating \( h \) from the measurement samples \( y \) for given \( P \) and \( A \).
\[ y = K \times 1 \quad A \quad g = N \times 1 \]

Measurement vector \quad Measurement matrix \quad UWB signal

\[ y = K \times 1 \quad A \quad P \quad h = N \times N \quad N \times 1 \]

Convolution matrix

Figure 4.15: Illustration of the discrete-time signal model for UWB signal without dictionary (upper) and with impulse shape dictionary (lower).
4.2 Compressed Sensing

4.2.4 Simulation Results from Simulated Channels

We look at the performance of the UWB signal reconstruction with compressed sensing in three scenarios: ideal channel, AWGN channel and multipath propagation channel. We use MATLAB for simulations and for BP and OMP, we use the implementation of toolbox from SparseLab [123].

Ideal Channel

First, we demonstrate the importance of the dictionary $\mathbf{P}$ in (4.27) for the UWB signal reconstruction. The channel is an ideal channel, and therefore, $\mathbf{n}_A = 0$. The symbol interval $T_s$ is 5 ns and the number of samples per period $N = 512$. $p(t)$ is the 5-th derivative Gaussian impulse with $\sigma = 51$ ps.

We first look at an example of the reconstruction of an ideal received signal with and without impulse shape dictionary $\mathbf{P}$. In this example, the signal vector $\mathbf{h}_p$ is directly reconstructed according to (4.26) by BP with $K = 80$ for the case without dictionary. On the other hand, $\mathbf{p}$ is reconstructed by BP with $K = 40$ as in (4.27) for the case with dictionary, and $\mathbf{h}_p$ can be calculated from that result. The UWB signals are relatively sparse but, for this example, including the impulse shape dictionary can reduce the number of non-zero elements from $M = 59$ to $M = 1$. The original and the recovered signals are shown in Fig. 4.16. We can see that perfect reconstruction from less number of measurements is possible with the inclusion of the impulse shape dictionary. The reconstruction signal without dictionary does resemble the original signal but it requires more measurements to give a perfect result.

We now consider results from BP and OMP as a function of the number of measurement (sample) $K$. The reconstruction $\hat{\mathbf{h}}_p$ of the signal vector $\mathbf{h}_p$ is considered successful if the reconstruction error is less than 1 percent of the original signal energy, i.e. $\frac{\|\mathbf{h}_p - \hat{\mathbf{h}}_p\|_2^2}{\|\mathbf{h}_p\|_2^2} < 0.01$. The results are shown in Fig. 4.17. We can clearly see the big improvement achieved by introducing the dictionary. The number of measurements required to achieve successful reconstruction with 95 percent success probability are $K = 45, 55$ for BP and OMP with dictionary, and $K = 225, 120$ for BP and OMP without dictionary.

From this point on, only the reconstruction with the dictionary matrix $\mathbf{P}$ will be considered. Moreover, the dictionary $\mathbf{P}$ acts similar to an impulse-shape filter which will be a very important part to deal with noisy signals in following scenarios.
4 Advanced Concepts for UWB Ranging Systems

Figure 4.16: Received signal without noise and comparison between the reconstructed signal without dictionary (BP, $K = 80$) and with dictionary $P$ (BP, $K = 40$).

Figure 4.17: Probability of successful reconstruction without dictionary(solid) and with dictionary (dash) for BP (red) and OMP (black).
4.2 Compressed Sensing

**AWGN Channel**

Dealing with noisy signals is a challenging task for compressed sensing. We can see in (4.26) that the algorithm would try to solve for the solution of $g$ which consists of signal $h_p$ and noise $n$. Some constraints have to be added in order to reconstruct only the signal and suppress the noise. One method to cope with this problem is to use the BPDN in (4.23). The challenges for BPDN are the selection of the regularized parameter $\lambda$ and the computation time of BP in general. Alternatively, we can use OMP with a very limited number of iteration for the reconstruction. Each iteration in this algorithm, one path (atom) is added to the reconstructed signal. We can choose the number of iterations according to the expected number of paths.

Although the principle idea of using compressed sensing is to have $K \ll N$, we suggest that in the very low SNR scenario it is good to increase the number of measurements to average out the noise. The measurements are performed serially and the noise for each measurement is different. We can say that the in this case compressed sensing is used as a noise averaging algorithm. With increasing $N$, the length of the noise vectors $n_A$ in (4.27) grows. This gives the algorithm more knowledge about UWB signal and noise. As a result, the reconstruction of an UWB signal can be perfect even for a very noisy input signal. As mentioned above, the number of measurement $K$ shall be large for the low SNR case (possibly $K > N$), OMP is the preferred method for the signal reconstruction because of its low complexity. BPDN could be too slow for any practical implementation in this scenario.

We consider an example of UWB signal with SNR = 0 dB, $N=512$. The recovery algorithms are OMP with one iteration and BPDN with $\lambda = \lambda_p, 0.1\lambda_p$. The number of measurement $K$ is 200. The results are shown in Fig. 4.18. In this example, we can see that the reconstructed signal from OMP is perfect. BPDN with $\lambda = \lambda_p$ suppress the noise very well but also suppress the UWB signal, as we can see from the amplitude of the reconstructed signal. The reconstructed signal is not as sparse when the $\lambda$ get smaller, as shown in the result of BPDN $\lambda = 0.1\lambda_p$, but the UWB is not suppressed as much.

In the following, we consider the performance of OMP with one iteration for AWGN with different SNR ranging from -20 dB to 10 dB. The probability of successful reconstruction for different number of measurements $K$ is shown in Fig. 4.19. We can see that it is possible to recover a signal $h_p$ in a very low SNR scenario by increasing the number of measurement $K$.

In practice, there is a limit in the amount of measurements we can perform to make one reconstruction. This depends very much on the assumption that the channel has to be time-invariant within the reconstruction period $KT_s$. It has to be noted that, for
A large number of $K$, the sample functions can be repeated. It has been shown in the ideal case that $K = 55$ is enough to determine the UWB signal in the sparse domain. This set of sample functions can be repeated several times just for the noise averaging purpose. This means that a measurement matrix with $K > 55$ can be constructed by repeating rows from a measurement matrix with $K = 55$. This gives advantage in the practical implementation aspect, because the sample functions have to be known at the receiver for the reconstruction. The limited number of sample functions can be helpful in terms of required memory.
Figure 4.19: Probability of successful reconstruction using OMP with different number of measurements for different SNR.
Multipath Propagation Channel

In this part we want to address a scenario with multipath propagation channel. Compressed sensing is used as a super-resolution algorithm to extract the multipath components of unresolvable UWB signals. We look at the performance of OMP and BP in a deterministic 4-path propagation channel without noise. The period of the UWB signal is 5 ns and the discrete-time representation has $N = 1000$. Therefore, the time resolution of the signal is 5 ps (1.5 mm). In this example, there is one pair of unresolvable multipath components with a delay different of 5 ps. The number of measurements $K$ is 200 for both methods. The reconstructed effective channel impulse response $h_p$ and the extract multipath delay profile $h$ from OMP and NP are shown in Fig. 4.20.

Figure 4.20: Comparison between the original multipath propagation signal and the recovered signals from BP and OMP (top). Recovered multipath delay profile from OMP (middle) and BP (bottom) compared to the original channel impulse response.
4.2 Compressed Sensing

We can see that only the BP can extract the multipath delay profile $h$ perfectly. OMP has no problem with extracting the resolvable paths, but it gave completely wrong result for the unresolvable pair. The two unresolvable paths were interpreted as only one single path for OMP. This problem comes from the way the OMP algorithm approaches the sparse recovery problem. As mentioned before, the algorithm builds the solution vector in the bottom-up manner. By adding the path one by one, the bias from the unresolvable paths is unavoidable. In order to solve this problem, some modification in the algorithm has to be done, i.e. add several paths (atoms) simultaneously. Interestingly, both algorithms estimate the effective channel impulse response $h_p$ perfectly. It is possible to use the OMP in applications where only the effective channel impulse response $h_p$ is needed. For example, we can implement a twofold operation where OMP is used for the ADC (because it is faster), and BP is used later in the post-process to extract the MDP.

4.2.5 Simulation Results from Measurement Data

We now look at the performance of the reconstruction of UWB signals with compressed sensing from two measurement scenarios. The data is collected by equivalent-time sampling and the compressed sensing is used for the post-process. The first scenario is a UWB ranging system with one-way TOA, i.e. estimating the distance between a transmitter and a receiver. The compressed sensing is used for extracting the propagation delay of the signal in a noisy scenario. The background application is the localization of an active beacon transmitter that is located deep inside a lossy medium (e.g. a human body). The second scenario is a UWB ranging system with two-way TOA, i.e. estimating distance between a transceiver and a reflector. The compressed sensing is used for extracting the propagation delays of multi-scattering of an object with complex-shape from different angles. The estimated delays are used for the imaging of the object.

Localization of Active Beacon Transmitter

The motivation for this measurement setup is the scenario where a beacon transmitter inside a human body (interventional devices, e.g. a catheter tip) transmits a train of UWB impulses for the localization purpose. An array of transmitting/receiving antennas around the human body can be used for the estimation of the transmitter location, as illustrated in Fig. 4.21 (a). The operation is twofold. The surface is first estimated from back-scattered signals of the transceivers, and then the transmitter inside of the body starts sending impulses to the receive antennas. The propaga-
tion delays are estimated and combined for the localization. We focus on the second operation, i.e. the transmitter position estimation, and assume that the surface is estimated correctly. The signal can be highly attenuated and the UWB impulse shape can be linearly distorted.

In this work, the body was modeled by a sugar-water solution with dielectric constant $\varepsilon_R = 30$ which resembles a human body. The surface is flat and the array of receiving antennas was emulated by using one antenna moving along the x-axis. The measurements were performed 51 times from different positions, and this results in a setting equivalent to having an array of 51 antennas. The illustration of the measurement setup is shown in Fig. 4.21 (b). Further details on the measurement setup can be read from [124].

The experiment was performed with the depth of the transmitter approximately 2.5 cm from the surface. The received signal was acquired with the equivalent-time sampling principle with an impulse correlator, as shown in Fig. 2.26. The number of samples per period for this experiment is $N = 1832$. The dictionary $P$ is constructed from a measurement which was less noisy but the distance in the liquid was smaller. Therefore the results discussed here are in a certain way sub-optimum. The SNR of the received signals range from -11 dB to -5 dB. An example of a signal from receiving antenna number 25 with SNR $\approx -7$ dB is shown in Fig. 4.22.
4.2 Compressed Sensing

Figure 4.22: Received signal at antenna number 25 with SNR = -7 dB.

We can see that the signal is heavily disturbed by noise. A conventional method is to find the maximum of the received signal. For compressed sensing, we consider OMP with 1 iteration and $K = 400$. The results of distance estimations for each antenna are shown in Fig. 4.23 (a). For comparison, the results of the conventional method for distance estimation are also shown. It is clear that the results from compressed sensing are far superior to the conventional method. The estimated distances are then used to find the exact position of the transmitter using the algorithm from [124]. The localization result is shown in Fig. 4.23 (b). We can see that the estimated position is approximately 2.5 cm from the surface which corresponds to the measurement setup.

It can be argued that the result from conventional methods can be improved by filtering out the noise (smoothing) but still even after this the distance estimation contains big errors for low SNR received signal i.e. for antenna number 1-10. On the other hand the reconstruction with compressed sensing could additionally also benefit from such techniques resulting in a lower number of random samples.

Additionally, we would like to thank Michael Mirbach from Institute of Microwave Techniques, University of Ulm for providing us the measurement data and the localization result.
Figure 4.23: (a) The estimated distances for different positions by conventional method and compressed sensing. (b) The estimated location of the transmitter calculated by the estimated distances.
Imaging of an Unknown Object

The objective of the second measurement setup is to verify the use of compressed sensing as a super-resolution imaging algorithm. We have seen from the earlier result that the BP algorithm can efficiently extract the multipath delay profile in a dense multipath environment. In this experiment, the shape of an unknown metal object is estimated from backscatter (reflected) signals from different angles. The m-sequence UWB radar system from [125] was used for this measurement. The measurements were performed by one fixed-position UWB transceiver, and the metal object is placed on a rotatable platform with a distance of 1 m. The platform is rotated with a 1 degree grid and the measurements were performed 360 times. The measurement setup is illustrated in Fig. 4.24. Two metal objects are investigated, and their cross-section are shown in Fig. 4.25. More details on the measurement setup can be found in [126,127].

Figure 4.24: Measurement setup for the UWB imaging system.

Figure 4.25: Cross-section of the two investigated metal objects.

Examples of the received signals from two different angles of the ‘object 2’ are shown in Fig. 4.26. The first example, in Fig. 4.26 (a), shows the received signal which was reflected back from the flat surface. There are some visible interfering signals,
i.e. ringing, but the target path can be clearly seen in this case. In Fig. 4.26 (b), the received signal is reflected from the non-flat surface part. We can see that multiples reflections are not resolvable and are very difficult to be distinguished.

![Figure 4.26](image)

(a) 260 degree (flat surface) (b) 120 degree (non-flat surface).

For this measurement setup, the number of samples per period $N$ is 1601. The received signals are interfered by ringing, and therefore BPDN is considered to suppress the effect of the interference in the sparse reconstruction. Random sampling, according to (4.26), was performed on the received signal with $K = 100$. The signal-to-interference ratio is different for each measurement, and it is difficult to select an optimum regularization parameter $\lambda$ for each reconstruction. If $\lambda$ is too high, some of the wanted signals are suppressed along with the interference. On the other hand, ringing would be included in the solution when the $\lambda$ is too low, which gives a shadowing effect to the constructed image. The value of $\lambda$ for our results is arbitrarily selected to be 100 for all measurements. With this parameter setting, ringing was included in some solutions. The mistaken paths are suppressed using a priori knowledge that the measurements were perform in a horizontal-horizontal polarization, i.e. all the reflected paths from the object have positive amplitude. From the solution vectors of BPDN, only three strongest elements with positive amplitude are kept. The multipath delay profiles extracted from all measurements are then used for the shape estimation using the imaging algorithm from [128]. The normalized multipath delay profile and the result from the imaging algorithm for both investigated objects
are shown in Fig. 4.27 and Fig. 4.28. We can see that the estimated shapes match very well with the actual shape of the objects from Fig. 4.25. Alternative delay extracting algorithms applied to the same test objects can be found in [126, 127].

Figure 4.27: Estimated multipath delay profile of ‘object 1’ from 360 measurements (left). Constructed image of ‘object 1’ from the estimated multipath delay profile (right).
Additionally, we would like to thank Rahmi Salman from Chair of Communication Systems, Universität Duisburg-Essen for providing us the measurement data and the results from imaging algorithm.
4.3 Comb Filter Receiver for UWB Ranging Systems

As mentioned in the previous chapter, the comb filter based receiver can also be used for improving the performance of UWB ranging systems. The benefits from using the comb filter are similar to those for the communication systems, i.e. SNR improvement, interference suppression and multiple users (sensor nodes) capability. The comb filter output signal is a function of the effective channel impulse response $h_p(t)$, as shown in (3.6). All of the ranging techniques discussed so far, i.e. impulse correlation, particle filtering and compressed sensing, can be directly applied to the comb filter output signal. An overview of the comb filter based receiver structure for different ranging methods is showed in Fig. 4.29.

![Comb Filter Receiver Structure](image)

Figure 4.29: Block diagram of the comb filter based receiver structure for ranging applications.

As an analogue of a DS-UWB waveform for a digital transmission, the impulse period $T_c$ is also called ‘chip period’, and the ranging algorithms are applied every ‘symbol period’ $T_s = NT_c$. The spreading sequence multiplication at the transmitter and the receiver can be omitted, if no interference, i.e. interchip/intersymbol interference, multiuser interference and narrowband interference, are presence. We present two types of signal acquisition techniques after the comb filter. The first one is the equivalent-time sampling, as illustrated in Fig. 2.26. The equivalent-time samples are performed by the impulse correlator, and they can be used for the conventional
method (min./max. tracking), particle filtering and compressed sensing. For the compressed sensing, the samples are used for post-processing, i.e. super-resolution radar in Sec. 4.2.5. The second type of implementation is the random acquisition with compressed sensing, as discussed in Sec. 4.2.3.

The ranging performance of the conventional impulse correlation based method can be significantly improved through the SNR improvement from the comb filter. As illustrated by the Ziv-Zakai performance bound in Fig. 2.24, there is a lower threshold in which the performance of the conventional impulse correlator becomes significantly worse. In this scenario, the noise is large enough for the estimator to decide on the wrong peaks in the impulse correlation function. In other words, the results are largely biased. This effect was demonstrated in Sec. 4.1.4. We can see that the performance for the conventional method are very good in Fig. 4.5. However, it became much worse because of the bias when the SNR is decreased as shown in Fig. 4.6. For particle filtering, the number of particles can be reduced because of the SNR improvement, and as a result the computational complexity is lower. Moreover, the amplitude vector was estimated directly from the received signal in our setting, as shown in (4.14), and the accuracy of this estimation depends largely on the SNR of the received signal. Improving the SNR would result in better amplitude vector estimations. In addition, delay estimations become more accurate. However, one should be careful with the SNR improvement for the particle filtering. The algorithm does not work properly under noise-less scenario, since the likelihood function becomes too narrow. For the compressed sensing, the SNR affects directly the number of measurements which is required for the perfect signal reconstructions as shown in Fig. 4.19.

In Sec. 3.3, we have shown that the effective channel impulse response $h_p(t)$ can be partially extracted using the shortened delay comb filter. If the effective channel impulse response $h_p(t)$ has a duration longer than $T_c$, the comb filter output signal is a ‘windowed’ version of the effective channel impulse response with time duration of $T_c$. The position of the window can be adjusted by shifting the spreading sequence at the receiver cyclically. In Sec. 3.3.2, the shifting was performed with a grid of $T_c$, but arbitrary shifting is also possible. The windowing of the channel impulse response is illustrated in Fig. 4.30. The shortening of the chip period also give advantage in reducing the computational complexity for the advance ranging techniques. The length of the incoming signal vector becomes smaller for the particle filtering in (4.13), and the compressed sensing in (4.26). For the particle filtering, the number of particles can be reduced because the search space is smaller. The computation time of the recovery process in compressed sensing is reduced with the size of the incoming vector.
The sliding window is controlled by cyclicly shift the spreading sequence.

Figure 4.30: Illustration of the effective channel impulse response windowing with the shortened delay comb filter receiver.
In this thesis, the applications of UWB in communications and ranging are discussed. Our main goal is to present novel solutions for problems in typical UWB systems.

The fundamentals of UWB were presented in Chapter 2. A brief overview of the definition of UWB, signal models as well as typical UWB channel models were given. UWB propagation channels have some unique characteristics compared to typical propagation channels for narrowband systems. The multipath components are usually resolvable, and arrive at the receiver in groups (clusters). There are unresolvable components that produce fading but not severe, i.e. no deep fades. Furthermore, we also looked at basic modulation techniques and basic receiver structures. The UWB receivers can be, in general, classified as methods based on correlation detection, e.g.
channels matched filter receiver, impulse correlator and rake receiver, and methods without channel knowledge, e.g. energy detector and autocorrelation receiver. Moreover, spread spectrum techniques, i.e. direct sequence and time hopping, for impulse radio UWB are introduced. Finally, basic UWB ranging techniques were briefly discussed in Chapter 2. Impulse correlation is a widely used method for the distance estimation (ranging). We looked at its performance bounds, i.e. Cramer-Rao bound and Ziv-Zakai bound, for the AWGN channel case to get a rough idea about achievable accuracy for different SNR levels. The performance bounds suggested that the error in the distance estimation from the conventional method can significantly increase if the SNR is lower than a certain threshold. Moreover, analog-to-digital conversion (sampling) cannot be performed with a reasonable power consumption for UWB signals because of their large bandwidth. Practical implementation techniques, i.e. the equivalent-time sampling and the impulse sweeping method, were discussed. The sampling was performed once every period on a repetitive UWB signal by a conventional sampler and impulse correlator, respectively.

In Chapter 3, we first looked at the BER performance of the basic UWB receivers. For AWGN channel with perfect synchronisation scenario, correlation based receivers give the best performance. However, they are very sensitive against any small mismatch, e.g. synchronization error and lack of complete channel knowledge. The energy detector shows a much more robustness for multipath propagation channels and also for non-perfect synchronization scenarios. Despite of the robustness, there are still several issues needed to be addressed. The main drawbacks are the performance in the low SNR regime, the low multiple access capability, and its weak resistance against narrowband interference. A comb filter based receiver was proposed, and we have shown that the performance in all of these aspects can be significantly improved. The receiver is designed for the detection of direct sequence UWB signals. SNR improvement is achieved through the coherent combination performed at the comb filter. With proper setting, the comb filter output signal is an effective channel impulse response, i.e. the UWB impulse convolved with the channel impulse response with improved SNR. The SNR gain from the spread spectrum technique is already achieved at this point. All of the basic detection methods, i.e. correlation based detection, energy detection and autocorrelation detection, can be directly applied after the comb filter. With this approach, the energy detector can achieve a SNR gain, which is not possible for conventional approach. The despreading is performed before the comb filter, and the multiuser interference and narrowband interference are suppressed at the comb filter. This allows the use of the energy detector for the direct sequence UWB signal detection. We have also shown that the performance from the chip-based correlation detection after the comb filter is the same as the conventional
symbol-based correlation detection.

The main challenge for the comb filter implementation is the realization of the analog delay element, the longer the delay the more difficult it is. The primary assumption of the comb filter was that the delay has to be longer than the multipath propagation of the channel. This condition was assumed to avoid the overlapping of the effective channel impulse responses, i.e. interchip interference, at the receiver. The performance can be largely degraded if interchip interference occurs, especially for the pulse position modulation (PPM) technique. We have shown that, with an appropriate choice of the spreading sequence, the interchip interference can be suppressed by the comb filter. Furthermore, different parts of the channel impulse response can be selected by cyclically shifting the spreading sequence at the receiver. Then a comb filter receiver based on a rake reception concept with several receiving branches was possible. In comparison to the basic comb filter receiver, the total delay is the same but each individual delay element is shortened. This leads to an easier implementation while the BER performance remains nearly unchanged.

Additionally, we looked at a specific type of modulation technique, i.e. code reference ultrawideband (CR-UWB). The current state of the art for this modulation technique was discussed. We pointed out the weakness of the current detection method, i.e. no SNR gain, low multiple access capability and weak resistance against narrowband interference. We have shown that the comb filter based receiver for this modulation technique can be easily constructed, and the BER performance is superior to the conventional methods. Under certain conditions, i.e. time-invariant channel for long periods and ideal comb filters, the performance of the comb filter based receiver for CR-UWB detection without explicit channel estimation can reach the matched filter bound (correlation detection with channel knowledge). Moreover, the practical implementation of the comb filter based receiver for CR-UWB is flexible. We have proposed two types of practical implementations, i.e. resetting the comb filters after several symbols and using attenuated comb filter as memory. All of the settings outperformed the conventional methods. Another advantage for using the CR-UWB and the comb filter based receiver is the scalability. Unlike in the conventional methods, the data rate can be easily increased by multi-level modulation techniques for the data encoding, e.g. 4ASK, and the threshold is easy to calculate because the detection is based on correlation. The increase of data rate is not limited by the family size of the spreading sequences, and the receiver structure remains unchanged.

In Chapter 4, we looked at the performance of UWB in ranging applications. We first introduced two advanced methods from UWB ranging systems, i.e. particle filtering and compressed sensing. Particle filtering implements a sequential Bayesian
estimation by using Monte-Carlo methods. The estimations are performed based on
the posterior density, which is regarded as the complete solution to the estimation
problems, since all of the available statistical information is included in it. We veri-
fied the performance of the particle filtering approach in UWB ranging systems with
measurement data from a setup based on a breathing rate detection problem. We
have shown that particle filtering gave a much better estimation compared to the con-
tventional max./min. tracking in the low SNR scenario and unresolvable multipath
propagation channel scenario.

The second advanced ranging method is compressed sensing. For UWB systems,
analog-to-digital conversion is one of the most challenging tasks. Directly sampling
of UWB signals cannot be performed with reasonable power consumption because
of their large bandwidth. Compressed sensing acquires the analog signals with a
different approach. The samples were taken by random signals instead of Dirac im-
pulses. This sampling technique is well-suited for ‘sparse’ signals, and impulse radio
UWB signals are relatively sparse. We have shown that, with proper setting, UWB
signals can be reconstructed in the digital domain with sub-Nyquist rate sampling
even for low SNR cases. Another use for compressed sensing in UWB ranging sys-
tems is for super-resolution radar applications. We have shown that unresolvable
multipath components can be precisely extracted by using compressed sensing in the
post-processing. The performance of compressed sensing is verified by measurement
data from two different setups. The first measurement setup is for the localization of
a transmitting beacon in a lossy media, and the second is for the imaging of an un-
known metal object. We have shown that the results from compressed sensing were
accurate and outperformed conventional methods.

Finally, the comb filter based receiver structure for ranging systems was discussed.
The integration of ranging techniques to the comb filter based receiver is straightfor-
ward. The channel impulse response is available at the comb filter output, therefore
all of the ranging techniques, i.e. conventional max./min. tracking, particle filtering
and compressed sensing, can be directly applied after the comb filter. We also dis-
cussed the shortened delay comb filter for ranging applications. We have shown that
the channel impulse response can be partially extracted, if the chip duration (impulse
period) was shorter than the channel impulse response duration. The comb filter out-
put is a windowed version of the channel impulse response with duration equal to the
chip period. The position of the window can be easily adjusted by cyclically shifting
the spreading sequence at the receiver.
Appendix A

Shortened Delay Comb Filter Received Signal

In Sec. 3.3, we introduced the cyclic-prefix impulses in the UWB transmit symbol for the case where the chip period is shorter than the duration of the channel impulse response. This gives the possibility to describe each received symbol separately by a cyclic convolution operation, as in (3.16). Based on the cyclic property, the received symbol can be expressed in a chip-based form as in (3.21). In this appendix, we look at the transition between (3.16) and (3.21) in more details. We first consider a DS-UWB received symbol without the cyclic-prefix impulses. The cyclic property will be added later. One symbol of the DS-UWB received signal for the $i$-th user can be written as
A Shortened Delay Comb Filter Received Signal

\[ g_i(t) = \left( \sum_{n=0}^{N-1} c_{i,n} p(t - nT_c) \right) * h(t) \]

\[ = \left( \sum_{n=0}^{N-1} c_{i,n} \delta(t - nT_c) \right) * h_p(t) \]

\[ = \left( \sum_{n=0}^{N-1} c_{i,n} \delta(t - nT_c) \right) * \sum_{m=0}^{M-1} \hat{h}_p^{(m)}(t - mT_c) \]

\[ = \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} c_{i,n} \hat{h}_p^{(m)}(t - mT_c - nT_c), \]  

(A.1)

where \( c_{i,n} \) is the spreading sequence for the \( i \)-th user. \( T_c \) is the chip period and \( N \) is the number of chips per symbol. \( \hat{h}_p^{(m)}(t) \) is the chip-based effective channel impulse response, as introduced in Fig. 3.17. The duration of the effective channel impulse response is \( MT_c \). (A.1) can be alternatively expressed as

\[ g_i(t) = \sum_{n=0}^{M-2} \sum_{m=0}^{n} c_{i,n-m} \hat{h}_p^{(m)}(t - nT_c) + \sum_{n=M-1}^{N-1} \sum_{m=0}^{M-1} c_{i,n-m} \hat{h}_p^{(m)}(t - nT_c) + ... \]

\[ ... + \sum_{n=N}^{(N-1)+(M-1)} \sum_{m=n-(N-1)}^{M-1} c_{i,n-m} \hat{h}_p^{(m)}(t - nT_c). \]

(A.2)

The illustration of the relationship between (A.1) and (A.2) for \( N=6 \) and \( M=3 \) is shown in Fig. A.1. From (A.2), we can see that \( g_i(t) \) can be divided into three parts. We now focus on the third part, i.e. \( \sum_{n=N}^{(N-1)+(M-1)} \sum_{m=n-(N-1)}^{M-1} c_{i,n-m} \hat{h}_p^{(m)}(t - nT_c) \).

This part is the intersymbol interference for the next received symbol. In general, similar intersymbol interference from the previous received symbol will also be present in the current received symbol interval. The cyclic-prefix impulses were introduced to make this part of the received signal predictable. The duration of the intersymbol interference is \( (M-1)T_c \), which is the same as the duration of the cyclic-prefix impulses. The intersymbol interference would fall into the cyclic-prefix period, and does not disturb the information part. The contribution from the cyclic-prefix impulses in the current symbol can be described by time-shifting the third term by \( NT_c \), as illustrated by the dash boxes in Fig. A.1. We now want to consider only the information part of the current received symbol, and the third term can be replaced by the contri-
bution from the cyclic-prefix impulses. The information part of the current received symbol has a duration of $NT_c$, which can be written as

$$g(t) = \sum_{n=0}^{M-2} \sum_{m=0}^{n} c_{i,n-m} \hat{h}_p^{(m)}(t-nT_c) + \sum_{n=M-1}^{N-1} \sum_{m=0}^{M-1} c_{i,n-m} \hat{h}_p^{(m)}(t-nT_c) + \ldots$$

(A.3)

... $+ \sum_{n=0}^{M-2} \sum_{m=n+1}^{M-1} c_{i,n-m} \hat{h}_p^{(m)}(t-nT_c).$

Notice that the contribution from the cyclic-prefix is the third term in A.3. The first term and the third term can be combined, and A.3 can be rewritten as

$$g_i(t) = \sum_{n=0}^{M-2} \sum_{m=0}^{M-1} c_{i,n-m} \hat{h}_p^{(m)}(t-nT_c) + \sum_{n=M-1}^{N-1} \sum_{m=0}^{M-1} c_{i,n-m} \hat{h}_p^{(m)}(t-nT_c).$$

(A.4)

Finally, we can expressed one symbol of the DS-UWB received signal in the chip-based form as

$$g_i(t) = \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} c_{i,n-m} \hat{h}_p^{(m)}(t-nT_c).$$

(A.5)
Figure A.1: Illustration of the relationship between (A.1) and (A.2). The contributions from the cyclic-prefix in (A.3) are illustrated by the dash boxes.
# List of Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADC</td>
<td>Analog-to-digital conversion</td>
</tr>
<tr>
<td>AWGN</td>
<td>Additive white Gaussian noise</td>
</tr>
<tr>
<td>BER</td>
<td>Bit error rate</td>
</tr>
<tr>
<td>BP</td>
<td>Basis pursuit</td>
</tr>
<tr>
<td>BPAM</td>
<td>Binary pulse amplitude modulation</td>
</tr>
<tr>
<td>BPDN</td>
<td>Basis pursuit denoising</td>
</tr>
<tr>
<td>BPPM</td>
<td>Binary pulse position modulation</td>
</tr>
<tr>
<td>BPSK</td>
<td>Binary phase shift keying</td>
</tr>
<tr>
<td>CRB</td>
<td>Cramer-Rao bound</td>
</tr>
<tr>
<td>CSK</td>
<td>Code shift keying</td>
</tr>
<tr>
<td>CWC</td>
<td>Centre of wireless communications</td>
</tr>
<tr>
<td>DAA</td>
<td>Detect-and-avoid</td>
</tr>
<tr>
<td>DPSK</td>
<td>Differential phase shift keying</td>
</tr>
<tr>
<td>Acronym</td>
<td>Description</td>
</tr>
<tr>
<td>---------</td>
<td>------------------------------------------</td>
</tr>
<tr>
<td>DS</td>
<td>Direct sequence</td>
</tr>
<tr>
<td>ED</td>
<td>Energy detection</td>
</tr>
<tr>
<td>EIRP</td>
<td>Equivalent isotropically radiated power</td>
</tr>
<tr>
<td>ERP</td>
<td>Exact reconstruction principle</td>
</tr>
<tr>
<td>FCC</td>
<td>Federal communications commission</td>
</tr>
<tr>
<td>FDTD</td>
<td>Finite difference time domain</td>
</tr>
<tr>
<td>FH</td>
<td>Frequency hopping</td>
</tr>
<tr>
<td>FR</td>
<td>Frequency reference</td>
</tr>
<tr>
<td>ICI</td>
<td>Interchip Interference</td>
</tr>
<tr>
<td>IR-UWB</td>
<td>Impulse radio Ultrawideband</td>
</tr>
<tr>
<td>ISI</td>
<td>Intersymbol Interference</td>
</tr>
<tr>
<td>LCZ</td>
<td>Low-correlation zone</td>
</tr>
<tr>
<td>LNA</td>
<td>Low noise amplifier</td>
</tr>
<tr>
<td>LTI</td>
<td>Linear time-invariant</td>
</tr>
<tr>
<td>MAP</td>
<td>Maximum a posteriori</td>
</tr>
<tr>
<td>MB-OFDM</td>
<td>Multiband orthogonal frequency-division multiplexing</td>
</tr>
<tr>
<td>MMSE</td>
<td>Minimal mean squared error</td>
</tr>
<tr>
<td>MP</td>
<td>Matching pursuit</td>
</tr>
<tr>
<td>MRC</td>
<td>Maximal ratio combining</td>
</tr>
<tr>
<td>MUI</td>
<td>Multiuser interference</td>
</tr>
<tr>
<td>OC</td>
<td>Optimal combining</td>
</tr>
<tr>
<td>OFDM</td>
<td>Orthogonal frequency-division multiplexing</td>
</tr>
<tr>
<td>OMP</td>
<td>Orthogonal matching pursuit</td>
</tr>
<tr>
<td>OOK</td>
<td>On-off keying</td>
</tr>
<tr>
<td>PAM</td>
<td>Pulse amplitude modulation</td>
</tr>
<tr>
<td>PDF</td>
<td>Probability density function</td>
</tr>
<tr>
<td>PPM</td>
<td>Pulse position modulation</td>
</tr>
<tr>
<td>RC</td>
<td>Raised-cosine</td>
</tr>
<tr>
<td>RIP</td>
<td>Restricted isometry property</td>
</tr>
<tr>
<td>SIR</td>
<td>Signal-to-interference ratio</td>
</tr>
<tr>
<td>SNR</td>
<td>Signal-to-noise ratio</td>
</tr>
<tr>
<td>SV</td>
<td>Saleh-Valenzuela</td>
</tr>
<tr>
<td>TOA</td>
<td>Time-of-arrival</td>
</tr>
</tbody>
</table>
### List of Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>TR</td>
<td>Transmitted reference</td>
</tr>
<tr>
<td>UUP</td>
<td>Uniform uncertainty principle</td>
</tr>
<tr>
<td>UWB</td>
<td>Ultrawideband</td>
</tr>
<tr>
<td>WBAN</td>
<td>Wireless body area network</td>
</tr>
<tr>
<td>WLAN</td>
<td>Wireless local area network</td>
</tr>
<tr>
<td>WPAN</td>
<td>Wireless personal area network</td>
</tr>
<tr>
<td>ZCZ</td>
<td>Zero-correlation zone</td>
</tr>
<tr>
<td>ZZB</td>
<td>Ziv-Zakai bound</td>
</tr>
</tbody>
</table>
Appendix

List of Frequently Used Symbols and Functions

\( a(t) \) measurement signal
\( a_k \) measurement vector, i.e. discrete-time representation of \( a(t) \)
\( A \) measurement matrix
\( b_k \) \( k^{th} \) transmission symbol
\( B \) dictionary of basis
\( d(t) \) spreading sequence waveform
\( D \) effective measurement matrix \( D = AB \)
C List of Frequently Used Symbols and Functions

- \( E_b \): energy per bit
- \( e(t) \): basic waveform
- \( G_c \): comb filter loop gain
- \( G_p \): comb filter SNR gain
- \( g(t) \): received signal
- \( h(t) \): channel impulse response
- \( h_p(t) \): effective channel impulse response \( h_p(t) = p(t) * h(t) \)
- \( h^{(m)}_p(t) \): windowed version of \( h_p(t) \)
- \( h^{(m)}_p(t) \): shifted version of \( h^{(m)}_p(t) \)
- \( H(f) \): transfer function
- \( N \): number of chip per symbol
- \( N_s \): number of particles
- \( N_0 \): noise power spectral density
- \( n(t) \): additive noise
- \( p(t) \): UWB impulse
- \( q(t) \): direct sequence basic waveform
- \( s(t) \): transmitted signal
- \( t \): time
- \( T_c \): chip period
- \( T_m \): multipath delay spread
- \( T_s \): symbol period
- \( u(t) \): received signal after multiplier
- \( v(t) \): received signal after comb filter
- \( w(t) \): receive filter
- \( w^{[n]}_k \): weight of \( n^{th} \) particle at time instant \( k \)
- \( x(k) \): transmitted data sequence
- \( \hat{x}(k) \): received data sequence
- \( x_k \): state vector at time instant \( k \)
- \( x_{1:k} \): state vector from time instant 1 to \( k \)
- \( y \): received signal after sampling
- \( y(t) \): received signal before sampling
- \( z_k \): measurement vector at time instant \( k \)
- \( z_{1:k} \): measurement vector from time instant 1 to \( k \)
\( \alpha_m \)  amplitude of \( m^{th} \) path
\( \phi_{cc}(k) \) periodic autocorrelation of sequence \( c \)
\( \delta(t) \) Dirac delta function
\( \lambda \) regularization parameter
\( \varphi_{xx}(t) \) autocorrelation function of \( x(t) \)
\( \varphi_{xy}(t) \) cross-correlation function of \( x(t) \) with \( y(t) \)
\( \sigma \) standard deviation
\( \sigma^2 \) variance
\( \tau_m \) propagation delay of \( m^{th} \) path
Bibliography


Bibliography


Bibliography


[56] T. Zasowski, F. Althaus, M. Stager, A. Wittneben, and G. Troster. Uwb for non-


Bibliography


[103] B. Denis, L. Ouvry, B. Uguen, and F. Tchoffo-Talom. Advanced bayesian filter-


