Wi-Fi based people tracking in challenging environments

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Abstract

People tracking is a key building block in many applications such as abnormal activity detection, gesture recognition, and elderly persons monitoring. Video-based systems have many limitations making them ineffective in many situations. Wi-Fi provides an easily accessible source of opportunity for people tracking that does not have the limitations of video-based systems. The system will detect, localise, and track people, based on the available Wi-Fi signals that are reflected from their bodies. Wi-Fi based systems still need to address some challenges in order to be able to operate in challenging environments. Some of these challenges include the detection of the weak signal, the detection of abrupt people motion, and the presence of multipath propagation. In this thesis, these three main challenges will be addressed.

Firstly, a weak signal detection method that uses the changes in the signals that are reflected from static objects, to improve the detection probability of weak signals that are reflected from the person's body. Then, a deep learning based Wi-Fi localisation technique is proposed that significantly improves the runtime and the accuracy in comparison with existing techniques.

After that, a quantum mechanics inspired tracking method is proposed to address the abrupt motion problem. The proposed method uses some interesting phenomena in the quantum world, where the person is allowed to exist at multiple positions simultaneously. The results show a significant improvement in reducing the tracking error and in reducing the tracking delay.

Finally, a tracking based multipath mitigation method is proposed that can distinguish between real objects and ghost objects. The proposed method integrates the aspect dependence feature of the multipath signals into the tracking framework. The use of the tracking framework allows integrating information in the time domain in order to make a more accurate decision and to relax some constraints in the space domain such as the large number of antennae that are placed over a large area. An important feature of the proposed method is that it can suppress/mark the entire multipath track; furthermore, it does not assume any prior knowledge of the environment.

The proposed methods were simulated using Matlab, and their performance in terms of accuracy, robustness, and computational time were analysed.

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Abbreviations

AD	Aspect Dependence
AMM	Autonomous Multiple Models
AMP	Approximate Message Passing
AOA	Angle of Arrival
AP	Access Point
ASAMC	Adaptive Stochastic Approximation Monte Carlo
CA	Constant Acceleration
CFAR	Constant False Alarm Rate
CNN	Convolutional Neural Network
CP	Cyclic Prefix
CS	Compressive Sensing
CSI	Channel State Information
CV	Constant Velocity
DFP	Device-free Passive
DL	Deep Learning
DNN	Deep Neural Network
DOA	Direction of Arrival
DSSS	Direct Sequence Spread Spectrum

ECA	Extensive Cancellation Algorithm
ECG	Electrocardiogram
EKF	Extended Kalman Filter
FSMM	Fixed Structure Multiple Models
GD	Gradient Descent
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
GRU	Gated Recurrent Unit
H-PMHT	Histogram Probabilistic Multi-Hypothesis Tracker
ILSVRC	ImageNet Large Scale Visual Recognition Competition
IMM	Interacting Multiple Mode
IMMPF	Interacting Multiple Mode Particle Filter
IPM	Interior Point Method
ISI	Inter-Symbol Interference
ISM	Industrial Scientific and Medical
KF	Kalman Filter
LMS	Least Mean Square
LOS	Line-Of-Sight
LSTM	Long Short-Term Memory
MCMC	Markov Chain Monte Carlo

MIMO	Multiple Input Multiple Output
ML-PDA	Maximum Likelihood Probabilistic Data Association
MMSE	Minimum Mean Square Error
NLMS	Normalized Least Mean Square
OFDM	Orthogonal Frequency Division Multiplexing
OMP	Orthogonal Matching Pursuit
PSO	Particle swarm optimization
QPF	Quantum Particle Filter
ReLU	Rectified Linear Units
RLS	Recursive Least Square
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
RSS	Received Signal Strength
SAR	Synthetic Aperture Radar
SCA	Sequential Cancellation Algorithm
SDR	Software Defined Radio
SGD	Stochastic Gradient Descent
SINR	Signal-to-Interference-Noise Ratio
SMS	Short Messaging Service
SNR	Signal to Noise Ratio

SVM	Support Vector Machine
TBD	Track before Detect
TBM	Track before Mitigate
TOA	Time of Arrival
UKF	Unscented Kalman Filter
UWB	Ultra-Wideband
VSMM	Variable Structure Multiple Models
WL	Wang–Landau
WLANs	Wireless Local Area Networks

List of symbols

T	The duration of an OFDM symbol
Δf	The subcarriers spacing
B	The bandwidth of an OFDM symbol
N_s	The number of subcarriers
f_c	The carrier frequency
f_m	The frequency of the mth subcarrier
$x(t)$	An OFDM symbol in the baseband
$s[m]$	An OFDM symbol on the mth subcarrier
$q(t)$	A rectangular window
$w(t)$	White Gaussian noise
Ap	The attenuation which includes the path loss and the reflection
τ_p	The delay of received signal
a_p	The range rate of the pth path divided by the speed of light
$a(\theta_p)$	The steering vector of the received signal
λ	The signal wavelength
d	The antennae array inter-element spacing
L	The number of antennae.

ψ_i	The basis vectors of a signal
s_i	The weighting coefficients
Φ	The measurement matrix
$x^{`}$	The reconstructed solution
$x^{\sim}$	The space of all possible solutions
ε	The upper bound of the noise in the signal
P	The number of data points in the range dimension
Z	The number of data points in the angle dimension
V	The number of data points in the Doppler dimension
$y(t_0)$	The received signal when the room empty at time t_0
$y(t)$	The received signal when the room full at t
X_E	The reconstructed scene when the room is empty
X_F	The reconstructed scene when the room is full
TP	The number of correct detections
PC	The number of positive cases
x_k	The system state at time k
u_k	The control input at time k
y_k	The observed state at time k
w_k	The process noise at time k

v_k The measurement noise at time k

f_k The state transition function at time k

h_k The observation function at time k

$w_k^{(i)}$ The weight of the particle i at time k

R_i The distance from the current position to the ith mode

S_i The speed of ith mode

q The suppression speed

v The variance of the received signal across the antennae

Chapter 1

Introduction

"I do not think that the wireless waves I have discovered will have any practical application"

Heinrich Hertz

1.1 Overview

The discovery of the wireless wave by Hertz [1] has opened the doors for many technological revolutions. Most aspects of our modern life have been affected by this important discovery. In 1864, Maxwell showed theoretically using mathematics that electromagnetic waves could propagate in space [2]. The existence of electromagnetic waves was demonstrated in 1887 by Hertz in an interesting experiment that confirmed Maxwell's equations. He also showed that electromagnetic waves could be reflected from solid objects. Marconi began to pursue the idea of building a wireless communication system [3]. In 1896, he gained a patent on his system and started the development of a commercial communication system in the next few years. In 1897, Alexander Popov [4] at the Imperial Russian Navy observed that when a vessel passes between two ships, it causes interference of the communication between the two ships, he suggested that this phenomenon could be used for detecting objects. In 1904, Hülsmeyer [5] was able to demonstrate the potential of using the wireless waves to detect the presence of a metallic object. Eleven years later, Watt used the wireless waves to create an early warning system for airmen. World War I accelerated the development in this field particularly for military communication applications, and in this period, the first vacuum tubes were used in radio transmitters and receivers. World War II again accelerated the research in communication, navigation, and radar. The development of televisions was continued after the war.

During World War II, the British Navy used the LORAN navigation system, which is a ground-based navigation system that uses wireless signals, the system was developed in the 1940s [6]. The United States Navy launched the first satellite-based navigation system TRANSIT in 1960, the system is based on a constellation of five satellites. The Global Positioning System (GPS) was launched in 1973 in the United States to overcome the limitations of existing navigation systems. It was opened for civilian use in the 1980s, and it became fully operational in 1995.

In 1991, the former prime minister of Finland made the world's first Global System for Mobile communication (GSM) call with the mayor of the city of Tampere [7]. One year later, the first Short Messaging Service (SMS) was sent. Wi-Fi was invented by a group of Australian scientists [8], they were working for the commonwealth scientific and industrial research organization. Wi-Fi was first introduced for commercial use in 1997 when the 802.11 committee was created. This led to the IEEE802.11 standards, which define the communication standards for the Wireless Local Area Networks (WLANs), and in 1999, Wi-Fi was introduced for home use.

Today, 130 years after Hertz's discovery, there is a wide range of applications of the wireless waves, such as activity detection, gesture recognition, and elderly people monitoring. Future access points will be also able to recognise gestures and take commands, analyse and classify different activities of people inside and outside the house, monitor the health conditions of elderly people by monitoring their breath, fall, etc. Fig. 1.1 summarises the potential applications of using the Wi-Fi signals. The range of applications is not limited to indoor applications but also include outdoor areas.

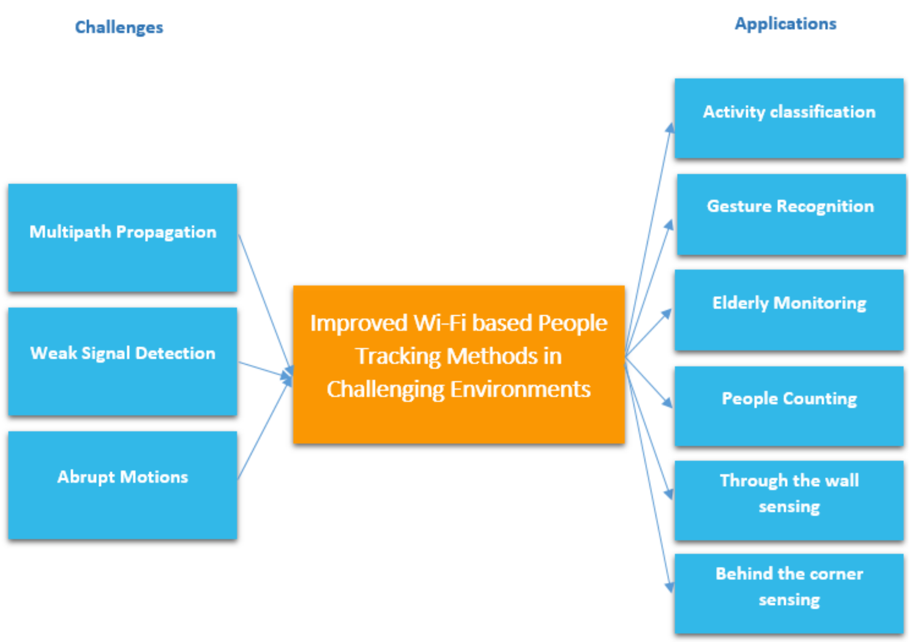

Fig. 1.1 Applications and challenges.

Video-based people tracking systems have many limitations making them ineffective in many situations; for example, they require users to stay within the device's Line-Of-Sight (LOS), they cannot operate in dark, through smoke or walls, and they violate people's privacy; furthermore, video-based tracking algorithms suffer from high computational cost and low localisation accuracy.

Wi-Fi provides an easily accessible source of opportunity for people tracking, it does not have the limitations of video-based systems; furthermore, it has higher availability and longer range than other signal-based systems such as Ultra-Wideband (UWB). Fig. 1.2 summarises the advantages of using the Wi-Fi over other sensing technologies. The possibility to provide people tracking by using this ubiquitous source of opportunity, and without transmitting any additional signal, nor require co-operative objects as other signal-based systems, offers major opportunities. The proposed system will detect, localise, and track people based on the available Wi-Fi signals that are reflected from their bodies.

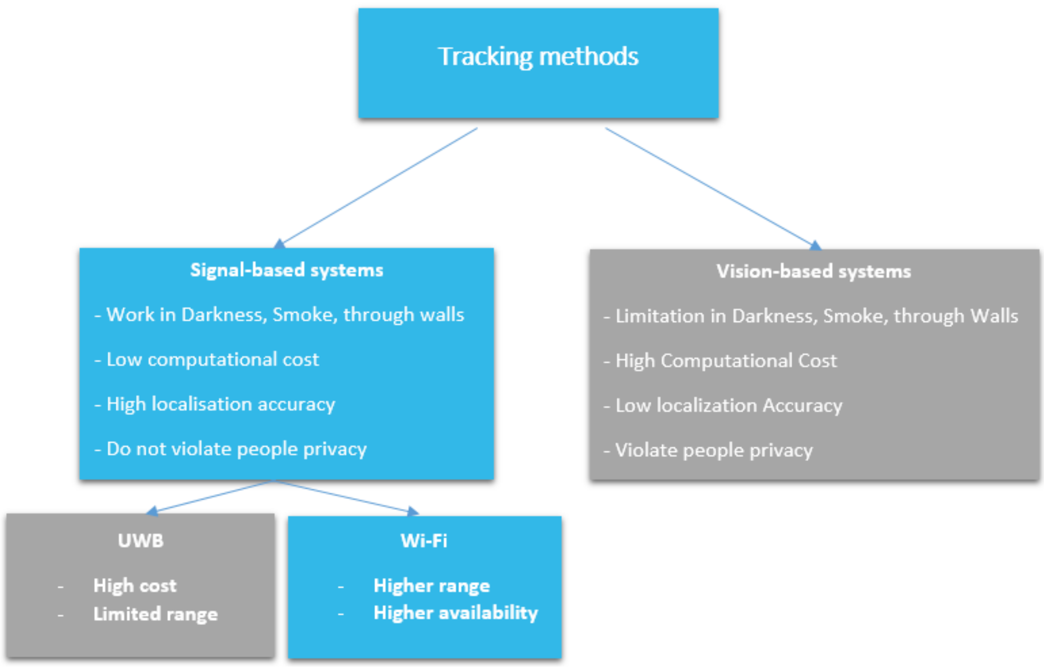

Fig. 1.2 Advantages of using Wi-Fi signals over other sensing technologies.

The proposed system uses the pre-existing Wi-Fi infrastructures to perform people tracking which results in an interesting opportunity for low-cost surveillance. The system performs a matched filtering between the transmitted signal and the reflected signal from the object. The Time of Arrival (TOA) of the reflected signal is used to determine the object range. The object velocity is determined from the Doppler frequency of the object echo. The phase difference of the reflected signal at the antennae is used to determine the Direction of Arrival (DOA).

The low-power signals reflected from the objects are collected by the receiver. The best analogy to the proposed system would be the camera; however, instead of using the light reflected from the object, the Wi-Fi signals are used.

The phase variation of the received signal is used by the Doppler radar to obtain the Doppler information. A key property of the Doppler radar is the ability to suppress clutter effectively, which results from the reflections of the wireless signals from a room's furniture, floors, or walls.

Wi-Fi based people tracking systems still need to address some challenges in order to be able to operate in real-world environments. Some of these challenges include the detection of weak signals caused by the low reflectivity of the human body, the detection of abrupt people motion, and the presence of multipath propagation, which introduces multipath ghosts in the observed scene. The main contribution of this work is to address these three main challenges.

The main theme of the research is the using of the tracking framework to address the above challenges, where the tracking stage will allow us to gain more useful information that will help us in addressing the challenges in the sensing stage. In chapter 4, the tracking framework is used to address the abrupt motion problem, where a quantum mechanics inspired tracking method is proposed. In chapter 5, the tracking framework is used to improve the performance of the multipath mitigation stage, where the use of the tracking framework allows to make the use of useful information in the time domain in order to make more accurate decision and to relax some constraints in the space domain such as the large number of antennae that are placed over a large area.

The other main theme of the research is the use of Deep Learning (DL) in chapter 3 to build localisation techniques that significantly improve the accuracy and reduces the runtime in comparison with existing techniques. Deep learning has shown its ability to adapt to real-world imperfections, which cannot be always captured by analytical models. Currently, each of the proposed techniques works separately, future work will investigate using one tracking-based technique to address the three challenges simultaneously.

1.2 Research aim and objective

The aim of this research is to address the main limitations of existing signal-based people tracking methods to cope with real-world challenging environments where there are several challenges, namely: weak signal detection, abrupt people motion, and multipath propagation.

The main objectives of the research are:

- To investigate the advantages and limitations of people tracking systems using different sensing technologies such as video-based and signal-based systems.

- To study the characteristic of the Wi-Fi signal and conduct a literature survey on existing Wi-Fi based people tracking systems, their advantages, limitations, and applications, such as activity classification, gesture recognition, elderly people monitoring, people counting, through the wall sensing, and behind the corner sensing.

- To propose tracking methods that overcome the difficulties of Wi-Fi based people tracking systems in challenging environments where there are weak signals, abrupt people motion, and multipath propagation.

- To propose localisation methods that can improve the localisation accuracy and reduce the runtime under weak signal conditions.

- To propose tracking methods that can improve the tracking accuracy and reduce the tracking delay when there is abrupt motion.

- To propose tracking methods that require a smaller number of antennae and do not assume any prior knowledge about the environment to accurately suppress/mark the multipath track.

- To simulate the proposed methods and evaluate and compare their performance in terms of accuracy, robustness and computational time.

1.3 Assumptions of the work

During the course of this research, some assumptions have been made to achieve the research aims with the available resources, these assumptions can be summarised below:

- In chapter 3, the only difference between the signals reflected from the users and the multipath signals reflected from static objects is the zero Doppler shift of the latter.

- In chapter 5, the only difference between the signals reflected from the users and the multipath signals reflected from the users then from the wall is the angle of arrival, which will result in different variance across the antennae.

- Higher-order multipath returns, which involve more than two reflections, were not taken into account as the signal becomes weaker at each reflection. Furthermore, the number of multipath returns is usually higher in real-world environments than the number used in the simulations.

- The effect of the radiation pattern of the antennae was not taken into account in the simulations.

1.4 Outline of the contribution to knowledge

The main outcome of this research is the achievement of its main aim, namely: finding solutions to the three main challenges of Wi-Fi based tracking systems, which are weak signal detection, abrupt people motion, and multipath signal mitigation. The main contributions are described in Fig 1.3. The contributions can be highlighted as follows:

- A compressive sensing based localisation method that extends previous work to include Angle of Arrival (AOA) estimation.
- A combined reflection-based and shadowing-based weak signal detection method that significantly improves the detection probability of weak signals, where the detection of the weak signal reflected from the person's body is enhanced by taking into account the changes in the signals that are reflected from the surrounding environment.
- A deep learning based localisation method that significantly improves the accuracy and reduces the runtime in comparison with existing techniques. The proposed approach has shown a high ability to adapt to challenging environments. It has also shown that it is relatively robust to multipath signals, and no additional multipath mitigation techniques are required to be used.
- A tracking method that outperforms existing tracking methods when there are abrupt changes in the speed or in the direction. It also reduces the tracking delay when there is abrupt motion.
- A tracking based multipath ghosts mitigation method that requires a smaller number of antennae in comparison with existing methods, it can accurately suppress/mark the entire multipath track; furthermore, it does not assume any prior knowledge of the environment.

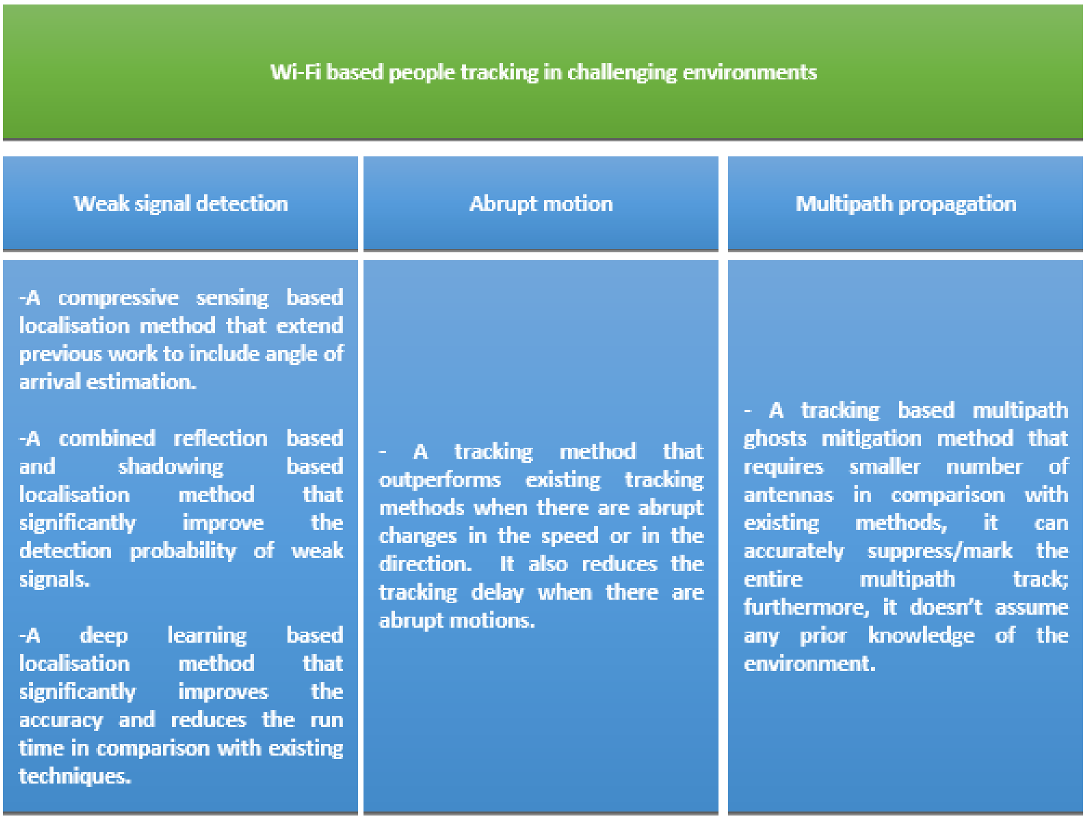

Fig. 1.3 Main contributions.

1.5 Publication arising from this work

A. Khalili, A. A. Soliman, and M. Asaduzzaman, "Quantum particle filter: a multiple mode method for low delay abrupt pedestrian motion tracking" IET Electronics Letters, vol. 51, no. 16, 2015.

A. Khalili, and A. A. Soliman, “Track before mitigate: aspect dependence-based tracking method for multipath mitigation” IET Electronics Letters, vol. 52, no. 4, 2016.

A. M. Khalili, Abdel-Hamid Soliman, and Md Asaduzzaman, “A Deep Learning Approach for Wi-Fi based People Localization”, IEEE Access, Submitted, 2018.

1.6 Outline of the thesis

This thesis is organised as follows.

Chapter 2

- Section 2.2 explains the reasons for using the Wi-Fi signal, then the main used approaches are summarised with their limitations.
- Section 2.3 surveys different applications of Wi-Fi based people tracking systems such as elderly people monitoring, activity classification, gesture recognition, people counting, through the wall sensing, behind the corner sensing and many other applications.
- Section 2.4 lists the main challenges of Wi-Fi based people tracking systems.

Chapter 3

- Section 3.2 surveys weak signal detection techniques with their limitations.
- Section 3.3 presents the used Wi-Fi signal model.
- Section 3.4 presents an overview of compressive sensing.
- Section 3.5 presents an overview of deep learning.
- Section 3.6 presents a new formulation of Wi-Fi signal detection that includes angle of arrival estimation.
- Section 3.7 presents a combined reflection-based and blocking-based weak signal detection method that improves the detection probability of weak signals.
- Section 3.8 presents a deep learning weak signal detection method that significantly improves the detection probability of weak signals.
- Section 3.9 lists the results.

Chapter 4

- Section 4.2 surveys abrupt motion tracking techniques with their limitations.
- Section 4.3 presents an overview of motion models
- Section 4.4 presents an overview of the particle filter
- Section 4.5 presents an overview of the multiple models approach
- Section 4.6 presents a tracking method that can cope with abrupt changes in the speed and direction.
- Section 4.7 lists the results.

Chapter 5

- Section 5.2 presents an overview of the multipath propagation environment.
- Section 5.3 surveys multipath mitigation techniques with their limitations.
- Section 5.4 describes the aspect dependence feature, which can help in separating real objects from ghost objects.
- Section 5.5 presents a tracking based multipath mitigation method that can distinguish between real objects and ghost objects in the observed scene.
- Section 5.6 lists the results.

Chapter 6

- Section 6.1 presents the main findings of the work.
- Section 6.2 presents the contributions to knowledge.
- Section 6.3 lists the main limitations of the work.
- Section 6.4 discusses some interesting future research directions.

Chapter 2

Wi-Fi based people tracking systems and their applications

2.1 Introduction

Wi-Fi provides an easily accessible source of opportunity for people tracking. It does not have the limitations of video-based systems; furthermore, it has higher availability and longer range compared to other signal-based systems. It is currently used in a wide variety of applications and it is expected to be used in many new applications. In this chapter, the reasons behind using the Wi-Fi signal will be explained, then the main used approaches of Wi-Fi based people tracking systems with their limitations will be summarised. Finally, a survey on different applications of the Wi-Fi based people tracking systems will be presented. The proposed techniques in this thesis are applicable for all the listed applications.

The chapter is organized as follows: The reasons behind using the Wi-Fi signal, and the main used approaches with their limitations are described in section 2.2. The application of the Wi-Fi signal in elderly people monitoring is described in section 2.3. The application of the Wi-Fi signal in activity classification is described in section 2.3.1. Section 2.3.2 describes the application of the Wi-Fi signal in gesture recognition. The application of the Wi-Fi signal in people counting is described in section 2.3.3. The application of the Wi-Fi signal in through the wall sensing is described in section 2.3.4. The application of the Wi-Fi signal in behind the corner sensing is described in section 2.3.5. Other Applications of the Wi-Fi signal is described in section 2.3.6. The gaps and the limitations of existing works are described in section 2.4, and the chapter is concluded in Section 2.5.

2.2 Wi-Fi based people tracking systems

Vision-based people tracking systems [9, 10, 11] have been widely used recently for different applications such as activity classification, gesture recognition, elderly people monitoring, and people counting. However, these systems have many limitations making them ineffective in many situations; for example, they require users to stay within the device's line-of-sight as described by Fig. 2.1, they cannot operate in the dark, through smoke or walls, and they violate people's privacy; furthermore, video-based detection and tracking algorithms suffer from high computational cost and low localisation accuracy.

Traditional radar systems have been recently used to perform people tracking and activity recognition [12, 13, 14, 15]. However, these systems use multiple antennae, expensive ultra-wideband transceivers, and specialized signal modulation.

Fig. 2.1 The limitation of the coverage of vision-based systems to the device's line-of-sight [85].

Wi-Fi provides an easily accessible source of opportunity for people tracking, it does not have the limitations of video-based systems; furthermore, it has higher availability and longer range than other signal-based systems such as the ultra-wideband. The possibility to provide people tracking by exploiting such a ubiquitous source of opportunity, and without transmitting any additional signal, nor requiring co-operative objects as other signal-based systems, offers major opportunities.

Within the European project ATOM [16, 17, 18], the potential of Wi-Fi for people tracking within different public areas such as airport terminals was investigated. The use of the Wi-Fi signals turned out to be very promising, where Wi-Fi signals represent a very suitable solution for the following reasons:

- Reasonable bandwidth, which will lead to a high range resolution.

- Wide coverage, Wi-Fi networks are spreading at a very high rate for both commercial and private use.
- Reasonable Transmitted power, which gives the Wi-Fi signal an advantage over short-range sensing technology such as UWB.

Colone et al. [17] investigated the use of Wi-Fi signals for people tracking, they conducted an ambiguity function analysis for Wi-Fi signals. They also investigated the range resolution for both the Direct Sequence Spread Spectrum (DSSS) and the Orthogonal Frequency Division Multiplexing (OFDM) frames, for both the range and the Doppler dimensions, large sidelobes were detected, which explains the masking of closely spaced users. Falcone et al. [18] presented the results of detecting the speed and the range of a car by correlating the received Wi-Fi signal with the transmitted one. It was shown that the moving car can be localised, but the user next to it is masked by the strong reflection from the car. Then they showed that ambiguity function control filter and disturbance removal techniques could allow the detection of both the car and the person.

Wi-Fi based systems use the variations in the wireless channel to track people in a given environment. Existing systems can be grouped into three main categories: (1) Received Signal Strength (RSS) based, (2) Channel State Information (CSI) based, and (3) Software Defined Radio (SDR) based.

RSS provides only coarse-grained information about the variations of the wireless channel and does not provide fine-grained information about the multipath effects. CSI was introduced to capture fine-grained variations in the wireless channel. Received signal strength measurements are only a single value per packet, which represents Signal-to-Interference-Noise Ratio (SINR) over the channel, channel state information on the other hand contains the amplitude and the phase measurements for each OFDM subcarrier. SDR based systems are low-level systems that have full access to the received signal and therefore can capture more valuable information such as the Doppler shift. Therefore, the SDR approach will be used in this work.

In the SDR based systems category, the first experiments to localise people using Wi-Fi signals were done by Guo et al. [19]. The Wi-Fi signals were utilised for localisation by matching the transmitted signal with the received one, the localisation of one person was achieved in an open field without much clutter. Chetty et al. [20] conducted experiments in high clutter indoor environments using Wi-Fi signals, they were able to detect one moving person through a wall.

A multi-person localisation system Wi-Track [21] was proposed by Adib et al. They pinpoint users' locations based on the reflections of Wi-Fi signals off the persons' bodies, their results show that their system can localise up to five users at the same time with an average accuracy of 11.7 cm. The system uses the reflection of the signal to estimate the time required by the signal to travel from the antennae to the person and back to the antennae. The system then uses the information of the antennae' positions to build a geometric model that converts the round trip delays of the reflected signal to a position of the user. Wi-Track removes the reflections from walls and other static objects by background subtraction where the distance of these objects does not vary over time, and hence they can be removed by subtracting consecutive frames of the constructed scenes. Reflections that include a combination of humans and static objects are addressed through taking into account the models of human's motion and their velocity in indoor scenarios. One limitation of the proposed system is that it needs the users to move in order to be able to locate them because the system cannot distinguish between static users and a piece of furniture.

When a person is conducting an activity, he will cause the blocking or the reflecting of transmitted signals. This will cause a variation in the received signal strength. The activities performed by people will leave a characteristic fingerprint on the received signals. The variation in the received signal can then be used in order to classify different activities. Woyach et al. [22] investigated the effect of human's motion on the received signal. Moreover, they showed that the speed of an object could be estimated by analysing the pattern of RSS variation of transmitted frames of a moving object. Krishnan et al. [23] expanded the work of Woyach by studying the differences between moving objects and stationary objects by analysing the variation of the RSS in a network of wireless nodes. Anderson et al. [24] and Sohn et al. [25] were able to distinguish between six speed levels, such as stationary, walking, and different driving speeds.

Youssef et al. [26] introduced a Device-free Passive (DFP) localisation system. A DFP system can localise objects that do not carry any device. The system works by observing variations in the received signals to detect the presence of objects in the environment. Bocca et al. [27] proposed a DFP system which localises the person based on the RSS variations of a line of sight link between two communication nodes, a sub-meter accuracy was reported; however, these methods have serious limitations in non-LOS environments due to the multipath effects. For non-LOS environments, Wilson et al. [28] also proposed a variance-based method to localise people; however, their method cannot locate static people, since they do not produce much RSS variance.

A more recent work by Wilson et al. [29] investigated the use of the particle filter to localise both static and moving people. The method works in both LOS and non-LOS environments; however, it cannot be easily implemented in real-time. Furthermore, the accuracy of RSS based methods requires a high density of communication nodes.

Kosba et al. [30] proposed a system to detect motion using standard Wi-Fi hardware. Their system uses an offline training phase where no movement is assumed as a baseline. Then, the anomaly is detected by detecting changes from the baseline. Lee et al. [31] also used the RSS fluctuation of communication nodes for intrusion detection. They reported changes in the standard deviation and the mean of RSS values in five distinct indoor scenarios.

RSS is an unreliable measure, because it is roughly measured, and can be easily affected by multipath. In [32] the Channel State Information is used, CSI is a fine-grained information, it gives information about the frequency diversity characteristic of the OFDM systems. In [32] the authors used the CSI to build an indoor localisation system FILA. FILA processes the CSI of multiple subcarriers in one packet and builds a propagation model that captures the relation between CSI and the distance. The effectiveness of the system is shown by using a commercial 802.11n device. Then, a series of experiments were conducted to evaluate the performance of the proposed system in indoor environments. The experiments results showed that the localisation accuracy could be significantly improved by using CSI, where for over 90% of the data points, the localisation error was in the range of 1 meter.

Authors in [33] showed that activity recognition can be achieved using the CSI measurements which are available by the IEEE 802.11n devices and with a small number of communication nodes. Their system E-eyes uses the wide bandwidth of 802.11ac, where a more fine-grained channel state information is used in Multiple Input Multiple Output (MIMO) communications. Different sub-carriers will encounter different multipath fading because of the small frequency difference. When taking a single RSS measurement, such effect is usually averaged out. Each subcarrier measurement will change when a movement changes the multipath environment. This will allow the system not only to detect changes in the direct path but also to take advantage of the rich reflected signals to cover the space. This will also allow the system to operate using one access point and a small number of Wi-Fi devices, which already exist in many buildings. However, the proposed system has many limitations: first, the system was designed and tested with the presence of only one person. Second, the system was tested without the presence of any pets. Large pets may require an additional signal processing stage. Third, the system requires a stable surrounding environment with no furniture movement, because changing the surrounding environment requires a profile update.

2.3 Applications of Wi-Fi based people tracking systems

Wi-Fi is currently used in a wide variety of applications such as activity detection, gesture recognition, and elderly people monitoring. Future access points will be able to recognise your gesture and take your command (adjust music volume, adjust room temperature, turn lights on and off, and change TV channels), analyse and classify different activities of people living inside and outside the house by using through the wall imaging, monitor the health conditions of elderly people by monitoring their breath, fall, etc, and finally provide a higher data rate and energy more efficient communication by directing the beam exactly toward the user position instead of the omnidirectional transmission. The different applications of the Wi-Fi based people tracking systems can be summarised in Fig. 2.2.

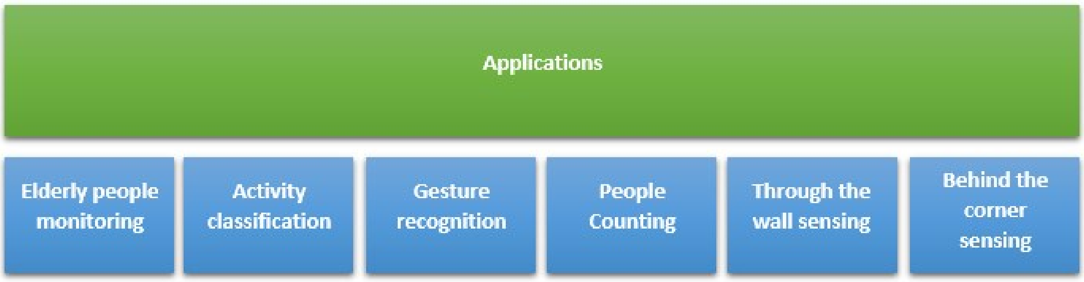

Fig. 2.2 Different applications of the Wi-Fi based people tracking systems.

2.3.1 Elderly people monitoring

The population of people aged 65 years or older is increasing, and their ratio to the population of people aged 20–64 will approach 35% in 2030 [34]. The worldwide population over 65 is expected to grow to one billion in 2030. The majority of elderlies spend their time within their own homes most of the day. Every year 33% of elderly people over the age of 65 will fall, and the percentage increases for the elderlies living in care institutions. The fall could cause injuries and reduction of the quality of life. Unfortunately, fall represents one of the main reason of the death of elderly people. Most of the time, the elderly at high risk of falling need to move to institutionalized care, which can approximately cost US$3,500 per month. A large number of elderlies cannot get up by themselves after the fall, and even without any direct injuries, 50% of those who had a long time of being on the floor (longer than one hour) died within six months after the falling. Therefore, fall detection could save many lives, it will help in achieving timely treatments, and can dramatically decrease medical expenses.

There are many competing fall detection technologies, existing technologies can be classified into four categories: wearable sensor based, smartphone-based, vision-based, and ambient device based techniques. Ambient device based fall detection systems [35] [36] [37] seek to use the ambient noise produced by the fall to capture risky situations. Examples of the ambient noise being used include audio and floor vibration. In these systems, specific devices should be placed in the environment. Detecting the pressure or the sound of the environment around the person produces a large percentage of false alarms. Vision-based fall detection systems [38] [39] [40] use activity classification algorithms based on the camera as a sensing technology. Vision-based fall detection systems can accurately detect a human fall. However, these systems violate people privacy and they fail to work in dark environments. Both wearable sensor [41] [42] and smartphone [43] [44] based fall detection techniques use sensors such as accelerators to determine the velocity. Sensors are widely used in fall detection systems; however, carrying a device is usually user-unfriendly, it is intrusive, and easily broken.

Recently, improved classification methods of radar signals corresponding to different types of motions have been proposed to classify falls from other types of activities such as sitting, standing, kneeling, and so on [45]-[51]. Authors in [45] investigated the dynamic aspect of a fall signal and used machine learning techniques to differentiate between radar signals in falls and non-falls situations. This differentiation was achieved in [45], [47], [48], and [50] by extracting features from the time-frequency signal representations. Wavelet transform was used to analyse radar fall signals in [49] and [51]. In [46], a number of Doppler sensors were used to improve the accuracy of fall detection by monitoring the movement of the user from many directions, this will also help in combating occlusions. They used data fusion by combining or selecting features. Although the combination method is more complex to implement, it outperformed conventional methods in different fall and non-fall scenarios. In [45]–[47], [49], and [50], a fall is separated from a previous motion by determining the start and the end of a possible fall. Then, the Doppler features of the fall are extracted within the fall time interval. A 2.5 GHz bandwidth UWB range-Doppler radar is used in [52] to provide range measurements for object localisation. Range-Doppler radar is also used in [53] to detect physiological parameters such as respiration, heartbeat, and other motion parameters to detect a fall. Features related to respiration, heartbeat, and motion, or combinations of them, are used to differentiate between a pet present in the room and the fallen person. A range-Doppler radar can resolve many objects and therefore allows the radar to take into account more than one user in the observed environment (e.g., [54]). In this situation, both the elderly and other persons in the environment will be monitored.

Authors in [55] proposed a Wi-Fi based fall detection system WiFall, by taking advantage of the channel state information measurements. The basic idea is to analyse the change in CSI when human activities affect the environment. The system consists of two stages architecture: the first one is an algorithm to detect abnormal CSI series, and the second one is an activity classification based on Support Vector Machine (SVM) technique to distinguish falls from other activities. WiFall achieved comparable precision to device-based fall detection systems with 87% detection rate and 18% false alarm rate.

Patwari et al. [56] reported that they were able to detect the breathing rate of a person by analysing the fluctuation of RSS in the received packets from 20 nodes around the person. By using the maximum likelihood estimation, the breathing rate was estimated with an error of 0.3 breaths per minute. The nodes transmit every 240ms with a 2.48 GHz frequency, which means that the overall transmission rate is about 4.16Hz. The prediction was performed after a 10 to 60 second measurement period. Longer measurement periods did not significantly improve the accuracy. The achieved accuracy was related to the number of nodes, where with 7 nodes, an RMSE rate of 1.0 approximately was achieved.

2.3.2 Activity classification

The growing concern about law enforcement and public safety has resulted in a large increase in the number of surveillance cameras. There is a growing interest in both the research community and in the industry to automate the analysis of human activities and behaviours. The main approach of these techniques is to model normal behaviours, and then detecting the abnormal behaviour by comparing the observed behaviour and the normal behaviour. Then the variation is labelled as abnormal. Abnormal behaviour detection has gained increasing interest in surveillance applications recently. Hu [57] has recently discussed that most surveillance techniques are based on the same approach; where the moving object is first detected. After that, it is tracked over many frames, and finally the resulted path is used to differentiate normal behaviour from abnormal ones. In general, these techniques have a training stage where a probabilistic model is built based on the normal behaviour.

Researchers have achieved remarkable precision in recognising human activities such as, running, walking, climbing stairs, cycling, and so on [58], [59], [60]. However, one limiting requirement of these sensing techniques is that the person to monitor has to actually cooperate and wear a device. In contrast to this, in device-free approaches, no device is needed to be worn by the monitored person. One can distinguish between two types of systems, the first one is classical systems, which are installed particularly for the sensing task and the second one is systems, which are utilised for sensing but were originally installed for other purposes. Classical device-free systems cover for instance video [61], [62], infrared [63], [64], pressure [65] and ultrasound sensors [66], [67]. The main limitation of these systems is that they require high installation effort.

Authors of [68] classified simple activities by capturing features from the variation of the signal between two communication nodes. They also investigated the performance of the system under multipath environments. It was also demonstrated that activities conducted at the same time from multiple persons could be easily distinguished by using signal strength based features [69]. However, the highest classification accuracy was achieved when the activity was less than one meters from the receiver. At larger distances, the classification accuracy decreased rapidly. Recently in [70], they considered the recognition of general activities based on RSS in a sensor network, where activities such as sitting, standing, walking, and lying have been recognised with high accuracy.

Authors in [71] proposed the use of the wireless channel, where they monitored the fluctuation in the RSS, which is calculated for each packet at the receiver, they attempted to recognise activities performed in front of a mobile phone. This approach allows activity recognition when the device is not carried by the person but near to him. The proposed system fails to determine the direction of the activity, it needs a modified Wi-Fi firmware, and it is limited to a small set of smartphones. Furthermore, the achieved accuracy is still below the accuracy of conventional sensors such as accelerometers, where an accuracy of 74% inside the room and an accuracy of 61% through the wall was achieved.

For activity recognition, many simple RSS features have been used such as average magnitude squared, signal-to-noise ratio [72], [73], [74], and signal amplitude [75]. In [76] the learning approach was able to detect and count up to 10 moving or stationary users. Then, after using additional frequency domain features, the accuracy was further improved [77], [78].

2.3.3 Gesture recognition

As computers become increasingly embedded in the environments, there is an increasing need for novel ways to interact with the computers. The Xbox Kinect [79] is a recent example of a sensor that enables interaction based on gesture using computer vision and depth sensing. The success of these devices has increased the interest in building novel user interfaces that decrease the dependence on traditional interfaces such as the mouse and the keyboard. Gestures can be used as a new interaction technique for computing that is embedded in the environment. For instance, by a hand motion in the air, the person can adjust the volume of the music while sitting, or turn down the air conditioning when he is in bed. Such capabilities can enable applications in many domains including gaming, home automation, and elderly health care as described in Fig 2.3 and Fig 2.4. Conventional gesture recognition systems are based either on vision technology such as Kinect or wearable sensors such as Magicrings [80].

Fig. 2.3 Application of gesture recognition in gaming [85].

Fig. 2.4 Application of gesture recognition in home automation [85].

Aumi et al [81] presented an ultrasonic-based gesture recognition approach. It uses the integrated audio hardware in smartphones to determine if a particular phone is being pointed at, i.e., the person waves at a phone in a pointing motion. They evaluated the accuracy of the system in a controlled environment. The results show that, within 3 meters, the system has an accuracy of 95% for device selection. The basic idea of the proposed system is that the intended target phone will have the maximum Doppler shift compared to the other potential target phones. By comparing the peak Doppler shift in all the phones, they can determine the intended phone.

Gupta et al [82] presented SoundWave, a gestures recognition system that uses the microphone and the speaker that are already integrated into most smartphones to recognise gestures around the phone. They generated an inaudible tone, which will have Doppler shift when it bounces off moving objects such as the hand. They calculated this Doppler shift using the microphone to recognise different gestures.

Abdelnasser et al. [83] presented a Wi-Fi based gesture recognition system by using variation in RSS resulting from hand gestures. The system can recognise many hand gestures and translate them into commands to control different applications. The gesture recognition accuracy was 87.5% when a single access point was used and 96% when three access points were used. However, RSS is not an accurate metric because the high variation in RSS measurements causes a high rate of misdetection. Moreover, the proposed system and other RSS based gesture recognition systems are still unable to operate through walls.

Cohn et al. [84] used the electromagnetic noise resulted from electronic devices to recognise different gestures. They presented accurate gesture recognition with an accuracy of 93% for 12 gestures. They also presented promising results for people localisation inside a building. They used variations in the received signal that happen when the body moves. In addition to the ability to recognise different whole-body gestures, they also showed accurate localisation of the person within the building based on a set of trained locations. Their system was based on electromagnetic noise resulted from electronic devices and the power lines. However, the system requires the user to train and calibrate the gestures and locations for his home, the classification works well if the home is in the same state during the training; however, large changes in the state (such as turning on the lights) drop the classification accuracy significantly. Some devices also generate broadband noise that might mask other noise signals.

Gupta et al. [85] proposed WISEE, a gesture recognition system that uses Wi-Fi signals to recognise human gesture. WISEE can recognise user gestures without introducing any additional sensing device on the user body. The system uses the Doppler shift, which is the frequency change of the wireless wave when its source moves toward the observer. There will be many reflections from the user body, and the user gestures will result in a certain pattern of Doppler shift. For instance, if the user moves away from the device, this will produce a negative Doppler shift, and if the user moves toward the device, this will produce a positive Doppler shift as described by Fig. 2.5.

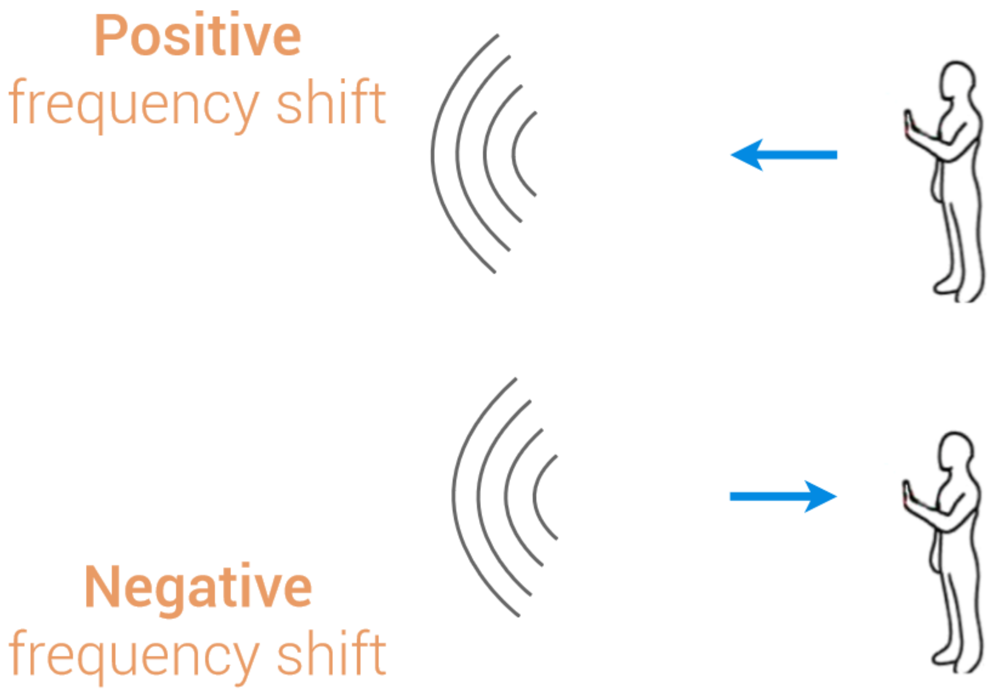

Fig. 2.5 The effect of the movement direction on the Doppler shift [85].

The main challenge for the proposed system was that the user gesture produces very tiny changes in Doppler shifts, which is very difficult to detect using WI-FI signals. A movement of 0.5 m/sec produces 17 Hz Doppler shift if the 5 GHz frequency is used. For gesture recognition applications, a Doppler shift of few Hertz should be detected. The solution for this challenge was achieved by converting the received signal, which is reflected from the moving object to a narrowband signal with few Hertz bandwidth, then the system extracts the frequency of this signal to recognise small Doppler shifts. The results of classifying 9 gestures in LOS and NLOS environments show that 94% of gestures were classified correctly and 2% of gestures were not detected.

Wang et al. [86] presented WiHear, which investigated the potential of using Wi-Fi signals to hear the talk of people. The proposed system locates the mouth of the user and then recognises his speech by analysing the signals reflected from his mouth. By analysing the mouth moving patterns, the system can recognise words in a similar way to lips reading. The results show that using a pre-defined vocabulary, the system can achieve recognition accuracy of 91% for single user speaking no more than 6 words and 74% accuracy for no more than 3 people speaking at the same time. The accuracy decreases when the number of persons increases. Furthermore, the accuracy decreases dramatically when more than 6 words were spoken by each user. The system also assumes that people do not move while they are speaking, and the recognition accuracy of 18% is very low for through the wall scenarios.

2.3.4 People counting

Crowd counting is increasingly becoming important in a number of applications, such as crowd control and guided tour. However, crowd behaviours are usually unpredictable which pose many challenges for crowd counting and estimation. Other challenges include object occlusions and real-time processing requirement. There are many applications that can benefit from people counting. Smart building management is one example, where the heating can be optimised based on the number of people, which can result in a large energy saving. There are many other similar applications that can be also optimised based on the number of people. Crowd estimation may also play an important role in emergency situations where a crowd needs to be evacuated from an area.

Mostofi et al. [87] proposed a Wi-Fi based system that counts the number of walking people in an area using only RSS measurements between a pair of transmitter and receiver antennae. The proposed framework is based on two important ways that people affect the propagation of the Wi-Fi signal, the first one is by blocking the line of sight signal, and the second one is the scattering effects. They developed a basic motion model, then they described mathematically the effect of a crowd on blocking the line of sight. Finally, they described mathematically the effect of the number of people on the resulted multipath fading and the scattering effects. By integrating these two effects together, they were able to develop a mathematical equation describing the probability distribution of the received signal amplitude in term of the number of people. In order to test the proposed approach, large outdoor and indoor experiments were conducted to count up to 9 persons as described by Fig 2.6, the results show that the proposed approach can count the number of persons with a high accuracy using only one Wi-Fi transmitter and one Wi-Fi receiver. For example, an error of 2 or less was achieved 63% of the time for the indoor case, and 96% of the time for the outdoor case when using the standard Wi-Fi omnidirectional antennae. When directional antennae were used, an error of 2 or less was achieved 100% of the time for both the indoor and outdoor cases.

Fig. 2.6 People counting in outdoor and indoor environments using only one pair of Wi-Fi cards [79].

In [88], multiple Wi-Fi nodes and RSS measurements were used to count the number of up to 4 persons. They reported an accuracy within an error of 1 person 84% of the time approximately. In [89] a similar approach was used but with fewer nodes, they were able to count up to three people. In [90], a transmitter-receiver pair was used to estimate the number of people based on RSS measurements. An extensive training data was used to develop the underlying model, an error up to 6 persons were reported in experiments limited to 9 persons.

In [91], the authors measured the channel state information of different sub-carriers, they developed a model to relate the channel state information to the number of persons through a training stage. They tested their model using one transmitter and three receivers to count up to 9 persons. However, measuring channel state information of different sub-bands is not available for most current Wi-Fi cards. In [92], the authors used UWB radar to count up to 3 stationary persons behind walls. In [93], the authors used a pulsed radar to estimate the number of people by using machine learning techniques.

Xi et al. [94] proposed a people counting system based on channel state information measurements. The basic idea of the proposed approach is that the number of people can be accurately estimated by analysing the changes in the channel state information. They theoretically studied and experimentally validated the relationship between the variation of the wireless channel and the number of moving persons. Their results show that CSI is very sensitive to the influence of the environment, they also showed that there is a monotonic relation between the number of moving persons and CSI variations. This provides a solid ground for crowd counting. They proposed a metric, which is the percentage of non-zero elements in the CSI Matrix. To estimate the number of people, the metric can measure the changes in CSI in a very short time. The value of the metric increases as the number of active persons increases, and it reaches the saturated state when the number of persons reaches a certain threshold. The Grey-Verhulst model was applied to estimate the number of persons. To estimate the number of persons in a large area, multiple devices were used to form a grid array. The main challenge was that CSI is very sensitive to the environment, i.e., users moving in one grid will result in CSI variations in adjacent grids. To address this challenge, an interference cancelation technique was proposed to adjust the sensing range for each receiver to enhance the estimation accuracy in a large monitored area. The system was built using 802.11n Wi-Fi devices. The system was evaluated with large-scale experiments. The results showed that the proposed approach outperforms other approaches in terms of accuracy and scalability.

In [95], [96] the locating procedure was divided into two stages: the training stage and the operating stage. Xu et al. [96] formulated the localisation problem as a probabilistic classification problem to cope with the error caused by the multipath in cluttered environments. Yuan et al. [95] used a classification algorithm to estimate the number of persons. Arai et al. [97] proposed an approach to link the crowd movement patterns with the feature of the radar chart. This approach requires a survey over the used areas to build a fingerprint database. The efforts, cost, inflexibility, and the environment dynamics are the main limitations of this approach. In crowd counting, the training cost is a main limiting factor particularly for large-scale scenarios; furthermore, it is very challenging to get the ground truth when the number of persons is large.

In [98], [99] if the person is nearby a link, the RSS will change remarkably. However, if the person moves away from the link, the performance decreases rapidly. Nakatsuka et al. [100] demonstrated the effectiveness of using the average and the variance of RSS to estimate the crowd density. Patwari et al. [101] proposed a statistical approach to model the RSS variance as a function of a person's position with respect to the antennae locations. Xu et al. [102] used a link-based approach to estimate the number of persons and locate their positions using RSS measurements.

2.3.5 Through the wall sensing

Through the wall sensing is a new research area that was introduced to address the increasing need to see through the walls for many applications, such as recognising and classifying objects in the building. It could be also used in emergency situations such as earthquakes to check whether a person exists under the rubble Fig 2.7.

Fig. 2.7 Through the wall sensing could help in determining the presence of people under the rubble [103].

Through the wall sensing is highly desirable by emergency workers and the police. Accurate through the wall sensing and imaging can help the police forces to get a precise description of the person movement inside a building Fig 2.8, it can also help firefighters to locate people who are trapped inside a burning building.

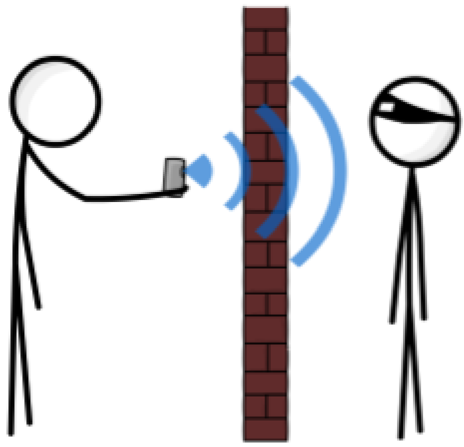

Fig. 2.8 Through the wall sensing and imaging can help police forces to get a precise description of a building interior in a hostage crisis [103].

Through the wall imaging has attracted much interest recently particularly for security applications [103]. Through the wall imaging uses radio frequency sensors to penetrate walls that obscure objects of interest and to map the building interior behind the walls. These features make through the wall systems more suitable for search and rescue, and covert surveillance. Through the wall sensing systems must take into account signal attenuation caused by the walls, where the attenuation is lower at low frequencies. It must also take into account the need for large bandwidths to get a high range resolution. The majority of through the wall sensors are UWB radars, which have many advantages over classical narrow band sensors.

Through the wall imaging based on radar sensors has drawn significant interest recently [104], [105], [106], [107], [108], for both motion detection and static imaging.

Most Synthetic Aperture Radar (SAR) techniques do not take into account propagation distortions resulting from the passing of signals through walls. These distortions will degrade the performance and may cause an error in the localisation of objects of interest. Free space assumptions do not hold anymore because the electromagnetic waves propagate through walls now. Therefore, new modelling for propagation effects through the wall is needed. Attenuation, shadowing, multipath, refraction, reflection, dispersion, and diffraction, all play an important role in how the signals propagate through the first interface. Without taking into account these propagation effects, surveying the interior of buildings will be largely affected. Other important factors such as array processing techniques, image formation techniques, image sharpening, object detection techniques, and multipath cancelation techniques, must be taken into account and be adapted and optimised based on the nature of the sensing problem. A common cause of incorrect localisation is the illumination of objects outside the building by the reflection from the first wall, which creates an ambiguous image that is visible inside the building. In addition, the strong reflection from the front wall may cause nearby weak objects inside the building to go undetected. Multipath propagation may introduce ghost or false objects in the constructed image. Refraction through walls could lead to localisation error, causing blurring and offsets of objects in the constructed image.

In [109] and [110] a series of experiments were conducted to investigate the effectiveness of using Wi-Fi signals as an illuminator of opportunity for through the wall people localisation. In [110] an indoor events detection system was proposed by using the time reversal technique to detect changes in indoor multipath environments. The proposed system enables a single antenna device that operates in the Industrial Scientific and Medical (ISM) band to capture indoor activities through the walls. The system uses the time reversal technique to detect changes in the environment and to compress high-dimensional features by mapping the multipath profile to the time reversal space, which will enable the implementation of fast and simple detection algorithms. Furthermore, a real prototype was built to evaluate the feasibility and the performance of the system. The experimental results showed that the system achieved a detection rate of 96.92% with a false alarm rate of less than 3.08% in both LOS and NLOS environments. However, when the person is close to the transmitter or the receiver, the miss detection rate increased significantly.

In [111] a new method for localisation and motion tracking through walls was presented. The method takes advantage of variations in received signal strength measurements caused by people motions. By using a model for the multipath channel, they showed that the signal strength of a wireless link is highly dependent on the multipath components that contain moving objects. A mathematical model relating the locations of movement to the RSS variance was used to estimate the motion. From that motion, the Kalman filter is then used to track the positions of the moving objects. The experimental results were presented for 34 nodes that perform through the wall tracking over an area that covers a 780 square foot. The system was able to track a moving object through the walls with a 3ft average error approximately. An object that moves in place can be localised with 1.5ft average error approximately.

Authors in [112] designed and implemented a through the wall people localisation system. Their methodology depends on detecting when people cross the links between the receivers and the transmitters. When two Wi-Fi 802.11n nodes were used, the methods achieved approximately 100% accuracy in detecting line crossings and movement direction. They also found that the proposed method achieved 90−100% accuracy when a single 802.11n receiver is used. However, the systems proposed in [111] and [112] require a large number of communication nodes which limits the range of applications of these systems.

2.3.6 Behind the corner sensing

Detecting and localising people situated behind obstacles could have many applications, obstacles might partially or completely block the propagation of wireless signals. Such situations may arise when for instance police forces want to inspect a corridor for possible threats before entering it Fig 2.9. Wi-Fi has the potential for “seeing” behind corners using the diffraction and reflection of electromagnetic waves, for both indoors and outdoors applications.

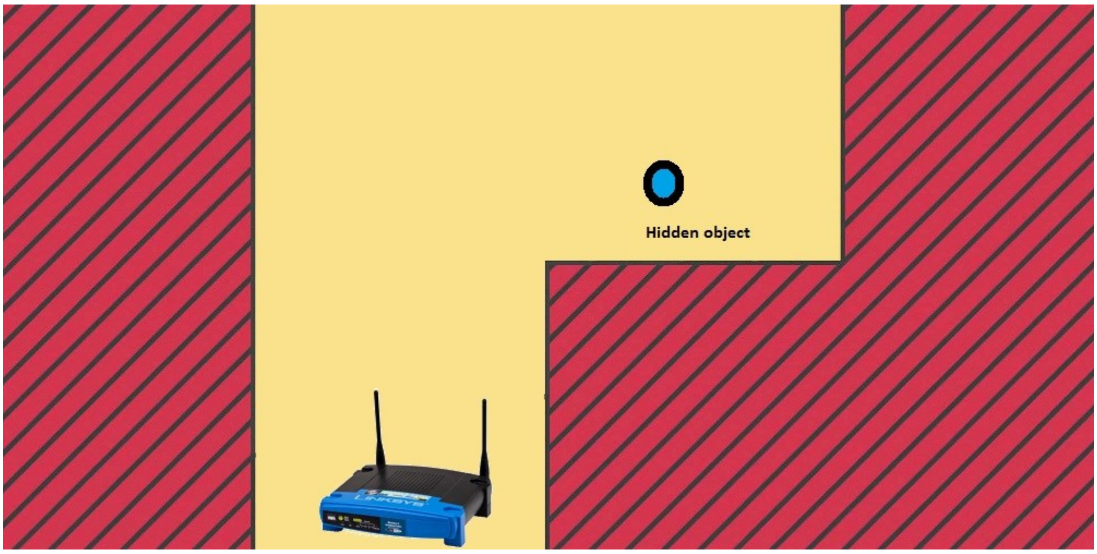

Fig. 2.9 An example of the need of behind corners sensing where the object exists outside the direct field of view.

Darpa developed a multipath exploitation radar program [113–115], the system tracks moving objects by utilising the multipath effect to maintain the track even when the objects are not in the line of sight. The same approach was used in [116–118] for behind the corner localisation of mobile terminals in urban environments. The multipath represented by the multiple echoes that are diffracted and reflected by an object and its surrounding environment are usually nuisance signals for conventional localisation systems [119, 120]. In [121], rather than considering them a nuisance, the multipath is used for localisation of people invisible to police forces. In addition to the reflection-based multipath, they used the diffraction and the combination of diffraction and reflection for the localisation. The proposed approach does not need a priori information about the geometry of the environment. It only needs information about the distance between the walls and the antenna, as well as the distance between the corner that diffracts the electromagnetic waves and the antenna. This information could be either obtained directly from the UWB data or extracted from other additional measurement devices. This approach could be more suitable for handheld portable devices that can be carried by security operators because it uses only one monostatic antenna or a small antenna array of two collocated transmitting and receiving antennae. They showed results of successfully detecting and localising a person standing up to five meters away from the corner. The precision of the proposed approach depends on the size of the object. When only one single path is available, the localisation accuracy significantly decreases. In this condition, the operator will be notified about the presence of an object. Such information could be very important in many security situations. One other limitation of the proposed approach is that the antenna should be directed toward the diffracting corner to increase the power of the diffracted path since it is very weak.

In [122], the authors showed that micro-Doppler signatures from person gait could be captured in an urban environment by using multipath propagation to illuminate the object in NLOS regions. A high-resolution radar system was used for data collection. The high resolution will enable multipath contributions to be separated individually. Two scenarios with 1 and 2 walking users are tested, the experimental was arranged to detect the multipath object response from up to 5 wall reflections. The main results showed that human micro-Doppler signatures could be used for classification purposes even after multiple wall reflections.

In [123] the authors have demonstrated the feasibility of X-band radar to detect moving persons behind concrete walls. The detection was achieved using stepped-frequency radar in a controlled scenario. Different measurements of the transmission and reflection properties of the material of the wall have indicated low transmission through the used wall type, leaving the diffracted, and reflected wave components as the main way for the interaction with objects behind the wall. However, the main challenge facing the proposed system is the multipath propagation.

2.3.7 Other applications

Emotion recognition is an active research area that has drawn growing interest recently from the research community. It seeks to answer a simple question: can a device that senses our emotions be built. Such a device will enable smart homes to react according to our emotions and adjust the music or the television accordingly. Movie makers will have new interesting tools to evaluate people experience. Advertisers will get people reaction immediately. Computers will automatically diagnose symptoms of anxiety, depression, and bipolar disorder, allowing early detection and response to such problems. More broadly, computers will no longer be limited to usual commands, it will interact with the users in a way similar to the way humans interact with each other. Emotions can be recognised from body gesture [124] as accurately as from faces [125], [126], [127]. The role of the human body in expressing emotions has evidence from psychology [128] and nonverbal communication [129]. The role of body expressions has also been confirmed in emotion detection [130], [131], [132]. Walter et al. [128] showed that emotion detection from postural expression has similar accuracy to detection based on facial expression alone, although hands and faces were covered. Bull [133] indicated that dynamic configurations of the human body hold a large amount of information about emotions. He showed that body motions and positions could be used as an indicator of the human state such as boredom or interest along with other 14 emotions. Other researchers [134], [135] have gone further by investigating the contribution of each body parts to particular emotional states. Emotion can be detected from simple daily life actions [136], [137], [138]. Wi-Fi could play an interesting role to detect body pose and gesture, and to use this information to recognise human emotions.

The researchers in [139] presented a new system that can recognise user emotions using RF signals that are reflected off his body. The system transmits a wireless signal and analyses the reflections from the user body to recognise his emotions such as happiness, sadness, etc. The key building block of the system is a new algorithm that extracts the heartbeats from the wireless signal at an accuracy close to Electrocardiogram (ECG) monitors. The extracted heartbeats are then used to extract features related to emotions, then these features are used in a machine learning emotion classifier. The researchers demonstrated that the emotion recognition accuracy is comparable with the state of the art emotion recognition systems based on ECG monitors. The accuracy of emotion classification is 87% in the proposed system and 88.2% in the ECG based systems.

Attention is a key measure in human-computer interaction. It helps to determine the potential to affect the decisions and actions taken by a user for an interactive system [140]. The same action could be considered differently depending on whether the user was focusing his attention towards the system or not. Various definitions that classify attention and its characteristics can be found in the literature [141], [142]. The tracking of the gaze is a commonly used measure of attention [143], other features may also indicate attention. Aspects such as effort, saliency, and expectancy are important cues that indicate the attention [144], [142], [140], [145]. The researchers in [146] discussed various aspects of attention, they identified changes in walking direction or speed as the most distinguishing factors. In [147] they investigated -using wireless signals- how these factors, namely the walking direction, the location of the person, and the walking speed can be used for detecting and monitoring attention.

Keystroke privacy is very important to ensure the privacy of users and the security of computer systems, where what being typed can be sensitive information or passwords. The research community has studied many ways to recognise keystrokes, which can be grouped into three categories: vision-based approaches, electromagnetic-based approaches, and acoustic-based approaches. Acoustic-based approaches recognise keystrokes based on different typing sounds that different keys of a keyboard generate [148, 149]. Acoustic based approaches could also recognise keystrokes based on the observation that the sound of different keys arrive at different times as the keys are at different locations on a keyboard [150]. Electromagnetic-based approaches [151] recognise keystrokes using the observation that the electronic circuit of different keys in a keyboard is different, which will result in different electromagnetic emanations. Vision-based approaches recognise keystrokes using vision technologies [152].

In [153], it was shown that Wi-Fi signals could be used to recognise keystrokes. Wi-Fi signals are now everywhere, at offices, home, and shopping centres. The basic idea is that while typing a specific key, the fingers and hands of the person move in a unique formation, and therefore produce a unique time-series pattern of channel state information values, which can be called the CSI waveform of that key. The keystrokes of the keys produce relatively different multipath variations in Wi-Fi signals, which can be used to recognise keystrokes. Due to the high data rates of recent Wi-Fi devices, Wi-Fi devices produce enough CSI values within the duration of a keystroke, which will help in building more accurate keystrokes recognition systems. In [153], a keystroke database of 10 human subjects was built. The keystroke detection rate of the proposed system was 97.5% and the recognition accuracy for classifying a single key was 96.4%. The proposed system can recognise keystrokes in a continuously typing situation with an accuracy of 93.5%. However, the system works well only in controlled environments. The accuracy of the system is affected by many factors such as changes in distance and orientation of transceivers, human motions in surrounding areas, typing speed, and keyboard size and layout.

In [154], it was demonstrated that it is possible to use Wi-Fi signals to enable hands-free drawing in the air. They introduced WiDraw, a hand tracking system that uses Wi-Fi signals to track the positions of the user's hand in both LOS and NLOS environments, without requiring the user to hold any device. The prototype used a wireless card, less than 5 cm error on average was reported in tracking the user's hand. They also used the same system to develop an in-air handwriting app, a word recognition accuracy of 91% was reported. However, one limitation of the proposed system is that it requires at least a dozen transmitters in order to be able to track the hand with high accuracy. Furthermore, the 3D tracking error is higher than the 2D tracking error, the main cause for this is the difficulty in accurately tracking depth changes. The system achieved high tracking accuracy only when the hand is within two feet from the receiver. The error starts to increase at larger distances.

The advantages and limits of performing imaging based on Wi-Fi signals were investigated in [155]. They presented Wision, a system that enables imaging of objects using Wi-Fi signals. The system uses the Wi-Fi signals from the environment to enable imaging. The approach uses multipath propagation where the signals reflect from objects before they arrive at the system. These reflections "illuminate" the objects, which the system uses for imaging. However, the main challenge is that the system receives a combination of reflections from many objects in the environment. The evaluation demonstrated the system ability to localise and image relatively large objects such as desktops, and couches, or objects with high reflective properties such as metallic surfaces. Smaller objects with low reflective properties have smaller cross-sections and thus reflect a smaller fraction of the Wi-Fi signals, which make them harder to image. Moreover, when the size of the object becomes close to the wavelength of the Wi-Fi signal, which is 12 cm approximately at 2.4 GHz, the interaction of the object with the Wi-Fi signals decreases. This is a fundamental limitation of imaging based on Wi-Fi signals. This fundamental limitation could be addressed using higher Wi-Fi frequencies such as 5 GHz that has a smaller wavelength of 6 cm approximately. Using Wi-Fi signals in imaging still represents a significant opportunity with many potential applications. Imaging resolution with Wi-Fi signals also depends on the antenna array length. The imaging resolution can be increased by increasing the length of the antenna array. A resolution close to the optimal at 2.4 GHz was reported in [155] for the considered array lengths. They observed that the resolution does not depend on the number of antennae, but rather depends mainly on the length of the antenna array. Recent theoretical work has also shown that similar resolutions can be achieved with a smaller number of antennae given that the length of the antenna array is the same. The main constraint they observed with their implementation is that smooth metallic objects are acting like mirrors, where they could be oriented in such a way making them hidden from the view of some transmitter positions. To address this issue, one may use antennae with wider radiation patterns or optimising the antenna position to maximise their reach. One could also use signals from multiple Wi-Fi devices, which are more likely to be at various positions. Another approach is leveraging the mobility of the device to create images as the user moves around.

2.4 Challenges

During the course of this chapter, some challenges facing Wi-Fi based people tracking systems and their applications have been identified. These systems still need to address some challenges in order to be able to operate in real-world environments, some of these challenges include:

1) The presence of multipath propagation, which introduces multipath ghosts in the observed scene.

2) The detection of weak signals caused by the low reflectivity of the human body.

3) The occlusion of the Wi-Fi signal due to some obstacles.

4) The presence of a large number of people.

5) The detection of abrupt people motion.

6) The high power of direct signal interference, which will cause the masking of echoes from objects of interest.

7) Wi-Fi has limited range resolution in comparison with other sensing technology such as UWB. When the size of the object becomes close to the wavelength of Wi-Fi signals, which is 12 cm approximately at 2.4 GHz, the interaction of the object with the Wi-Fi signals decreases.

This work will address three of these challenges, which are the most important challenges facing Wi-Fi based people tracking systems, namely: the detection of abrupt people motion, the detection of weak signals, and the presence of multipath propagation.

2.5 Conclusion

This chapter has presented a survey on object localisation techniques based on Wi-Fi signals. It also presented different applications of the Wi-Fi based people tracking systems such as elderly people monitoring, activity classification, gesture recognition, people counting, through the wall sensing, behind the corner sensing, and many other applications. The gaps and the limitations of existing works were also highlighted. The chapter has extensively investigated the use of the Wi-Fi signal for people tracking, which turned out to have strong potential in indoor and outdoor tracking applications, Wi-Fi technology has several important features which makes it an appealing option compared to other sensing technologies, such as relatively high transmitted power, high resolution, and high availability. However, these systems still need to address some challenges in order to be able to operate in real-world environments. In the next chapter, the first challenge that is related to weak signal detection will be addressed.

Chapter 3

Weak signal detection

3.1 Introduction

In signal processing, the noise and the interference from the surrounding environment are very difficult to avoid. The noise is mixed with the desired signal, which makes it very challenging to extract the desired information. In many fields, very weak signals need to be detected. Therefore, it is of great interest to develop effective techniques to detect these weak signals. The main purpose of these techniques is to extract the weak signal that is usually buried in noise. Weak signal detection is of great significance in radar, sonar, communications, fault diagnosis of mechanical systems, industrial measurement, earthquake, astrophysics and other areas.

The signal reflected from the human body is usually very weak due to the low reflectivity of the human body. In this chapter, a signal detection method that significantly improves the detection probability of weak signals will be proposed. Firstly, a compressive sensing based localisation method is proposed to extend previous work to include angle of arrival estimation. Then a combined reflection-based and shadowing-based weak signal detection method is proposed, where the detection of the weak signal reflected from the person's body is enhanced by taking into account the changes of the signals that are reflected from the surrounding environment. Finally, a deep learning based Wi-Fi localisation technique is proposed that significantly improves the accuracy and reduces the runtime in comparison with existing techniques.

The chapter is organized as follows: A review of weak signal detection methods is given in section 3.2. The Wi-Fi signal model is described in section 3.3. An overview of compressive sensing is given in Section 3.4. An overview of deep learning and its application in signal processing and communication is given in Section 3.5. Section 3.6 describes the localisation method using the compressive sensing approach. The weak signal detection method is proposed in Section 3.7. The deep learning based localisation technique is proposed in section 3.8. The results are listed in section 3.9, and the chapter is concluded in Section 3.10.

3.2 Weak signal detection

Traditional tracking algorithm combines measurements across different time and estimates the required parameters. When a data image is produced by a sensor, each pixel represents the received energy in a specific location. The common approach in this case is to use a threshold to detect the signal where the cells that are higher than the threshold are treated as valid measurements. This approach works well if the Signal to Noise Ratio (SNR) is high. However, for low SNR objects, the threshold should be low enough to increase the probability of object detection. However, a very low threshold may increase the false detections rate, which causes the tracker to form false tracks. In the Track before Detect (TBD) approach [156, 157], the tracker uses all of the sensor data as an input without applying any threshold, where the accumulation of the measurements over time will allow the tracker to improve the tracking accuracy and allow the tracker to track low SNR objects.

The main challenge of the TBD approach is that the measurements are a nonlinear function of the object state, which describes the kinematic evolution of the object. One way to cope with the non-linearity is to discretise the state-space. When the state-space is discrete, estimation techniques such as Baum-Welsh filter [158], and the Viterbi algorithm [159] can be used. Several approaches for TBD were developed recently using these methods [160], [161], [162], [163], [164]. The main problem in using a discrete state-space is that it leads to a high computation cost.

An alternative approach to discretise the state-space is to use the particle filter to cope with the non-linear estimation problem [165], [166], [167]. The particle filter can be used to solve estimation problems that cannot be solved analytically. Particle filtering has been used recently in the TBD context [168], [169], [170]. The particle filter is a numerical approximation technique that uses random samples instead of the fixed samples.

The Histogram Probabilistic Multi-Hypothesis Tracker (H-PMHT) [171], [172] uses a parametric representation of the object probability density function (PDF) rather than using a numerical representation. This will result in significantly reducing the computation cost of the algorithm.

Instead of using the entire sensor data, Maximum Likelihood Probabilistic Data Association (ML-PDA) reduces the threshold to a very low level, then it applies a grid-based state estimation [173], [174], [175], [176]. The association of the measurements is performed by using the PDA.

Davey et al. [177] compared a number of TBD algorithms and investigated their performances in terms of the detection capability, and the required runtime. The results showed that the H-PMHT had a lower accuracy in detecting high-speed objects, while the particle filter and the Viterbi algorithm showed higher accuracy in detecting high-speed objects, where objects of speeds from 0.25 pixels per frame to 2 pixels per frame are considered. The number of false tracks of all the algorithms was comparable. The estimation error of the H-PMHT algorithm is significantly lower than the particle filter algorithm, which is better than the Viterbi algorithm. The H-PMHT was about two orders of magnitude faster than the Viterbi algorithm, and about one order of magnitude faster than the particle filter.

Some researcher found that when a signal was used as an input to a nonlinear system, the output SNR was enhanced instead of falling down by adding noise. As a result, Benzi [178, 179] proposed the concept of stochastic resonance. Fanve et al. [180] confirmed the phenomenon of stochastic resonance. An aperiodic stochastic resonance theory, which combines stochastic resonance with signal processing was proposed by Collins [181]. Stochastic resonance was also widely used in radar, sonar, image processing, and other areas. Hari et al. [182] proposed a stochastic resonance detector to detect signals that are buried in non-Gaussian noise. Adiabatic approximation theory [182] showed that when a bistable stochastic resonance system receives the noise, the power spectrum of the output will be located in the low-frequency region. Which means that in order to resonate with the noise, the input signal should be in the low-frequency range.

Most of the above approaches focus on the use of the tracking framework to improve the detection probability of weak signals; however, none of them tries to use the information available from the surrounding environments to improve the detection of weak signals; furthermore, the use of deep learning in addressing this challenge will be investigated.

3.3 Wi-Fi Signal Model

Wi-Fi standards IEEE 802.11 [8, 183] use both DSSS modulation in the 802.11b standard with 11MHz bandwidth and OFDM with 20MHz bandwidth in the newer a/g/n standards. An Access Point (AP) periodically sends a pilot signal to inform about its presence and the channel information. The AP usually uses the DSSS for the pilot signals to allow different modulation techniques to work at the same time in the wireless LAN environment.

In OFDM, the signal is divided into N_s symbols, then these symbols are modulated onto multiple subcarriers. The duration of an OFDM symbol is T. The subcarrier spacing is $\Delta f = 1/T$ and the bandwidth is $B = N_s \Delta f$. f_c is the carrier frequency, and $f_m = f_c + m\Delta f$ is the frequency of the mth subcarrier in the passband. A Cyclic Prefix (CP) is used to avoid Inter-Symbol Interference (ISI), T_{cp} denotes the length of the CP. One OFDM symbol in baseband is given by

$$x(t) = \sum_m S[m] e^{j2\pi \mathrm{m}\Delta \mathrm{f} t}\, q(t) \qquad (3.1)$$

Where s[m] is the symbol on the mth subcarrier and q(t) is a rectangular window of length T_{cp} + T.

A uniform linear array is considered with N elements and P signals impinge on the array from directions θ_1, θ_2, ..., θ_P, respectively, the received Wi-Fi signals can be expressed by

$$y(t) = \sum_p a(\theta_p) A_p e^{j2\pi f_c a_p t} x(t-\tau_p) + w(t) \qquad (3.2)$$

Where w(t) is white Gaussian noise and Ap is the attenuation which includes the path loss and the reflection, τ_p is the delay and a_p is the range rate of the pth path divided by the speed of light, x(t) is an OFDM symbol and the steering vector $a(\theta_p)$ is expressed by

$$a(\theta_p) = [e^{-j2\pi d cos(\theta p)/\lambda} \, .. \, e^{-j2\pi L d cos(\theta p)/\lambda}] \qquad (3.3)$$

Where λ is the signal wavelength, d is the array inter-element spacing and L is the number of antennae.

3.4 Compressive sensing

The Shannon sampling theorem [184] dictates that in order not to lose information when a signal sampled uniformly, sampling at least two times higher than the signal bandwidth must be performed. Some applications, such as video cameras require very high sampling rate, which results in a large number of samples, a data compression must then take place in order to store or send the data. In other applications, such as high-speed analogue to digital converters, it is very expensive to increase the sampling rate.

The "sample then compress" approach suffers from many limitations, where it must start with a high number of samples N, even though it will need only K of them. Compressive Sensing (CS) [185] is a more convenient data acquisition approach that directly takes a compressed representation of the signal without the phase of taking N samples.

Compressive Sensing is a convenient approach to improve accuracy and detect closely spaced people, which are difficult to separate in traditional methods. CS can also operate at a lower rate than the Nyquist rate. The use of CS in radar has been recently investigated [186-198]. Anitori et al. [199] presented an architecture for adaptive CS radar detection with Constant False Alarm Rate (CFAR) properties, they also provided a methodology to predict the performance of the proposed detector. Authors in [200] and [201] showed that compressive sensing could detect objects with high accuracy using Wi-Fi signals. The author in [202] showed that compressive sensing could successfully reconstruct the scene from only 100 samples out of 800 samples. However, a further samples reduction to 50 shows the limit of compressed sensing where several ghost objects are detected. The computational cost was close to the matched filter when the CS used 100 samples.

Consider a discrete-time signal x of length N. x can be represented in terms of basis vectors ψ_i

$$x = \sum_{i=0}^{N} s_i \psi_i \quad (3.4)$$

Where s_i is weighting coefficients. When x is a linear combination of a small number of K basis vectors, with K < N, i.e., only K of the s_i in (3.4) are non-zero; then, compressive sensing allows to sample x with a smaller number of measurements than the Nyquist rate. Measurements y with M < N are performed by linear projections

$$y = \Phi x + n \qquad (3.5)$$

With a measurement matrix Φ and additive noise n. When x is sparse with only a small number of non-zero entries K < N, CS can reconstruct x given that the measurement matrix Φ is incoherent with the basis ψ, i.e., the vectors $\{\varphi_j\}$ cannot sparsely represent the vectors $\{\psi_i\}$. The CS reconstruction problem then can be formulated as a convex optimization problem

$$\grave{x} = \min_{\tilde{x}} \|\tilde{x}\|_1 \text{ subject to } \|y - \Phi\tilde{x}\|_2 \leq \varepsilon \qquad (3.6)$$

Where ε bounds the noise in the signal. However, there is still no complete CS theory in the presence of noise. The performance of different reconstruction algorithms was reported in [201], the authors also showed how CS could outperform the matched filter approach in detecting closely spaced objects.

3.5 Deep learning

Deep learning [203, 204] is inspired from neural systems in biology, where the weighted sum of many inputs is fed to an activation function such as the sigmoid function, to produce an output Fig. 3.1. The neural network is then constructed by linking many neurons to form a layered architecture Fig. 3.2. A loss function, such as the mean square error should be used to get the weights that minimise the loss function between the expected output and output of the network. Optimisation algorithms such as the Gradient Descent (GD) are typically used in the training to find the best parameters. In [205] it has been shown that neural networks can be used as a universal function approximator by introducing hidden layers between the output and the input layers.

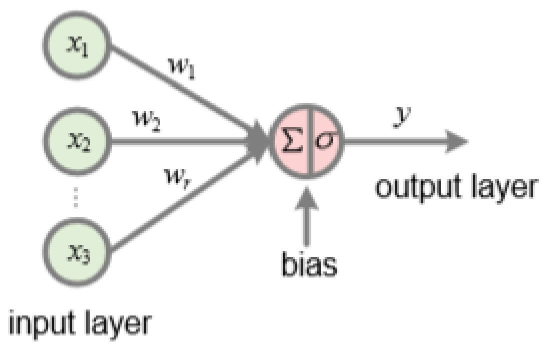

Fig. 3.1 A model of a neuron, where a weighted sum of different features is calculated and then fed into an activation function to produce an output [204].

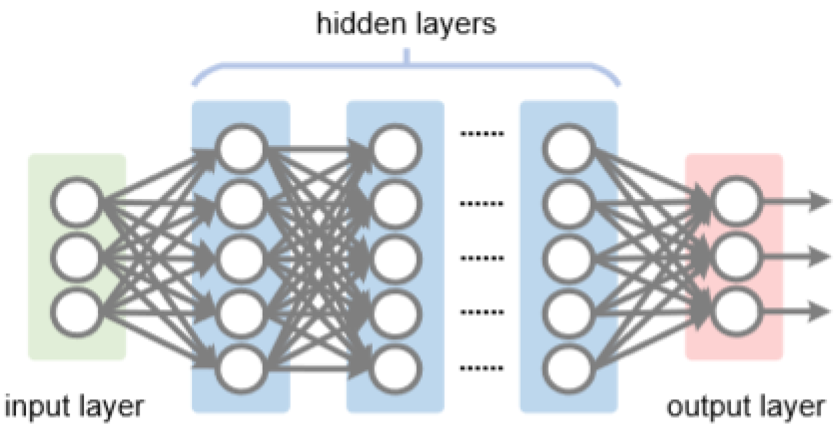

Fig. 3.2 A fully connected architecture where all neurons between adjacent layers are connected [204].

The basic deep learning model is the fully connected feedforward neural network, where each neuron is linked to the adjacent layer, but not to the neurons in the same layer. An efficient algorithm such as the backpropagation was proposed for training such networks. Many problems could arise during the training process, such as converging to a local minimum and vanishing gradients, where each weight is updated in proportion to the gradient of the error function; however, in many situations, the gradient will be very small which prevents the weights from updating their values. To address the vanishing gradient problem, the Rectified Linear Units (ReLU) activation function was introduced instead of the sigmoid function. Stochastic Gradient Descent (SGD) was introduced to improve the speed of the convergence over the gradient descent algorithm. However, this algorithm could still converge to local minimum solutions. To address this problem, many adaptive learning algorithms such as the Adam algorithm were proposed. However, the network could perform well using the training data, but give very poor performance using the testing data because of overfitting. Many techniques have been proposed to reduce overfitting such as dropout, and batch normalization.

Recurrent Neural Network (RNN) was introduced to provide neural networks with memory, where in many situations, the outputs need to depend on the input from previous time steps in addition to the current inputs. One example is translation, where the knowledge of previous words in the sentence would significantly help in producing a better translation of the current word. Unlike other neural network architectures where no connections exist in the same layer, the neurons in the RNN architecture are connected to allow former outputs to be the current inputs in the hidden layers to acquire memory. Some recently used RNN architectures that are showing promising results include Gated Recurrent Unit (GRU), and Long Short-Term Memory (LSTM).

The Convolutional Neural Network (CNN) is another promising architecture that is proposed to decrease the fast growth in the number of parameters. The basic idea of the CNN is to use convolutional layers followed by pooling layers before the fully connected network. In the convolutional layer, a number of filters are learned to represent local spatial patterns along the input channels. Which means that convolutional filters are combining spatial and channel information together. In the pooling layer, the mean value (average pooling) or the maximum value (max pooling) of the feature maps are computed. Thus, the number of parameters is significantly reduced before the fully connected layers. Therefore, by stacking a number of convolutional layers combined with down-sampling, the CNN is able to capture hierarchical patterns as image descriptions.

Deep Learning has recently shown promising results in image recognition and classification [206-208]. The key factors behind these significant results are the significant improvement in the performance of computing systems, and the use of large amount of data such as the ImageNet dataset [209], which contains more than one million images.

With the promising results of the CNN architecture in computer vision, many researchers have attempted to improve the CNN architecture proposed by Krizhevsky et al. [206] to achieve higher accuracy. For example, the highest accuracy architecture submitted to the ImageNet Large Scale Visual Recognition Competition (ILSVRC) in 2013 [208] used smaller stride and smaller window size for the convolutional layers. In [210], the researchers have addressed another important architecture design aspect, which is the network depth. They fixed other parameters of the network and started increasing the depth of the architecture by stacking more convolutional layers.

Recent evidence [210, 211] shows that the network depth is of crucial importance. However, the main challenge of using deeper networks is the vanishing gradients problem [212, 213], which affect the convergence significantly. This problem was addressed by introducing normalized initialization [213, 214] and intermediate normalization layers [215], which were able to make networks with tens of layers to begin converging. However, with the increased network depth, the accuracy gets saturated and then rapidly degrades, and stacking more layers to a deep model results in higher training error [216, 217]. In [218], the researchers have addressed the degradation problem by introducing a deep residual learning approach. To maximise the information flow, skip connections were introduced.

The 152 layers residual network was applied on the ImageNet dataset, it was able to win the first place in the ILSVRC 2015 competition. To ensure maximum information flow between different layers of the network, all layers are connected to each other directly in [219]. Where each layer connects its output to all subsequent layers and gets inputs from all preceding layers.

In communication, researchers have recently used Deep Learning for modulation detection [220], channel encoding and decoding [221-226], and channel estimation [227-230]. Wang et al. [231] have recently surveyed the applications of DL in communication.

In [227], different deep learning architectures such as Deep Neural Network (DNN), CNN, and LSTM were used for signal detection in a molecular communication system. Simulation results demonstrated that all these architectures were able to outperform existing approaches, while the LSTM based architecture has shown promising performance in the presence of inter-symbol interference.

In [228], a deep learning based detector called DetNet was proposed, the aim was to reconstruct a transmitted signal x using the received signal y. To test the performance of the proposed approach in complex channel environments, two scenarios were considered, the fixed channel model and the varying channel model. DetNet was compared with two algorithms, the Approximate Message Passing (AMP), and the Semi-Definite Relaxation (SDR) which provide close to optimal accuracy. In the fixed channel scenario, the simulation results showed that DetNet was able to outperform AMP and achieves comparable accuracy to SDR but with a significant reduction of the computational cost (about 30 times faster). Similarly, in the varying channel scenario, DetNet was 30 times faster than the SDR and showed a close accuracy.

In [229], a five layers fully connected DNN was used for channel estimation and detection of OFDM system by considering the channel as a black box. In the training phase, the data are passed through a channel model. The frequency domain signal representing the data information is then fed to the DNN detector to detect the sent data. When comparing with the conventional Minimum Mean Square Error (MMSE) method, the DNN detector was able to achieve comparable performance. Then it was able to show better performance when fewer pilots are used, or when clipping distortion was introduced to decrease the peak-to-average power ratio.

In radar, Yonel et al. [232] have recently used deep learning for radar imaging, they designed a recurrent neural network architecture. The results show that the proposed approach was able to outperform conventional methods in terms of the computation time and the reconstructed image quality.

Deep learning has been also recently used for compressive sensing [232-235]. Although compressive sensing has revolutionized signal processing, the main challenge facing it, is the slow convergence of current reconstruction algorithms, which limits the applicability of CS systems. In [233] a new signal reconstruction framework called DeepInverse was introduced. DeepInverse uses a convolutional network to learn the inverse transformation from measurements to signals. The experiments indicated that DeepInverse was able to closely approximate the results produced by state of the art CS reconstruction algorithms; however, it is hundreds times faster in runtime. This significant improvement in the runtime requires computationally intensive off-line training. However, the training needs to be done only once.

Recently, there is a trend of using deep learning for Wi-Fi based localisation [236-240]. Fang and Lin [236] proposed DANN, which uses a neural network with a single hidden layer to extract features from received signal strength. It was able to improve the localisation error to below 2.5m, which is a 17% improvement over state of the art approaches. DeepFi was proposed in [237] with four layers neural network. DeepFi was able to improve the accuracy by 20% over FIFS, which uses a probability-based model. CiFi was proposed in [239], it used a convolutional network for indoor localisation based on Wi-Fi signals. First, the phase data was extracted from the channel state information, then the phase data is used to estimate the angle of arrival, which is used as an input to the convolutional network. The results show that CiFi has an error of less than 1 m for 40% of the test locations, while for other approaches it is 30%. Moreover, it has an error of less than 3 m for 87% of the test locations, while for DeepFi it is 73%. In [240], ConFi was proposed, which is a CNN based Wi-Fi localisation technique that uses CSI as features. The CSI was organized as a CSI feature image, where the CSIs at a different time and different subcarriers were arranged into a matrix. The CNN consists of three convolutional layers and two fully connected layers. The network is trained using the CSI feature images. ConFi was able to reduce the mean error by 9.2% and 21.64% over DeepFi and DANN respectively. These results show the significant improvement in the runtime and the accuracy of deep learning based systems.

Table 3.1. Comparison between different deep learning based localisation systems.

System	Accuracy
DANN	17% improvement over conventional techniques
DeepFi	20% improvement over FIFS
CiFi	16% improvement over DeepFi
ConFi	22% improvement over DANN

3.6 Compressive sensing based detection

In this section, a Wi-Fi signal detection method using compressive sensing is proposed, where the works of [200] and [201] are extended to also include the angle of arrival estimation. The number of objects is often very small compared to the number of points in the scene, this implies that the scene is sparse, which enable us to formulate the CS reconstruction problem and solve a convex optimisation problem. The received signal should be matched to delay-Doppler-angle combinations, corresponding to objects detections. A sufficient delay-Doppler-angle resolution should be considered; however, a very high resolution may lead to a high number of combinations, many of them are highly correlated. The delay-Doppler-angle scene is divided into a $P \times V \times Z$ matrix, in which each point represents a unique delay-Doppler-angle point, the sparse vector x is composed of P data points in the range dimension and Z data points in the angle dimension at all considered Doppler shifts with V data points in the Doppler dimension. The size of vector x is Q = VZP. The vzp index will be nonzero if an object exists at the point (v, z, p). The measurements vector y contains the measured data from L antennae at time t_l. The measurement matrix Φ is generated by creating time-shifted versions of the transmitted signal (represented by the matrix F) for each Doppler frequency and each angle of arrival.

$$F = [\, x(t) \;\; x(t-\tau_1) \; \ldots . \; x(t-\tau_p) \,] \qquad (3.7)$$

Where $x(t)$ is assumed to be known, which can be fed back from the decoding process. The measurement matrix Φ establishes a linear relation between the measurements y at multiple antennae with the range profile x at different Doppler shifts ω_v and different angles θz. The scene is then reconstructed using the interior point method [45].

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_L \end{bmatrix} = \Phi \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_Q \end{bmatrix} (3.8)$$

$$\Phi = \begin{pmatrix} e^{-\frac{j2\pi d cos(\theta 1)}{\lambda}} e^{j\omega_1 t_1}F \,..\, e^{-\frac{j2\pi d cos(\theta z)}{\lambda}} e^{j\omega_1 t_1}F & \ldots & e^{-\frac{j2\pi d cos(\theta 1)}{\lambda}} e^{j\omega v t_1}F \,..\, e^{-\frac{j2\pi d cos(\theta z)}{\lambda}} e^{j\omega v t_1}F \\ e^{-\frac{j2\pi 2d cos(\theta 1)}{\lambda}} e^{j\omega_1 t_1}F \,..\, e^{-\frac{j2\pi 2d cos(\theta z)}{\lambda}} e^{j\omega_1 t_1}F & \cdots & e^{-\frac{j2\pi 2d cos(\theta 1)}{\lambda}} e^{j\omega v t_1}F \,..\, e^{-\frac{j2\pi 2d cos(\theta z)}{\lambda}} e^{j\omega v t_1}F \\ \vdots & \ddots & \vdots \\ e^{-\frac{j2\pi L d cos(\theta 1)}{\lambda}} e^{j\omega_1 t_1}F \,..\, e^{-\frac{j2\pi L d cos(\theta z)}{\lambda}} e^{j\omega_1 t_1}F & \cdots & e^{-\frac{j2\pi L d cos(\theta 1)}{\lambda}} e^{j\omega v t_1}F \,..\, e^{-\frac{j2\pi L d cos(\theta z)}{\lambda}} e^{j\omega v t_1}F \end{pmatrix}$$

To improve the detection probability, the result of 10 signals are combined before the threshold step, where the final value of the object is equal to the count of its appearance across all the 10 reconstructed scenes.

3.7 Combined reflection-based and blocking-based weak signal detection

The detection probability of the method introduced in the previous section will decrease rapidly for weak signals condition. In this section, a combined reflection-based and shadowing-based weak signal detection method is proposed. Fig. 3.3 shows how the presence of the person causes changes (blocking or attenuation) in the signals that are reflected from the surrounding environment, it also causes a reflection from the person's body, which is assumed to be much weaker than the signals that are reflected from the surrounding environment.

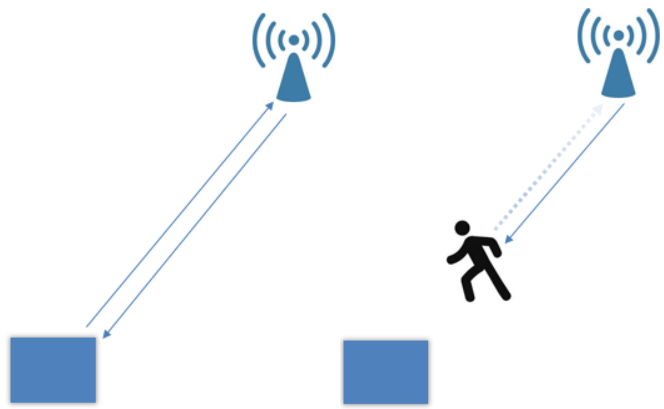

Fig. 3.3 Signal propagation in the empty (left) and the full (right) room, the presence of the person causes the blocking of the signals that are reflected from the surrounding environment, it also causes a reflection from the person's body

There are many RSS based tracking methods that use the variations of the RSS of the wireless links across the monitored area to localise and detect the presence or the movements of people. However, the main limitation of the RSS based methods is the requirement of a high density of radio sensing nodes that should be distributed across the monitored area, this introduces serious limitations of the applicability of these methods.

Unlike the RSS based methods, the proposed method does not use multiple sensing nodes, it improves the detection probability of the weak signal reflected from the person's body by taking into account the variations of the RSS in the signals that are reflected from the surrounding environment (walls and other static objects in the room). Where the presence of the persons will cause the blocking or the attenuation of some of these signals. The blocked/attenuated signal will enable us to determine that a person is present at angle θ. Then by using the fact that a signal is reflected from the person from the angle θ, only the strongest received signal that has the same angle need to be taken, instead of simply applying a threshold to discriminate the signal from the noise, this will enable us to detect the weak signal more robustly than the simple threshold approach.

The first step of the proposed method seeks to map the empty room. The received signal when the room is empty can be expressed by (3.9)

$$y(t_0) = \sum_m a(\theta_m) A_m e^{j2\pi f_c t} x(t_0 - \tau_m) + w(t_0) \quad (3.9)$$

The first term represents the signals that are reflected from the walls and other static objects in the room. When some people enter the room, the received signal can be expressed by

$$y(t) = \sum_p a(\theta_p) A_p e^{j2\pi f_c a_p t} x(t - \tau_p) + \sum_n a(\theta_n) A_n e^{j2\pi f_c t} x(t - \tau_n) + w(t) \quad (3.10)$$

The first term represents moving objects in the room and the second term represents static objects. The proposed method reconstructs the scene for the empty and the full room using the procedure described in section 3.6, X_E and X_F represent the reconstructed scene for the empty and the full room respectively. However, because of the noisy measurements, the simple threshold approach will decrease the probability of detecting the weak signals. Therefore, the next step of the proposed method will monitor the blocked/attenuated signals by monitoring the differences between X_E and X_F, this will enable us to determine the presence of persons at different angles, and then the strongest received signals that have the same angles of the blocked/attenuated signals are taken. The proposed algorithm is described by Algorithm 3.1. The received signal contains both the reflections from the users and the multipath returns from the static objects, the two are separated using background subtraction. The received signal also contains the measured data from L antennae, the measurement matrix establishes the relation between the measurements at multiple antennae with the range profile at different Doppler shifts and different angles of arrival as described in in section 3.6.

Algorithm 3.1. A combined reflection based and blocking based weak signal detection algorithm

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1) Reconstruct the scene when the room is empty (X_E at time t_0).

2) Reconstruct the scene when the room is full (X_F at time t).

3) Determine the angle of arrival of the person by determining the blocked/attenuated signal in X_E

4) Take the strongest received signal that has the same angle of arrival of the blocked/attenuated signal

---

3.8 Deep learning based method

Most signal processing techniques in communications and radar have solid foundations in information theory and statistics and are optimal using some assumptions such as linearity, and Gaussian statistics. However, many imperfections exist in real-world environments. Deep learning is a very appealing option because it can adapt to real-world imperfections, which cannot be always captured by analytical models.

Choosing the suitable architecture and its parameters that best suit the problem is an important question. many architectures with different number and size of layers have been tried, the best performing architecture is shown in Table 3.1 The network has three convolutional layers and three fully connected layers. The input of the network is the received signal y. Different kernels (filters) can detect different features from the input signal and will construct different feature maps. 50 kernels and kernels of size 5 were found to work best in our model. For the fully connected layers, the width of each layer is 800, and a 25% dropout is used to avoid overfitting. Dropout [241] means temporarily removing units from the network with all their connections, the choice of which units to remove is random. This will make each unit more robust and reduces its dependence on other units to create useful features. To introduce non-linearity into the network, the ReLU is used as an activation function. ReLU has shown higher performance than the sigmoid function, and it is more plausible in biological systems. To accelerate the training process and to further reduce the overfitting, batch normalization [215] is used in the proposed architecture. Vanishing gradients or getting trapped in a local minimum may occur when using a high learning rate. However, by normalizing the activations throughout the network, small changes are prevented from amplifying to large changes in activations in gradients. Batch normalization has also shown promising results in reducing overfitting. Softmax is used as an activation function in the output layer, softmax takes the advantage that the locations are mutually exclusive, i.e. the object can be at one location only, softmax will also output a probability for each location.

Table 3.1. The architecture of the network

Layer type	**Parameters**	**Activation Function**
Convolutional layer	Kernels number = 50 Kernel size = 5 Batch normalization	ReLU
Convolutional layer	Kernels number = 50 Kernel size = 5 Batch normalization	ReLU
Convolutional layer	Kernels number = 50 Kernel size = 5 Batch normalization	ReLU
Fully connected layer	800 neurons Batch normalization 25% dropout	ReLU
Fully connected layer	800 neurons Batch normalization 25% dropout	ReLU
Fully connected layer	800 neurons Batch normalization 25% dropout	ReLU
Fully connected layer	30 neurons	Softmax

The Adam optimiser is used to train the network and the training rate is set to 0.01. The used accuracy metric is given by (3.11)

$$Accuracy = \frac{TP}{PC} \quad (3.11)$$

Where TP is the number of correct detections and PC is the number of positive cases. To be able to compare the results of the deep learning approach with the compressive sensing approach, the same accuracy metric will be also used to evaluate the performance of the compressive sensing approach.

Three variants of the above architecture will be used, the first one seeks to simplify the problem and reduces its dimensionality by using several copies of the above network to estimate the location of each user alone. Where the first network will be trained to estimate the location of the first user, the second network will be trained to estimate the location of the second user, and so on. The second variant will use an end-to-end approach where the performance of the whole system can be optimised. The above network will be used to estimate the locations of all users at the same time; however, several output layers are added to estimate the locations of many users. The third variant will introduce prior knowledge to the network by feeding the used pilot signal as an input to the network, where the above network is modified by adding one more input layer for the used pilot signal, followed by three convolutional layers, then the two branches are merged and the same fully connected layers are used. Fig. 3.4 shows the modified architecture. The performance of these three variants will be compared in the next section. Similar to the CS based approach, the output of the network for 10 signals will be combined.

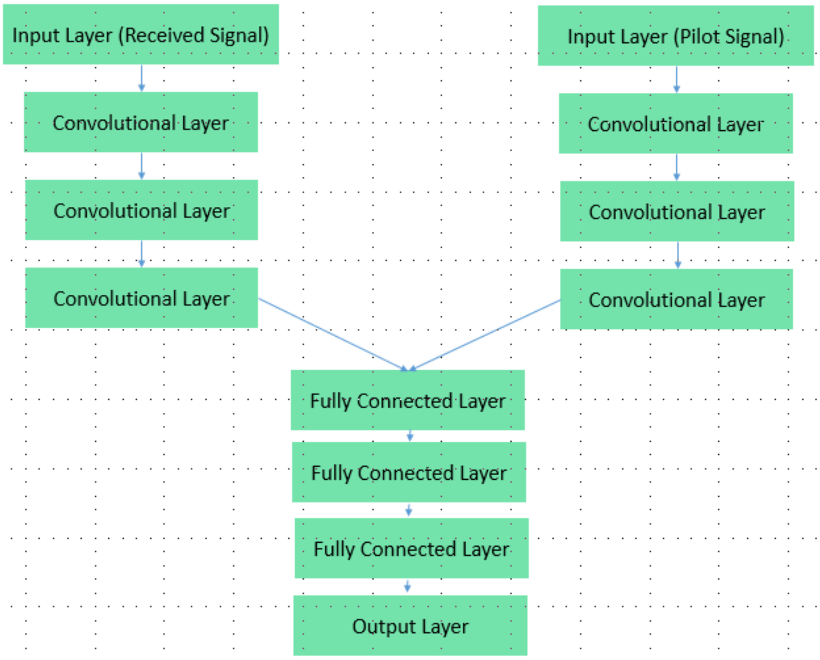


Fig. 3.4 A DL architecture where prior knowledge is incorporated

The training data is obtained by simulation. In each simulation, an OFDM frame is formed. The training data consists of 250000 examples, the input represents the received signal, which is described in section 3.3, and the output represents the locations of the users in the scene, where the output will be one at the user position and zero elsewhere. The training approach in [242] is used to train the network by starting the training process at high SNR and then gradually reducing it. The network is trained to minimise the difference between the output data and output of the neural network. A test set will be used after the training to test the performance of the network, the size of the test set is chosen to be 15% of the size of the training set. Since the network has not seen the test set during the training phase, using the test set in calculating the accuracy would be a good approximation of the generalization ability of the network.

3.9 Results

1. The combined reflection-based and blocking-based weak signal detection method

Computer simulations were performed to evaluate the proposed method. the 2.4GHz ISM band is considered. Three element array with d = $\lambda/2$ element spacing were used, a higher resolution could be achieved by using a larger number of antennae. The delay profile is represented by 20 samples, the Doppler resolution is represented by 20 samples, and the angular section is represented by 20 samples. Each reconstructed scene is the result of integrating 10 subsequent frames, which assumed to be recorded within a 50ms period. Fig. 3.5 shows the reconstruction of the sparse scene when the room is empty, the reconstructed scene is the result of a signal reflected from one static object in the room at (9m, 2º), the signal here can be easily discriminated from the noise, because of the high reflectivity of the object. At another time instance, two persons are assumed to be in the room at (6m, 2º) and (6m, 16º) respectively. Fig. 3.6 shows the reconstruction of the sparse scene when the room is full, the reflection coefficient is 0.2 and 0.5 for the first and second person respectively, the signal here cannot be easily discriminated from the noise, because of the low reflectivity of the human body. For simplicity, the presence of the first person is assumed to cause the blocking of the signal that is reflected from the static object.

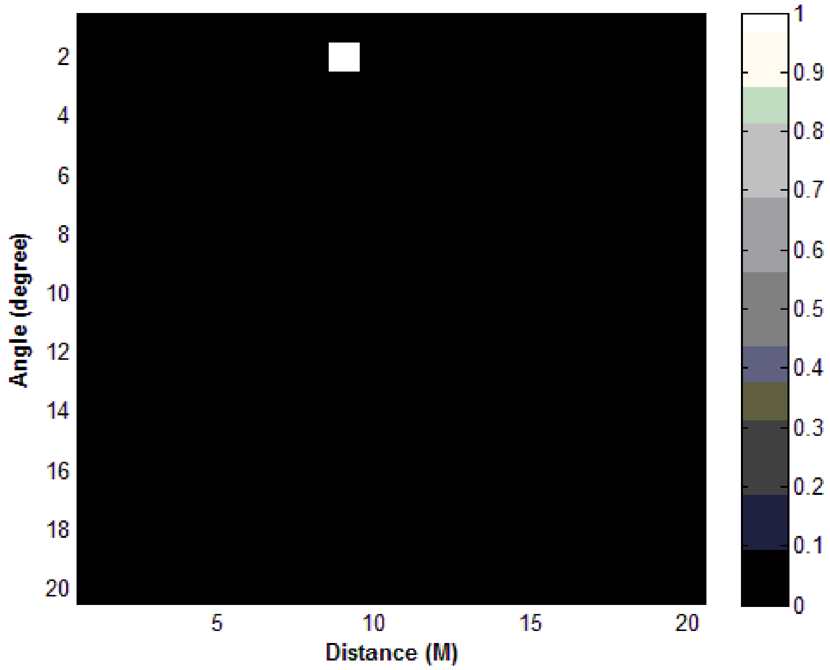


Fig. 3.5 Scene reconstruction of the empty room.

To enhance the detection probability of the weak signals that are reflected from the first person, the strongest signal that has the same angle of the blocked/attenuated signal is taken. Fig. 3.7 shows the final reconstructed scene.

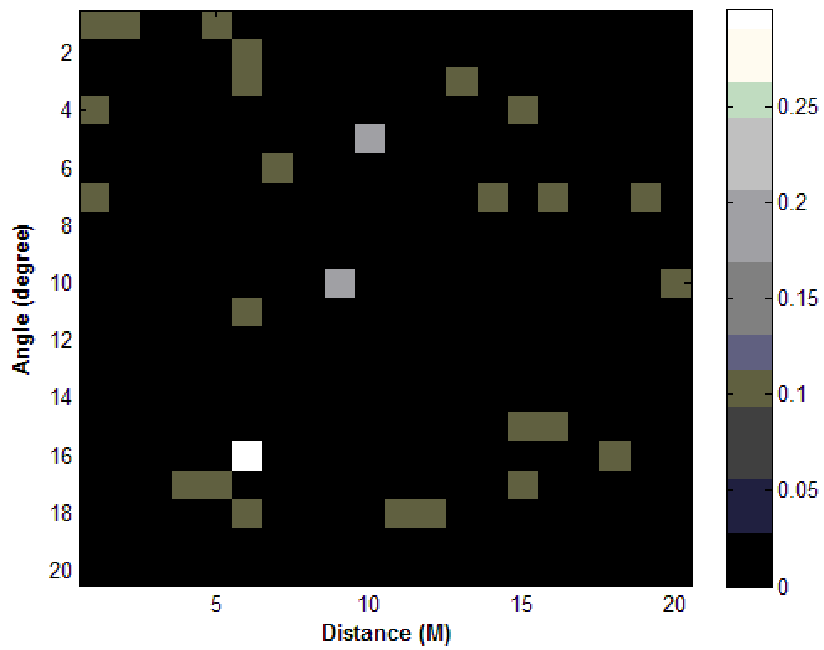


Fig. 3.6 Scene reconstruction of the full room.

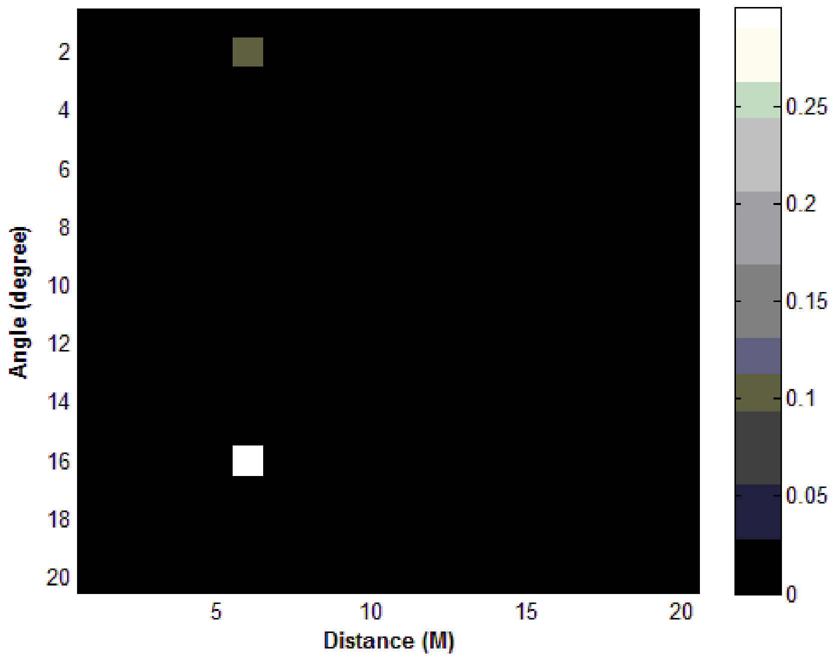


Fig. 3.7 The final reconstructed scene.

To compare the proposed method with the conventional reflection based method described in section 3.6, 1000 Monte Carlo run were performed to evaluate the proposed method under different SNR values. Fig. 3.8 shows the percentage of correctly detecting two persons for the reflection-based method (RM) versus the combined reflection-based and shadowing-based method (CRSM) for different SNR values. The CRSM method shows a clear improvement in comparison with the RM method.

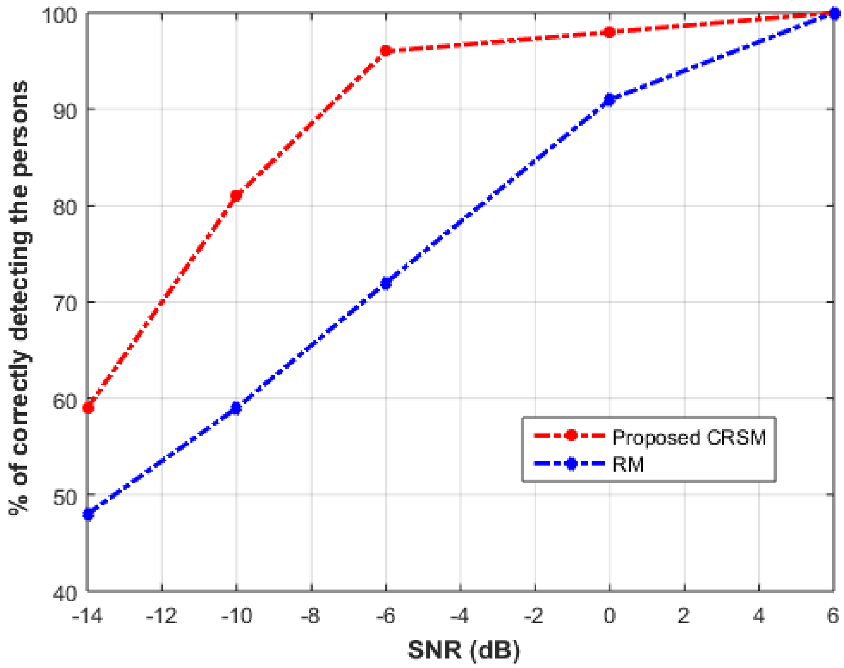


Fig. 3.8 RM versus the proposed CRSM for different SNR values.

One limitation of the proposed method is that it is restricted by the assumptions made on the availability of signals that are reflected from static objects in the surrounding environment.

2. The deep learning based method

Computer simulations were performed to evaluate the proposed approach. the 2.4GHz ISM band is considered. The delay profile is represented by 30 samples, the Doppler resolution is represented by 30 samples. The proposed approaches will be used to localise 4 users with random positions in the scene under different conditions. Training of the network took 12 hours on a standard Intel i3-4030U processor. First, the deep learning approach is compared with existing methods, then the performance of the proposed architectures will be compared. After that, the performance of the deep learning approach is evaluated in the presence of multipath propagation. Then, the role of each parameter of the training set is evaluated, and finally, the effect of each parameter of the network is investigated.

A. Comparison with other methods

To compare the proposed deep learning approach with the compressive sensing approach described in section 3.6, 1000 Monte Carlo runs were performed to evaluate the compressive sensing approach under different SNR values where the locations of the users are generated randomly.

Both the Orthogonal Matching Pursuit (OMP) [243] and the Interior Point Method (IPM) [244] were used to reconstruct the scene. Each reconstructed scene is the result of combining 10 signals. The same accuracy metric described in section 3.8 will be used to evaluate the CS approach.

Fig. 3.10 shows the percentage of correctly detecting four users for the OMP and the IPM versus the first DL architecture which estimates the location of each object alone, the comparison is done for different SNR values and when a different number of signals are combined.

The DL based approach is showing a significant improvement in the accuracy, particularly for low SNR signals. This shows that the DL based approach has a higher ability to adapt to noisy environments where the conventional approaches are challenged.

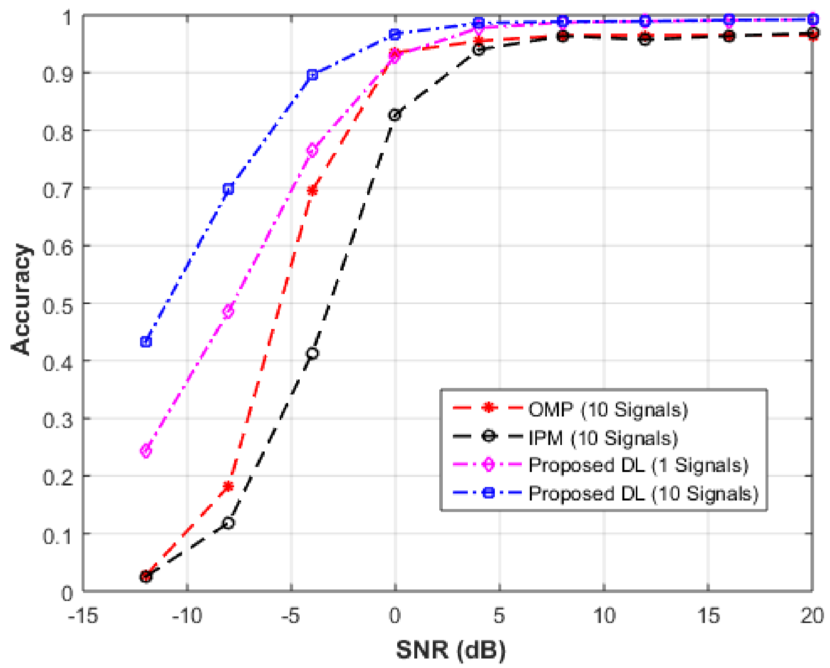


Fig. 3.10 The percentage of correctly detecting the persons for the OMP and the IPM versus the DL approach for different SNR values and a different number of combined signals.

B. Comparing with an end-to-end approach

Two DL approaches will be compared, the first one seeks to simplify the problem and reduces its dimensionality by estimating the location of each user alone as described in section 3.8. The second approach is an end-to-end approach where the locations of all users are estimated at the same time. The end-to-end approach has shown a better performance, which suggests that the gain from dividing this particular problem into simpler sub-tasks is lower than the gain from the overall optimisation of the whole problem. Fig. 3.11 shows the probability of correctly detecting the users under different SNR values for the two approaches.

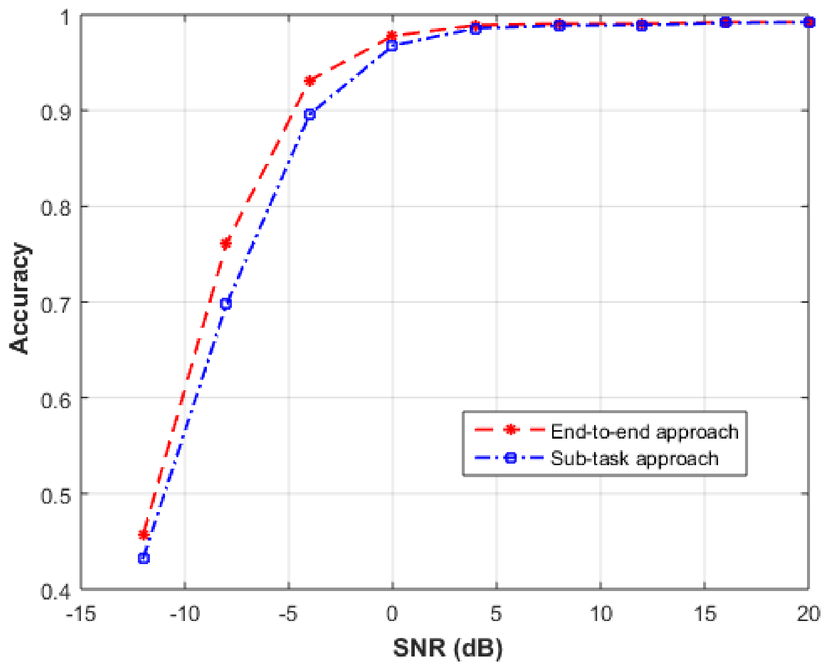


Fig. 3.11 The probability of correctly detecting the users under different SNR values for the sub-task approach and the end-to-end approach.

C. Comparing with an approach where prior knowledge is incorporating

Here the end-to-end architecture is compared with an architecture where prior knowledge is fed to the network. The used pilot signal is also used as an input to the network to see whether it will improve the performance of the network. The two approaches showed comparable results with very small improvement of the prior knowledge approach, which means that there is no much gain from using additional information as an input to the network and the network is able to extract the needed information from the received signal. Fig. 3.12 shows the probability of correctly detecting the users under different SNR values for the two architectures.

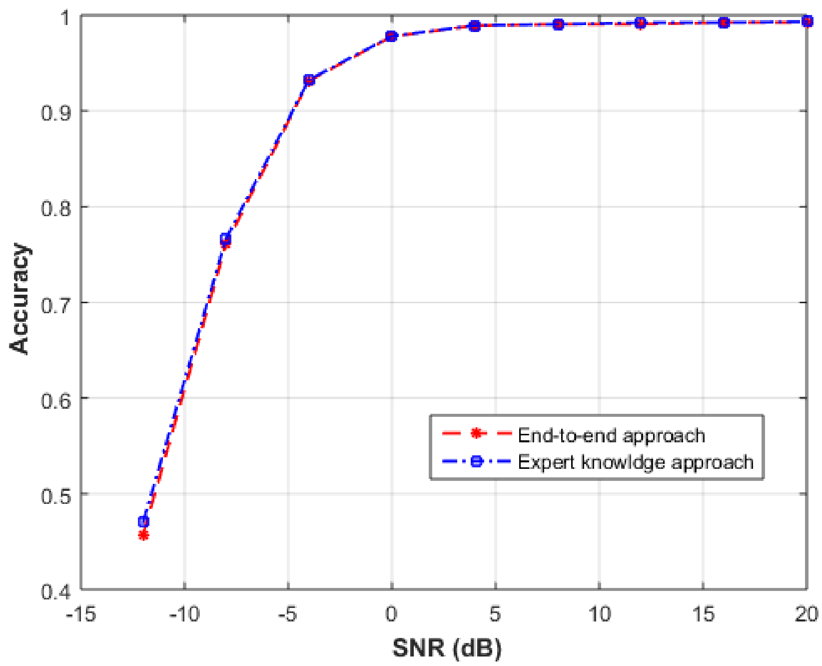


Fig. 3.12 The probability of correctly detecting the users under different SNR values for the end-to-end approach and the approach when prior knowledge is incorporated.

Table. 3.2 shows the runtime for the end-to-end approach versus the two CS approaches using a standard Intel i3-4030U processor.

The DL approach again has significantly lower runtime than the CS based approaches. Where, once the network is trained and the weights are calculated, predicting new output involves relatively simple calculations.

Table 3.2. The runtime for the DL, the OMP, and the IPM methods.

Method	**Runtime**
Proposed DL	0.1803 seconds
OMP	0.4618 seconds
IPM	22.099 seconds

D. The effect of multipath

To investigate the effect of multipath signals, the proposed approach will be compared when 4, 8, and 12 multipath signals are added to the received signal. Fig. 3.13 shows that the end-to-end approach is relatively robust to multipath propagation, where the network was able to cancel the multipath effect and correctly detect the users.

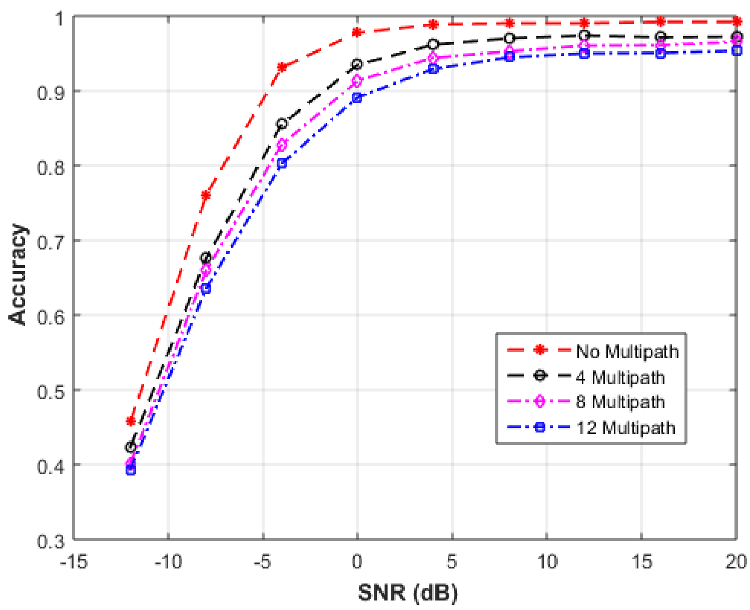


Fig. 3.13 The probability of correctly detecting the users under different SNR values when 4, 8 and 12 multipath signals are used.

E. The effect of the SNR of the training set

To compare the effect of the SNR of the training samples, five sets will be tested. The first one contains signals with 20dB SNR. The second one contains signals with 0dB SNR. The third one contains signals with -12dB SNR. The fourth one contains signals with varying SNR starting from high SNR values to low SNR values i.e. from 20dB to -12dB, and the final set contains signals with varying SNR; however, the signals here are sorted randomly. Fig. 3.14 shows the probability of correctly detecting the users under different SNR values for the five sets. Using the fourth and the fifth set have resulted in higher accuracy than the other sets, which means that the network should see examples from different SNR values. The -12dB set has shown higher accuracy at -12dB since there are more training samples at this SNR, however; the accuracy is much lower for other SNR values.

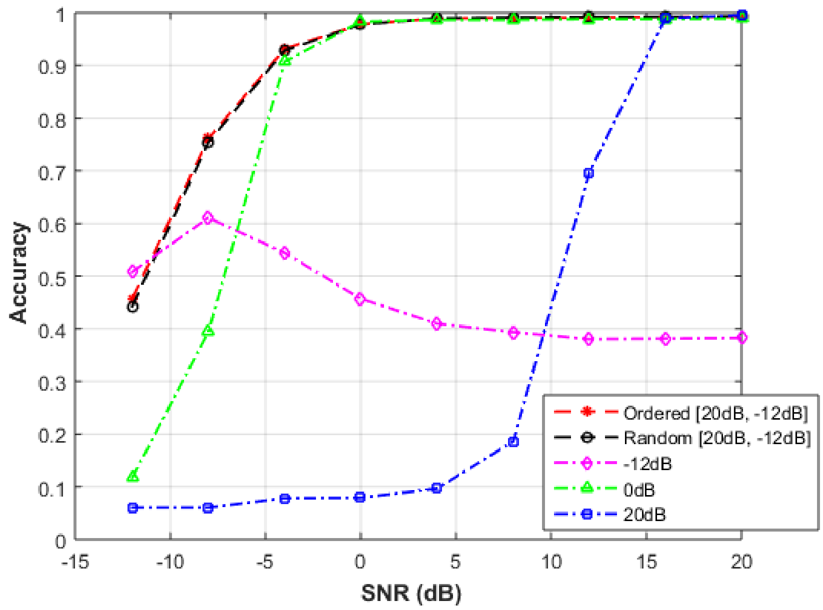


Fig. 3.14 The probability of correctly detecting the users using training sets with different SNR values.

F. The effect of the number of training examples

To investigate the effect of the number of the training examples on the performance of the proposed network, five sets with 10000, 50000, 100000, 250000, and 500000 training examples are compared. Fig. 3.15 shows the probability of correctly detecting the users under different SNR values for the five sets, the results show that the accuracy increases when a higher number of examples is used; however, the improvement becomes very small after 250000.

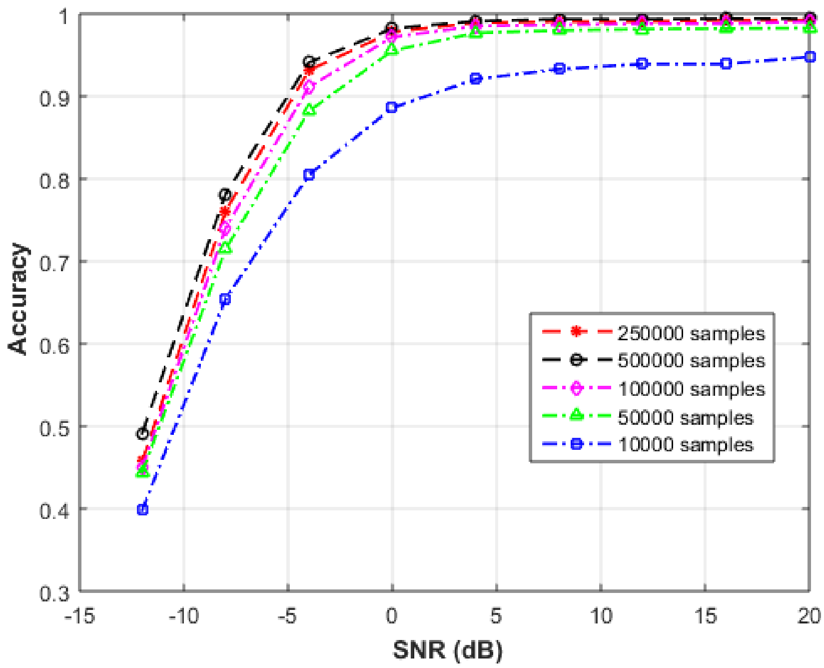


Fig. 3.15 The probability of correctly detecting the users under different SNR values when different sizes of the training set are used.

G. The effect of different parameters of the network

Here the effect of different parameters on the performance of the network is analysed. First, using a different number of neurons is compared, then using different number and sizes of kernels is compared, and finally, the role of dropout is compared.

1. The effect of the number of neurons in each layer

Here, using a different number of neurons in each layer is compared. 80, 200, 800, and 1200 neurons are compared. Fig. 3.16 shows the probability of correctly detecting the users under different SNR values for the four cases. Increasing the number of neurons increases the accuracy; however, the difference between 200, 800, and 1200 is very small.

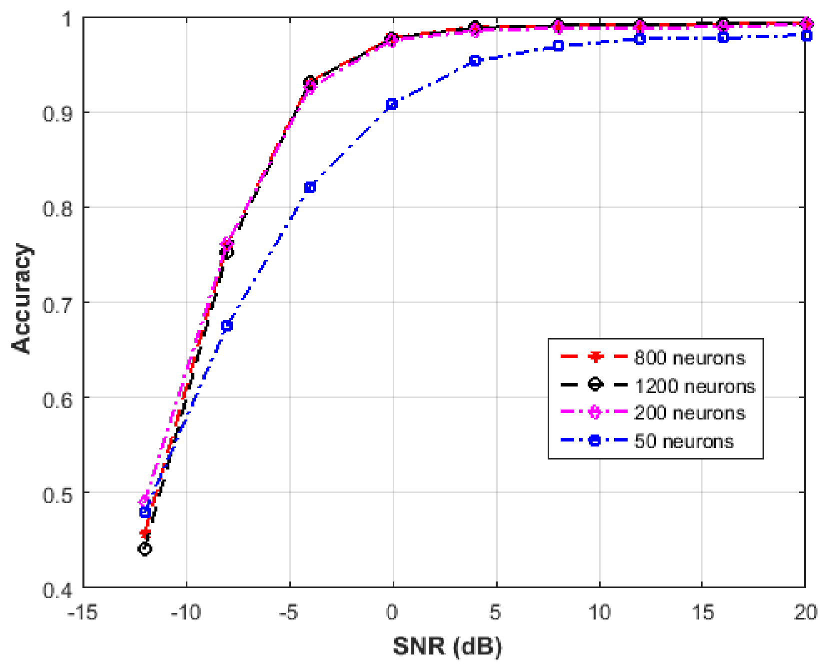


Fig. 3.16 The probability of correctly detecting the users under different SNR values when a different number of neurons is used.

Then, changing the number of the kernels in the convolutional layers is compared, where 25, 50, and 100 kernels are compared. Fig. 3.17 shows the probability of correctly detecting the users under different SNR values for the three cases. Increasing the number of kernels has not resulted in increasing the accuracy where the three cases have shown comparable results. Fig. 3.18 shows the results for different sizes of the kernels, where kernels of size 9 are found to be slightly better in capturing useful features from the signal.

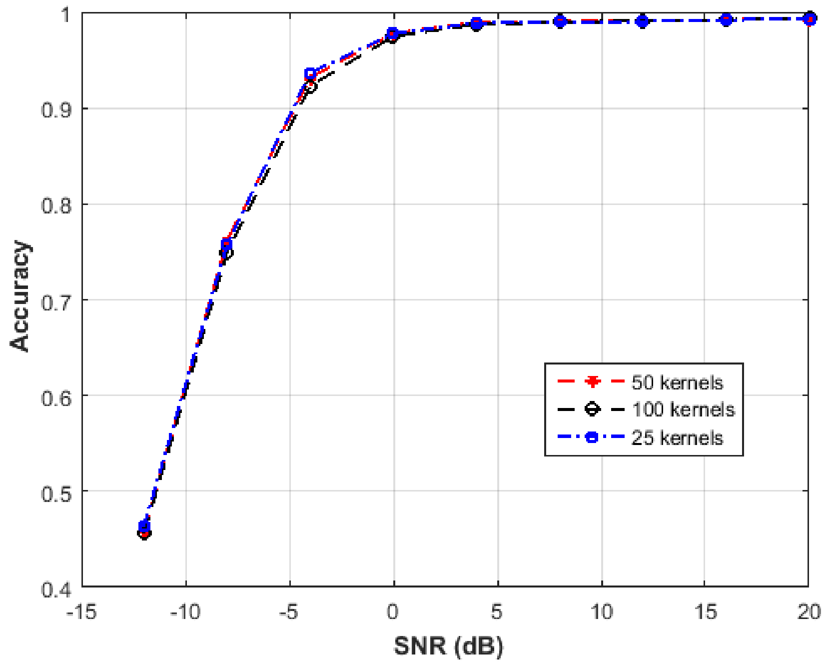


Fig. 3.17 The probability of correctly detecting the users under different SNR values when a different number of kernels is used.

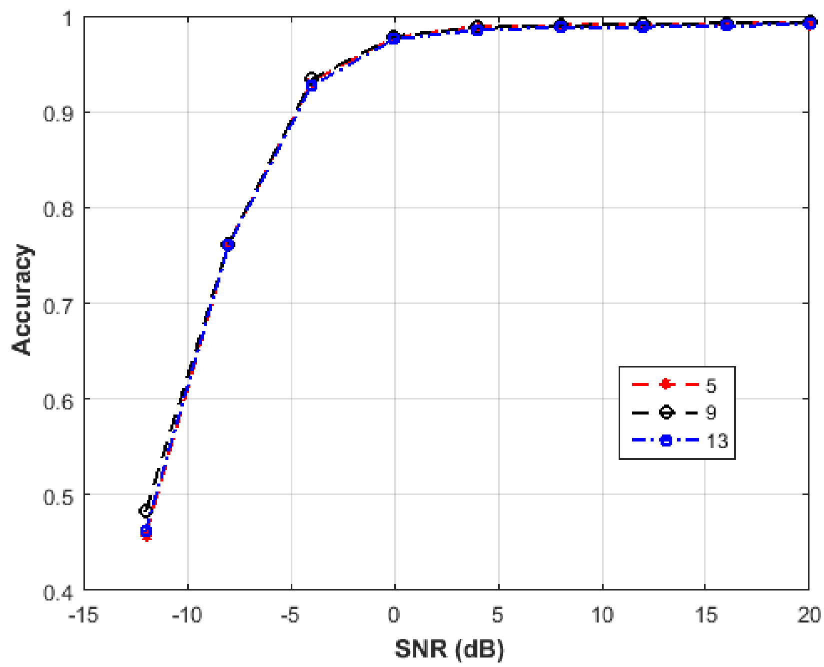


Fig. 3.18 The probability of correctly detecting the users under different SNR values when different sizes of the kernels are used.

2. The effect of dropout

Here, the performance of the network for four cases is compared, the first one is with no dropout, the second one is with 10% dropout, the third one is with 25% dropout, and the fourth one is with 40% dropout. Fig. 3.19 shows that increasing the dropout has resulted in more ability of the network to create useful features where 25% and 40% dropout are showing slightly higher accuracy.

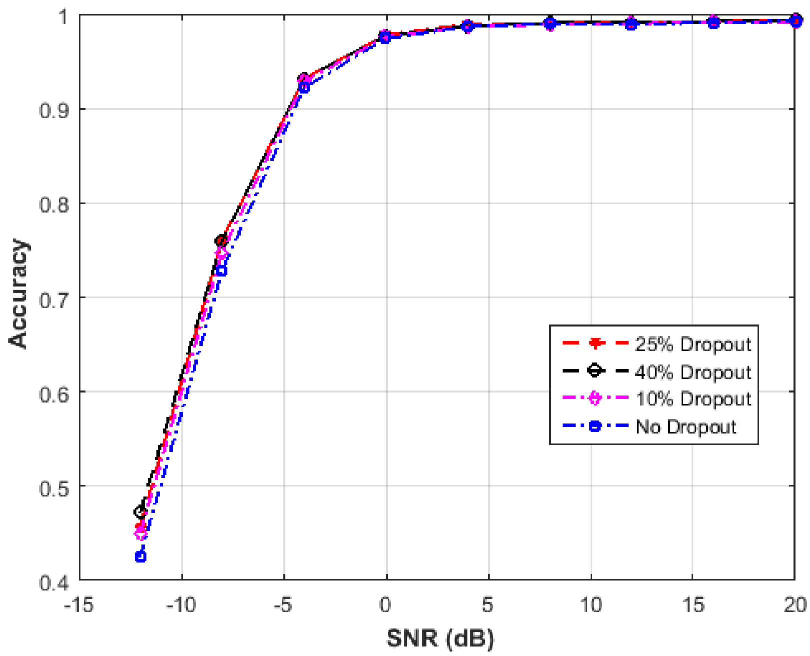


Fig. 3.19 The probability of correctly detecting the users under different SNR values when different percentages of dropout are used.

3.10 Conclusion

This chapter has presented a compressive sensing based localisation method that extends previous work to include angle of arrival estimation. Then a Wi-Fi weak signal detection method is proposed, where the detection of the weak signal reflected from the person's body is enhanced by taking into account the changes in the signals that are reflected from the surrounding environment. Simulation results demonstrated the significant improvement in the detection probability of the proposed method over existing methods. a localisation technique based on deep learning was also presented, the proposed deep learning approach has shown higher performance with less runtime in comparison with the CS approach. The proposed approach has also shown a high ability to adapt to challenging environments. For the studied problem, using deep learning for each sub-task and hence reduces the curse of dimensionality has resulted in less accurate results in comparisons with the end-to-end approach where the performance of the whole system is optimised. Introducing prior knowledge by using the pilot signal as an input to the network has not resulted in much improvement in the accuracy, where the network seems to be able to extract the needed information from the received signal. The proposed approach has also shown that it is relatively robust to multipath signals, and no additional multipath mitigation techniques are required to be used. This work along with many other recent works have shown that deep learning has many potential applications in future signal processing, communication, and radar systems where conventional approaches are challenged. It represents a promising research direction that is still in its early stage. Some challenges still worth further investigations. Further research must be conducted to propose deep learning architectures that best suit signal processing and communication systems. In the next chapter, the tracking framework will be used to address the abrupt motion problem, which is one of the main challenges facing people tracking systems.

Chapter 4

Abrupt motion tracking

4.1 Introduction

People tracking is very challenging because people usually change their motion abruptly. In this chapter, the abrupt motion problem will be addressed, which causes the failure of most tracking algorithms. A quantum mechanics inspired tracking method is proposed to address the abrupt motion problem. The proposed method uses some interesting phenomena in the quantum world such as the superposition (a particle exists at different positions at the same time) to address some problems in the classical world. To cope with the uncertainty caused by the abrupt motion, the method assumes that the person could exist at multiple positions simultaneously, where these positions are dictated by the person possible dynamics. The results show a significant improvement in reducing the tracking error and in reducing the tracking delay.

The chapter is organized as follows: Abrupt motion tracking methods with their limitations are reviewed in section 4.2. An overview of motion models is given in section 4.3. Section 4.4 gives an overview of the particle filter. Section 4.5 gives an overview of the multiple modes approach. The abrupt motion tracking method is proposed in section 4.6, the results are listed in section 4.7, and the chapter is concluded in section 4.8.

4.2 Abrupt motion tracking

In practice a prior knowledge about object motions is assumed, motion models such as Constant Velocity (CV) and Constant Acceleration (CA) are used to predict object motion [245]; however, these models are too general to model various types of motions such as abrupt changes in the speed or in the direction, which leads to a degradation of the tracking accuracy. One solution to the abrupt motion problem is to search the whole state space to cope with motion uncertainty; however, this requires a high computational cost. Kristan et al. [246] proposed a two-stage dynamic model: a liberal model and a conservative model to improve the accuracy of the particle filter; however, this method fails when the frequency of the abrupt motion is high. Other researchers [247, 248] proposed methods that use learned motion models, the main limitation of these methods is that they are limited to motions which they are trained for.

To cope with various pedestrian motions, some authors proposed to use the Interacting Multiple Mode (IMM) method [249], which is based on multiple trackers, each of them tries to track different motion model. IMM performance depends on how well the models match with the actual dynamics; furthermore, if there are many models used, the performance will degrade rapidly. IMM also suffers from the mode estimation delay problem, which is the time of probability convergence to the true model, this increases the error and causes serious limitations in some applications such as pedestrian avoidance for autonomous vehicles. Madrigal et al. [250] used the Interacting Multiple Mode Particle Filter (IMMPF) for pedestrian tracking, although IMMPF could be used for non-linear and non-Gaussian estimation problems, it is not computationally feasible and it has the same previously mentioned limitations of the IMM method.

Baxter et al. [251] extended the Kalman Filter (KF) to combine prior information about the person's directions based on where they are looking currently. They showed that the proposed tracker outperform the KF for sudden motion changes.

The Adaptive Markov Chain Monte Carlo (MCMC) algorithm [252] adaptively changes the distribution variance of the MCMC. This adaptive approach is very useful in tracking abrupt motion. However, the algorithm has many limitations. It does not have a systematic way to escape the local maxima and it does not have an effective sampling strategy to cope with large state-spaces.

Particle swarm optimization (PSO) [253] was also recently used to cope with abrupt motion. The proposed method uses two stages tracking framework. In the first stage, the PSO is used to detect the general motion of the object. In the second stage, the detailed deformations are captured. However, by using the PSO method, there is a chance that the majority of samples will be trapped in a small number of local maxima. Therefore, the PSO method is usually unable to track highly abrupt motion.

In [254], Kwon and Lee proposed a Wang-Landau (WL) based tracking algorithm that can effectively cope with the trapping in local minima problem by using a WL sampling scheme, which addresses the sampling problem and the weight estimation at the same time. The key idea of the proposed algorithm is to consider the density of states as a prior distribution of the Bayesian filtering, which is learned adaptively during the sampling process. However, no rigorous theory exists so far to guarantee its convergence, furthermore; the proposed approach has a limited accuracy in some applications.

Zhou et al. [255] proposed a sampling-based tracking algorithm, the Adaptive Stochastic Approximation Monte Carlo (ASAMC) addresses the abrupt motion problem by calculating the weights of the particles by learning the density of states, the proposal distribution is updated adaptively during the tracking process. ASAMC can effectively reduce the probability of getting trapped in a local optimum by taking samples in the global state-space; however, a large number of particles is required.

None of the existing methods fully use the available prior information about pedestrian possible motions to improve the tracking. In this chapter, this information is used to cope with abrupt motion and to reduce the tracking delay. A people tracking method is proposed that outperforms existing tracking methods when there are abrupt changes in the speed or in the direction.

4.3 Motion Models

The main goal of object tracking is to accurately estimate the trajectories of an object. The key factor to successful object tracking lies in capturing useful information about the object's movement from observations. A good model of the object's movement would defiantly facilitate the tracking process to a large extent. Most tracking algorithms are model-based, they outperform model free tracking algorithms when the used model can accurately capture the movement of the object. Many effective mathematical models to represent object motion have been proposed in the literature.

Model-based tracking algorithms assume that the object motion could be sufficiently represented by mathematical models. To be able to analyse and make predictions about a dynamic system, two models are often needed: the system model, which describes the evolution of the system over time, and the measurement model, which relates the state of the system to the noisy measurements. One of the most used models is the state-space model [256], which can be represented by equations (4.1) and (4.2),

$$x_{k+1} = f_k (x_{k,} u_k) + w_k \quad (4.1)$$

$$y_k = h_k (x_k) + v_k \quad (4.2)$$

Where x_k is the system state, u_k is the control input, y_k is the observed state at the discrete time k, w_k is the process noise and v_k is the measurement noise, f_k is the state transition function, and h_k is the observation function. The basic idea here is to update the estimate of the system model by using the measurements, which is represented by the stochastic process $y_{k,}$ as described by Fig. 4.1.

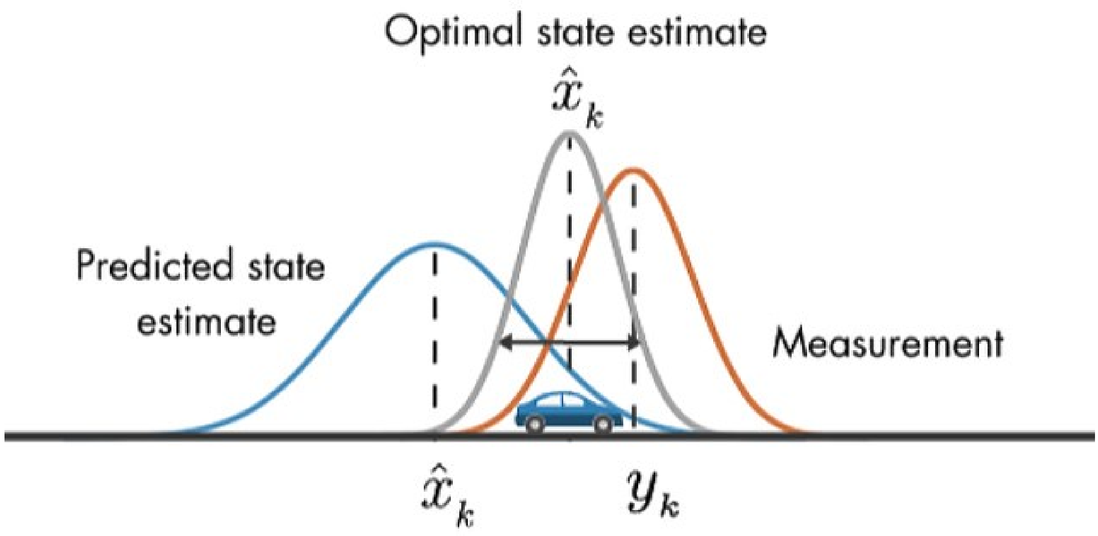


Fig. 4.1 Updating the estimate of the system model by using the measurements [257].

One of the main challenges of object tracking results from the uncertainty of the object motion. This uncertainty result from the fact that the actual motion model of the object being tracked is not always available to the tracker. Although the general form of the motion model might be adequate, the tracker usually lacks information about the real control input u of the object, the real form of f, or the statistics of the noise w of the object being tracked. Modelling object motion is therefore one of the key building blocks of object tracking. It aims to build an accurate model that can represent the object motion.

The constant velocity model depends on the assumption that the accelerations are small and assumes that the object is moving using constant velocity. In abrupt motion tracking, adding the acceleration to the state vector might degrade the performance of the tracking algorithm. The object acceleration is assumed an independent process in the white noise acceleration model, which can be represented by white noise. Simplicity is the main advantage of this model. It is often used when the abrupt motion is random or small. On the other hand, the acceleration is considered as a process that has independent increments in the Wiener process acceleration model. It is sometimes referred to simply as the constant acceleration model [245]. For the lateral motion, the constant turn model [245] is often used, which is a constant yaw rate model integrated with the CV model.

4.4 Particle filter

Kalman filter is the optimal solution to the tracking problem under linear and Gaussian assumptions [258], which are very restrictive assumptions. Extended Kalman Filter (EKF) [259] and Unscented Kalman Filter (UKF) [260] are proposed as an optimal solution for non-linear systems. However, they are not suitable for systems that exhibit non-Gaussian distributions, and generally, no closed-form solution exists to this problem [261]. Thus, numerical techniques should be used to calculate accurate approximations. Particle filter is a powerful numerical technique to address tracking problems in nonlinear and non-Gaussian situations. This technique can cope with noises of any distribution.

The particle filter overcomes the limitations of previous approaches by representing the distribution by a set of weighted particles and the higher the density of the particles at a particular position the higher the probability of the distribution at that position Fig 4.2. The particle filter has mainly two stages: the prediction stage and the update stage. In the prediction stage, the particles are propagated according to the used motion model, the system model is used to predict the state of the system from one measurement time to the next. The state of the system is often subject to many disturbances, which usually modelled as random noise; therefore, the prediction stage deforms and translates the state of the system. In the update stage, the latest measurement is used to update the prediction of the previous stage.

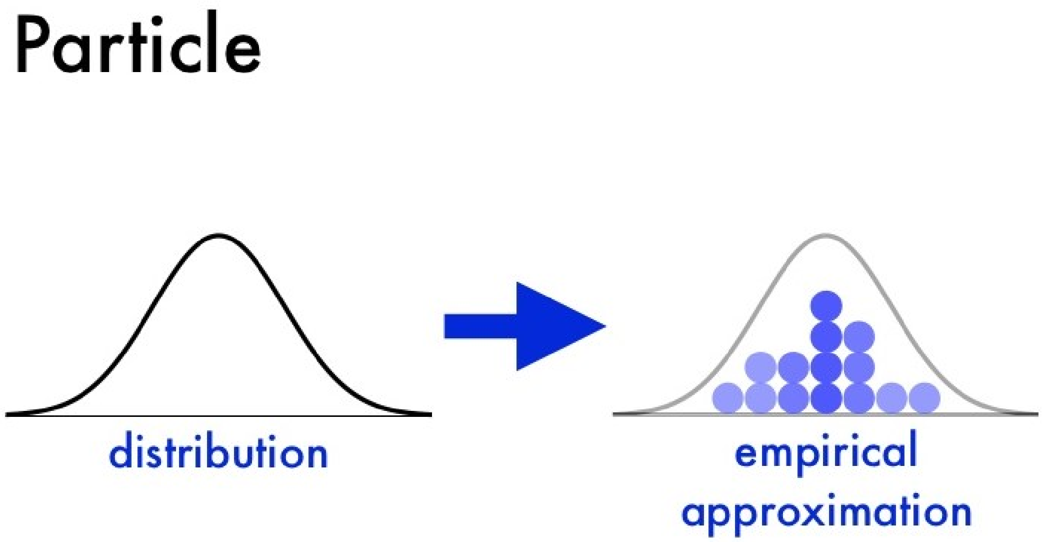


Fig. 4.2 Representing the distribution by a set of weighted particles [257].

The variable of interest is represented by multiple particles, each particle has a weight to represent the importance of the particle. A weighted sum of all particles is used to estimate the variable of interest. In the prediction stage, each particle is modified after each action according to the used motion model. In the update stage, the weights of the particles are recalculated according to the received information from the sensor Fig. 4.3. Particles with small weights are eliminated in a process called resampling.

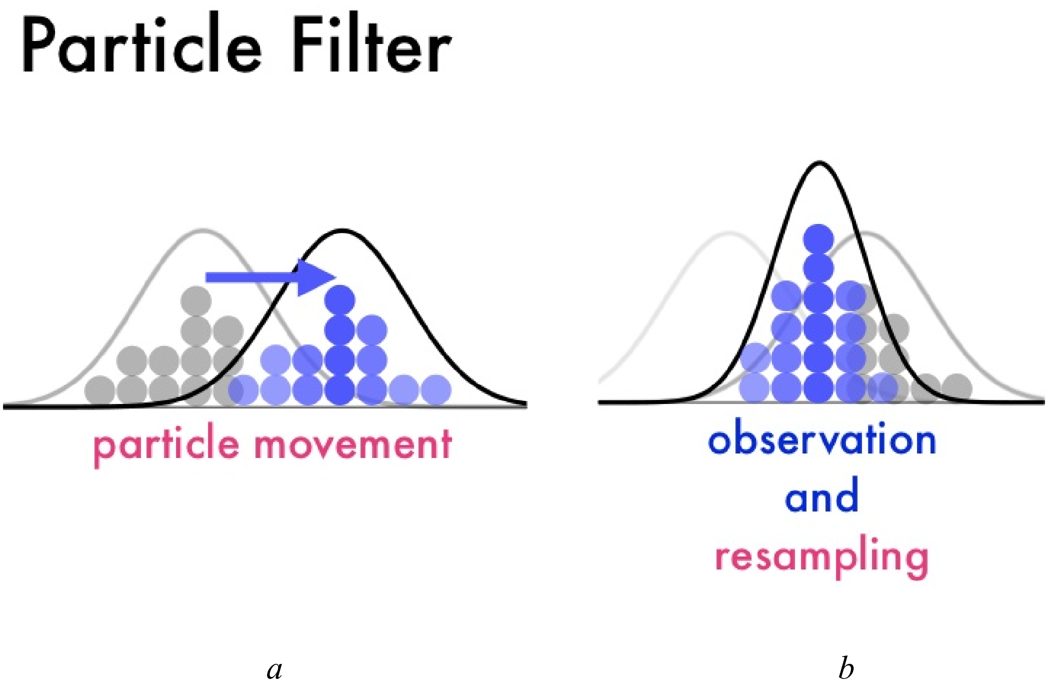


Fig. 4.3 The prediction stage and update stage of the particle filter [257].

a The particles are propagated according to the used motion model.

b The particles are updated after receiving information from the sensor.

The prediction stage is given by (4.3), where predictions are generated by taking samples from the proposal distribution q

$$x_{k+1}^{(i)} \sim q(x_{k+1} \mid x_k^{(i)}, u_k) \qquad (4.3)$$

Where i is the index of the particle, and the conditional prior of the state vector is commonly used as the proposal distribution

$$q(x_{k+1} \mid x_k^{(i)}, u_k) = p(x_{k+1} \mid x_k^{(i)}, u_k) \qquad (4.4)$$

The measurement update stage is given by (4.5)

$$w_k^{(i)} = w_{k-1}^{(i)} p(y_k|x_k^{(i)}) \qquad (4.5)$$

Where i is the index of the particle, $w_{k-1}^{(i)}$ is the previous weight of the particle, and $p(y_k|x_k^{(i)})$ is the probability of the measurement given the state of the particle, in other words, the position prediction of the previous step is updated by the observed measurements.

The final stage is the resampling stage where the unlikely samples are replaced by the more likely ones. Without this step, the particle filter will suffer from sample depletion. Which means that most particles after a short period of time will have very small weights. Resampling can solve this issue, however, it creates another problem, it ignores possible valuable information. Therefore, it is important to perform the resampling only when it is needed. Particle filter can be summarised by Algorithm 4.1.

Algorithm 4.1 Particle filter algorithm [261]

---

1) Initialize the particles.

2) Prediction (Sample particles using the proposal distribution).

3) Measurement update (Compute the importance weights).

4) Resample (Replace unlikely samples by the more likely ones).

5) Iterate from step 2.

4.5 Multiple Models Approaches

Recently, the multiple modes approach has become one of the main used approaches for state-space estimation. There are many advantages of using the multiple modes approach. In complex systems for instance, it is usually very difficult to represent the whole system with a single model only. The multiple models approach could also incorporate information from many sources in an easy way.

The main idea behind the multiple modes approach is to use a set of models to describe a hybrid system. It consists of a number of filters which run in parallel, each of the filters uses a particular model to represent one possible system behaviour, to obtain the overall model estimate, these models estimates are combined to produce the final estimate. The multiple models approach switches between the system modes based on the system behaviour.

The multiple modes method was proposed in [262] and is now one of the main used approaches for different estimation problems. There are three generations of the multiple modes approach as identified in [263]. The main difference between these generations is the structure of the models set. In the first two generations, the same fixed set of models is always used, these generations referred to as the Fixed Structure Multiple Models (FSMM). The third generation allows for a variable set of models that can adapt to the data, which leads to the Variable Structure Multiple Models (VSMM).

In the first generation, Autonomous Multiple Models (AMM) was proposed in [264], where each of its filters is operating independently and without any interaction with other filters. The overall estimate is the result of fusing the estimate of all elemental filters. However, AMM does not work well for systems with frequent changes in their behaviour, because of the used assumption that the mode does not change to another mode.

The second generation has the same power of output processing of the first generation, and its elemental filters can interact with each other, the mode can also be changed. The interacting multiple models is the most powerful algorithm in the second generation. The IMM has shown promising results for a wide range of applications. The main limitation of the second generation algorithms is that the model set has a fixed membership and therefore has a fixed structure.

The third generation [265, 266, 267] allows for a variable set of models to be used. This generation is known as variable structure multiple models. It works well for problems where the used model set does not match with the set of the true system.

Existing fixed structure multiple models methods perform usually well for problems that could be represented by a small set of models. These methods have shown a high success in addressing many problems that involve uncertainty, such as object tracking. However, using a small set of models cannot always produce accurate results because the true system model is usually unknown or vary over a large space. The research in [263, 268] showed that the use of more models does not result in a performance improvement; however, it dramatically increases the computational cost. The variable structure multiple models approach were introduced in [263, 268, 269] to overcome the limitations of the fixed structure approaches.

The variable structure multiple models approach is more advanced than the fixed structure multiple models approach. It augments new models or eliminates existing models to adapt to the environment. This learning ability of the model set in the VSMM results in an enhanced accuracy over the FSMM approach. The VSMM approach is very effective when the used models set do not match the true system.

In hybrid systems, since the system jumps between different modes, it is very desirable to detect the change as quickly as possible, this would provide very useful information for the state estimation stage. This problem is often formulated as a hypothesis testing problem, it is called the change point detection. Change point detection has been deeply studied in engineering and statistics.

The main idea behind the multiple modes approach is to use a set of models as possible candidates of the true models of the system. The multiple mode estimation can be summarised as follow

- A set of filters that operate in parallel will produce model estimates.
- The final overall result is obtained by combining these model estimates.
- Transitions between different models are performed to model transitions in the system mode.

In general, the multiple mode estimation includes the following steps:

• Models set design: The basic task here is to design a set of models to cover the true space of the system modes. The performance of the multiple mode estimator relies highly on the design of the model set, particularly for systems with a high number of modes.

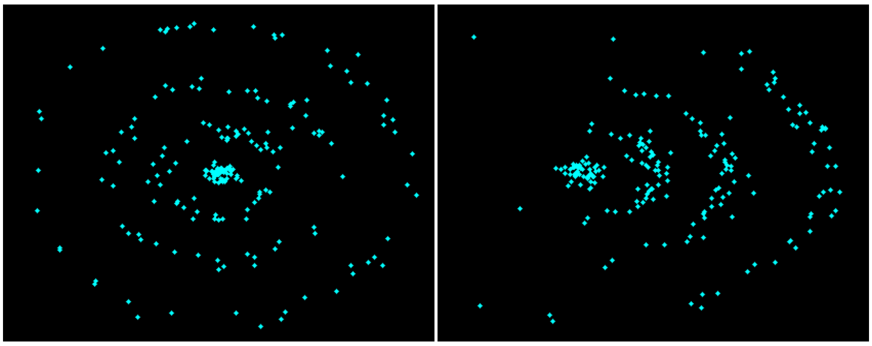
• Filter selection: The main task here is to select the filter for each model, the Kalman filter is usually used for linear problems, the extended Kalman filter or the particle filter are usually used for nonlinear problems. This step depends on estimation theory and it is related to the system under investigation.

• Cooperation strategy: The main task here is to determine the cooperative strategy between different filters to achieve the best performance, such as avoiding unlikely models, and merging similar models.

• Estimate fusion: The main task here is to determine the way to integrate the models estimates to obtain the overall estimate. This can be done by a hard decision such as taking the estimate of the most likely filter, or by a soft decision such as using the weighted sum of estimates of all filters.

4.6 Quantum Particle Filter (QPF)

People movement is generally nonlinear, the particle filter is essential to resolve estimation problems in nonlinear and/or non-Gaussian case; however, this method has serious limitations when there is abrupt motion. To address these limitations, solutions are proposed to quickly guide the algorithm to areas where the person is more likely to be.



a *b*

Fig. 4.4 Quantum particle filter.

a Particles are propagated in all directions

b Particles are propagated in the current direction

The approach tries to simulate the uncertainty of electron's positions around the nucleus by propagating particles in areas where the person is more likely to be. The proposed method uses the same structure of the particle filter, except for the prediction step. It is assumed that the person could abruptly change his direction by any angle. It is also assumed that at any time instance the person could switch to any of these three main modes: the stop mode, the walking mode and the running mode, various speeds inside each mode are taken into account by determining the variance of each mode, one more mode called the current mode is added to enforce the current dynamic.

The basic idea of the proposed method is to place the particles in areas that correspond to the person's possible motion if he has abrupt changes in the speed or in the direction. The particles are propagated according to all these modes simultaneously to cope with any abrupt changes. For example, if the person wants to suddenly stop, walk, run or change his direction, the particles will be already exist at these possible positions according to the proposed prediction model, which will solve the abrupt motion problem and reduce the tracking delay. To enforce the current dynamic, more particles are propagated using the current speed and direction; however, when the uncertainty of the speed estimation increases rapidly, the particles are equally distributed among all modes to cope with any abrupt changes in the speed as illustrated Fig. 4.4b. The variance of each mode in Fig. 4.4 is reduced initially for illustration purpose.

When the person stops suddenly or when the uncertainty of the direction estimation increases rapidly due to a possible hard turn for example, the angular variance of the particles will increase to cover all directions and the particles will be equally distributed in all directions to cope with any abrupt changes in the direction as illustrated Fig. 4.4a. The particles are propagated according to the following equations:

$$X_i = R_i \cos(ANGLES) + SV + x_{centre} \quad (4.6)$$

$$Y_i = R_i \sin(ANGLES) + SV + y_{centre} \quad (4.7)$$

$$ANGLES \sim N(\mu_{angle}, \sigma_{angle})$$

$$SV \sim N(0, \sigma_{pos})$$

ANGLES is a vector representing a set of angles sampled from a Gaussian distribution with mean and variance μ_{angle} and σ_{angle} respectively. *SV* is a vector sampled from a Gaussian distribution representing the uncertainty of particles positions with σ_{pos} variance. R_i Represents the distance from the current position to the ith mode, and it is related to the speed of each mode $S_i = R_i$ / (sampling interval). x_{centre} and y_{centre} represent the current position, X_i and Y_i represent the positions of the particles, they either form full circles or arcs depending on σ_{angle} taking into account that the modes with larger R_i should have more particles to cover the larger area they have. Quantum particle filter algorithm is given by Algorithm 4.2.

Algorithm 4.2 Proposed quantum particle filter algorithm

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1) Prediction

A) If the uncertainty of the speed estimation increases rapidly, propagate the particles equally among all modes.

B) Else, enforce particles at the current speed.

C) If the uncertainty of the direction estimation increases rapidly, propagate the particles equally among all directions.

D) Else, enforce particles in the current direction.

E) Propagate the particles according to equations (4.6), (4.7).

2) Measurement update (Compute the importance weights)

3) Resample (Replace unlikely samples by the more likely ones)

4) Iterate from step 1.

One limitation of the proposed method is that the resampling should be more frequent to cope with the large number of low weight particles, which will increase the computational cost.

4.7 Results

Computer simulations are performed to evaluate the proposed tracking method in abrupt motion situations. The person is stopping from time step 0 to 10, then he starts walking at 1 m/s from time step 10 to 30, then he turns 90º and continues to walk until time step 50, then he stops from time step 50 to 60, after that he starts running at 3.3 m/s from time step 60 to 80, and finally he stops from time step 80 to 90. Gaussian noise was added to the true positions with (μ = 0, σ = 0.01), the average S_0, S_1 *and* S_2 are approximated to 0 m/s, 1.3 m/s and 3.5 m/s respectively. For the comparative evaluation, the proposed method is compared with two different tracking methods, the multiple mode particle filter (MMPF), and the interactive multiple mode with the following two motion models: constant velocity and constant acceleration. MMPF is similar to the IMMPF but without the interaction step to reduce the mode decision delay, where each set of particles is propagated according to one motion model.

The results are obtained from 100 Monte Carlo run, Fig. 4.5 shows that the position estimation of the QPF outperformed the MMPF and the IMM. The performance of the IMM and MMPF decrease when there is severe abrupt motion. Although the MMPF shows a lower positioning error than the IMM, it frequently fails to track the person when the person abruptly changes his position.

Fig. 4.6 shows the positioning error for the three methods, QPF shows the lowest positioning error, IMM positioning error starts at time step 30 (at the turn) due to the linearity of the IMM, then the error increases largely starting from time step 60 (at the beginning of the abrupt motion), this is mainly due to the mode decision delay. MMPF positioning error starts at time step 60 and continues to increase until time step 90, this is mainly due to the failure to track the abrupt motion.

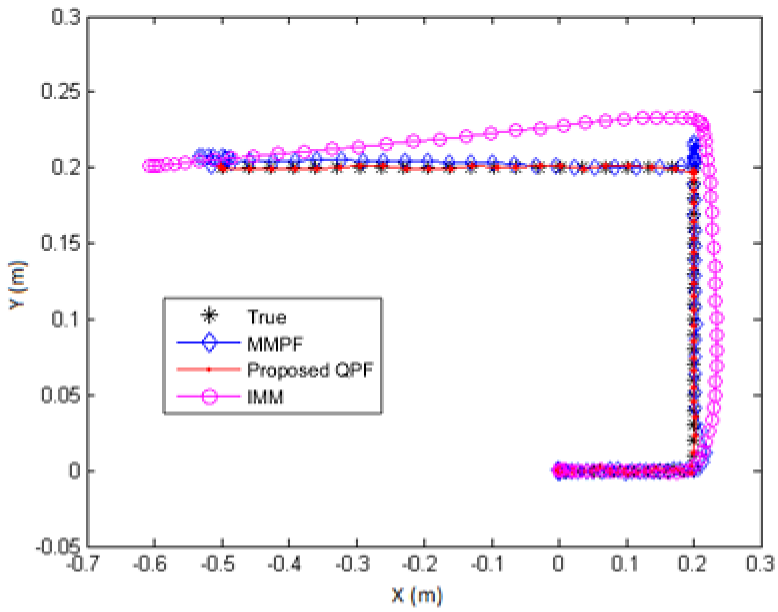

Fig. 4.5 Trajectory tracking.

Fig. 4.7 shows the tracking delay using the three methods, QPF shows the lowest tracking delay, IMM shows the highest tracking delay, particularly at time step 60 when the abrupt motion started, and this is mainly due to the mode decision delay, MMPF shows a lower delay than the IMM because of the absence of the mode decision delay and the multimodality of the particle filter. The analysis above shows that the QPF has a greater robustness, accuracy and lower delay in tracking abrupt motion. The simulation also indicated that the QPF can successfully cope with a large motion uncertainty.

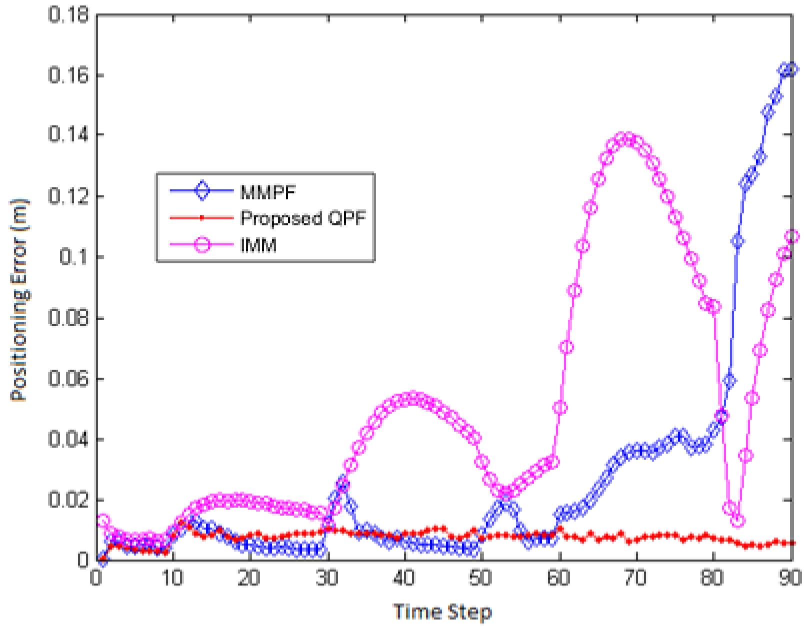

Fig. 4.6 Positioning error.

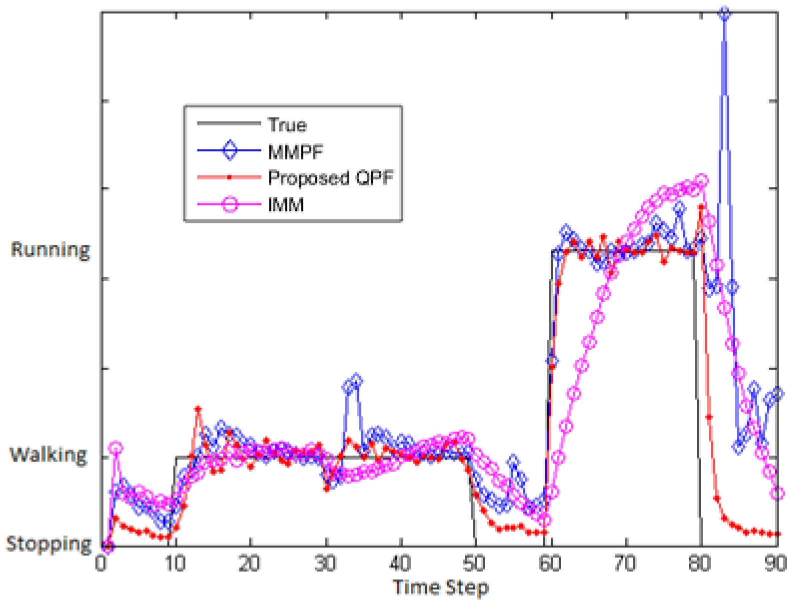

Fig. 4.7 Tracking delay.

4.8 Conclusion

This chapter has presented a novel approach for pedestrian tracking that outperforms existing tracking methods when there are abrupt changes in the speed or in the direction. It also reduces the tracking delay when there is abrupt motion. The proposed approach is inspired from quantum mechanics where it uses some interesting phenomena in the quantum world such as the superposition to address some problem in the classical world. The proposed method can track abrupt motion accurately by propagating particles in areas where the person is more likely to be. It was demonstrated through simulation that the QPF outperformed both the IMM and the MMPF methods. In the next chapter, the multipath problem will be addressed, which is one of the main challenges facing people tracking systems.

Chapter 5

Tracking in multipath-rich environments

5.1 Introduction

The cancellation of the multipath effect is a crucial issue to improve the localisation performance of Wi-Fi based people tracking systems. In this chapter, the multipath problem will be addressed, where several signals reflected from the same object will arrive at the receiver, which will cause ghost objects to appear in the scene. In particular, the Track before Mitigate (TBM) method is proposed, which is an efficient tracking based multipath ghost mitigation method that uses the aspect dependence feature of the multipath ghost. The proposed method requires a smaller number of antennae in comparison with existing methods, it can accurately suppress/mark the entire multipath track; furthermore, it does not assume any prior knowledge of the environment.

The chapter is organized as follows: An overview of multipath propagation is given in Section 5.2. Section 5.3 gives a review of multipath mitigation techniques. Section 5.4 gives an overview of the aspect dependence feature. The multipath mitigation method is proposed in Section 5.5, and the chapter is concluded in Section 5.6.

5.2 Multipath Propagations

Alongside the shortest path from the object to the receiver, the transmitted wave may take indirect paths caused by reflections from walls, ceiling, and floor. This leads to rich multipath related to the same object, which can have different effects on the scene interpretation and quality depending on the scattering environment. The energy of the multipath returns might accumulate at places where no actual objects exist, therefore creating virtual objects or 'ghosts' which do not really exist in the actual scene as illustrated in Fig. 5.1.

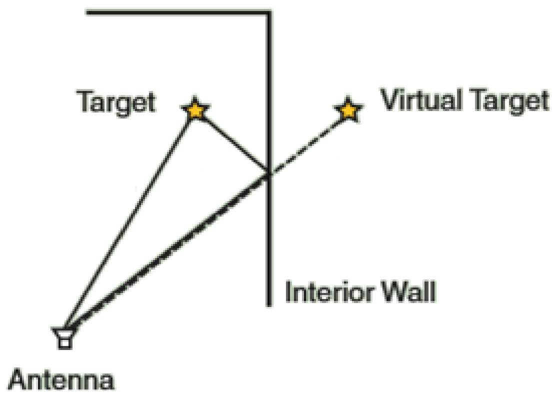

Fig. 5.1 Ghost objects.

The multipath returns can be classified into three categories:

- First-order multipath: This includes one reflection on the receive or the transmit path.

-Second-order multipath: This includes two reflections on the receive or the transmit path.

- Higher-order multipath: This involves more than two reflections on the receive or the transmit path.

As the signal becomes weaker at each reflection, higher-order multipath returns are not taken into account usually.

The multiple returns of the signal reflected from the same object will be combined at the receiver to produce destructive or constructive interference, which could lead to serious degradation of the accuracy of range measurements. In Wi-Fi based urban sensing, the multipath effect cannot be simply ignored because it will result in a range measurement error, the main reason is that a considerable energy is received in the multipath returns.

The equalisation of multipath returns is not an easy problem due to many challenges. The wireless propagation channel is not known in advance; moreover, the wireless propagation channel is time varying because of the movement of objects.

Depending on the path difference of the multipath and the direct signal, and the range resolution of the used waveform [270]-[272], the multipath will result in objects either smeared in the range dimension, offset from the actual range or ghost objects might appear. If the path difference is smaller than double the range resolution, then all the three degradations might appear, and if the path difference is larger than twice the range resolution, only ghost objects might appear, in this chapter, the focus will be only on the latter case.

When the scatterings increase, the stationary scene could become quite cluttered, which causes the masking of real objects, and making their detection more difficult. The effects of multipath and ghost objects in imaging of building interiors were shown in different works. Dogaru et al. [270] have used lengthy numerical simulations to show the existence of the ghost phenomenon. Others studied the same phenomenon using measurements in an indoor setup [271], [272].

5.3 Multipath mitigation techniques

Since multipath is often observed, it should be analysed and addressed using precise models. Generally, there are two ways to cope with multipath propagation: multipath exploitation and multipath suppression. The basic idea of the latter is to characterise the multipath returns and suppress their effects [273]-[282]. The direct path and the multipath returns have different characteristics that can be used to remove the multipath returns. The other way is inspired from the rake receiver in wireless communications [283], where the multipath is explored and used for imaging enhancements [271], [272], [284]-[290]. By accurately modelling the indirect paths, their energy can be detected and assigned to their respective objects, which will cause an increase in the signal to clutter and noise ratio, and thus improvement and enhancement of the resulted image. Furthermore, areas in the shadow regions, that cannot be illuminated directly, could still be imaged by using the multipath propagation. Multipath exploitation has many promising and potential benefits; however, it is computationally demanding, and often needs prior information about the environment.

Optimised imaging geometry might also help to reduce ghosting [281] where the synthetic aperture radar trajectory could be adjusted such that a small amount of energy is in the multipath returns.

The authors in [282] proposed a ghost mitigation approach, where the ghosts resulting from wall multipath in the SAR image, are matched to the respective objects to get a ghost-free image. A complete knowledge of the place geometry is required, particularly the positions of the walls. By exploiting this prior knowledge, the location of the ghosts could be predicted for any associated object position. The approach works as follows, an image of the scene which contains both ghost and real objects is obtained. Next, the energy of the ghost is matched to the associated object's location. However, this method will fail if the multipath returns are not resolvable, because they will lead to overlapping ghosts and objects in the SAR image. Such situations could arise in the presence of non-homogeneous walls or when using limited bandwidth or aperture. However, by using accurate modelling of the multipath returns, the energy, and additional information could still be used to get an improved scene reconstruction.

Time-reversal methods [288]–[290] could also be used for multipath exploitation in indoor environments. The effectiveness of this approach was shown by Fink [291] and Sarabandi et al. [288]. Time-reversal consists of two stages procedure. In the first stage, the signal is sent into the scene and the returns are received by an antenna array. This is done to get information about the scattering environment without the presence of the object of interest. In the second stage, the wireless signal is transmitted with the presence of the object of interest. In this way, the transmitted energy can be focused on the location of the object of interest, where the information about the scattering environment could be used to enhance the effective array aperture.

A sky-pointing camera was used in [292], [293] to get an image of the field of view, from which the blocked Global Navigation Satellite System (GNSS) signals could be predicted. A GNSS antennae array could be used to determine the angle of arrival of the received signal, and then compare them with the predicted angle of arrival to distinguish between the LOS and NLOS signals [294]. The main limitation of this technique is the additional power consumption, weight, size, and cost. Thus, although it is suitable for a number of professional GNSS applications, it is very unlikely to be suitable for hand-held devices.

A 3D model of the city could also be used to determine NLOS signals Fig. 5.2, and when the user location is known, then it is trivial to compare the signal paths with a 3D model of the city to decide the blocked signals. Then the NLOS signals are ruled out from the position calculation [295]. However, the location is usually known within tens of meters. In this case, the blocking of signals at many locations should be considered. If the number of visible signals at all positions is not sufficient to calculate the position, the NLOS signal should be used to improve the position estimation. Two possible approaches are proposed in [296]. However, 3D models of the environment cannot be easily built, furthermore; the environment might change frequently which requires changing the 3D models.

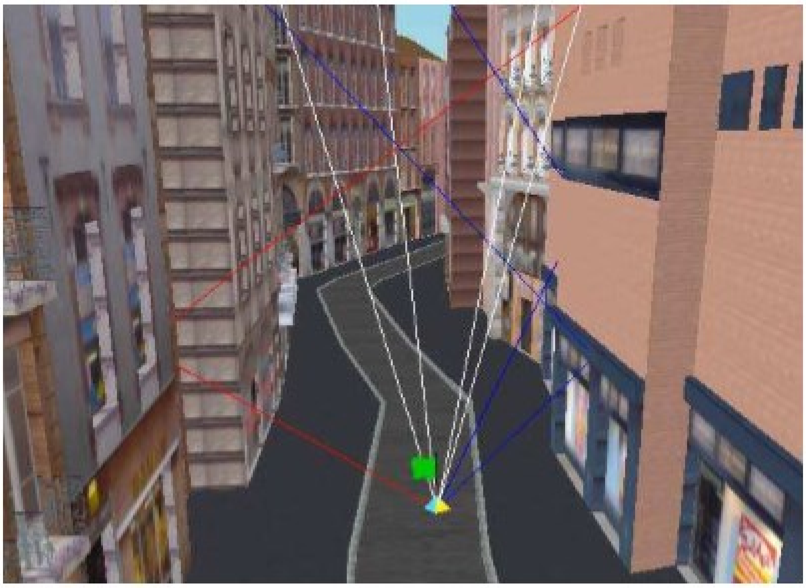

Fig. 5.2 A 3D city model of Toulouse downtown [26].

Consistency checking uses the fact that NLOS signals give a less consistent position solution than the direct LOS signals. Direct LOS signals containing multipath returns also give a position solution that is less consistent than multipath-free measurements. Therefore, when the position solution is calculated using signals from multiple satellites, the solutions obtained from using direct LOS signals alone must be in a higher agreement than solutions obtained using multipath and NLOS measurements. Results have shown that this works reliably in rural environments but does not work well in urban dense environments where there is a large number of reflected signals [297].

Authors in [298] showed the feasibility of localising and detecting people behind obstacles which completely or partially block the wireless signals, by using the multipath returns to determine the position, even when the object is not in the line of sight. Such situations could arise when security forces need to examine a corridor for possible threats before entering it.

A variety of temporal and spatial methods has been proposed for multipath clutter cancelation. The spatial methods to address the problem often use adaptive beamformers to produce nulls at the directions of multipath returns and direct path [299–302]. However, the performance of the spatial methods will decrease when the object of interest appears in the same beam of multipath returns. The temporal methods use the least mean square filter for multipath cancellation [303, 304]; however, the main limitation of these techniques is their convergence speed [300]. Colone et al. [306–308] proposed a number of multipath cancellation techniques to detected objects of interest in the presence of multipath clutters. The Extensive Cancellation Algorithm (ECA) projects the received signal into a subspace that is orthogonal to the multipath subspace. Then to achieve improved multipath cancellation performance with a lower runtime, ECA-B was proposed in [307]. In ECA-B, which is a batch version of ECA, the temporal extension is divided into a number of batches, and the ECA is then applied to each batch.

In [308], a review and comparison of many adaptive disturbance cancellation techniques are presented. In particular, the Normalized Least Mean Square (NLMS), the Recursive Least Square (RLS), and the Least Mean Square (LMS) are compared to the Sequential Cancellation Algorithm (SCA), and the extensive cancellation algorithm. The comparison is performed in terms of accuracy and computational cost. The SCA and ECA algorithms have shown a better performance in multipath cancellation. Furthermore, the SCA has shown to be a very appealing solution, due to the possibility of successful detection of weak objects by its ability to cancel strong disturbance; furthermore, it significantly reduces the computational cost.

Most of the previous approaches are static multipath mitigation techniques that can cancel the effect of static objects like walls; however, fewer works were dedicated to cope with the dynamic multipath problem, i.e. echoes from moving objects. Unlike the real object, the ghost intensity only has high values over a small part of the synthetic aperture, which implies that the effective aperture for ghost objects is smaller, this important feature of multipath ghosts is called Aspect Dependence (AD), which is a promising feature to suppress the multipath ghosts. Authors in [309] proposed a ghost suppression technique, which uses the AD feature in the context of through the wall SAR imaging. In [310] the authors also proposed a ghost cancellation technique based on the AD feature, where they used sub-aperture imaging. They distributed the antenna array over a large space at the front of the room. Then they used a sub-aperture, which cannot receive the multipath reflected by the left wall, and another sub-aperture which cannot receive the multipath reflected by the right wall. Then, the two sub-aperture images were multiplied to form the full aperture image. Authors in [311] used the prior knowledge of the environment to enhance the localisation accuracy in a multipath environment. While authors in [312] presented a survey of different approaches to cope with the multipath effects (mitigation and exploitation) in indoor scenarios. The main limitations of existing multipath mitigation techniques are either the large number of antennae that are placed over a large area or the assumption of prior knowledge of the observed environment.

5.4 The aspect dependence feature

Ghost objects have unique attributes that can be used to distinguish them from real objects. These attributes could be inferred from the changes in the scattering geometry with the aspect angle as it observed by the localisation system. Most objects exhibit aspect dependent scattering; however, unlike the real objects, the ghost intensity only has high values over a small part of the synthetic aperture, which implies that the effective aperture for ghost objects is smaller.

5.5 Track before mitigate

Two antennae are used in this work, the first one is placed at position (0.125m, 0m), and the second one at (0.375m, 0m). Fig. 5.3 shows an example of different multipath reflections along the person path (the person is moving from the left to the right), only the direct signal is received by the antennae for most of the person path. The multipath signal starts arriving at the second antenna before the person makes the turn and continues for a short time, after that the multipath signal is received by the two antennae.

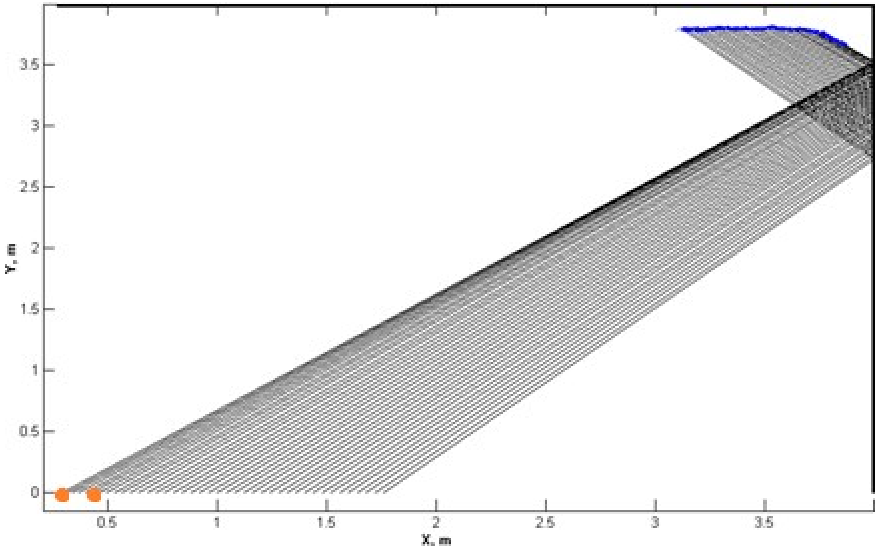

Fig. 5.3 Multipath reflections for different positions of the person, the two orange dots represent the positions of the antennae.

The tracking approach is the most appropriate framework to mitigate the multipath effect particularly if the AD feature is used, where the accumulation of measurements from multiple scans, allows to make the full use of more potentially useful information contained in the measurements. It also helps in building more confidence to judge whether the object is a ghost or not, for example, the person movement will allow the antennae to observe different variance of the multipath signal. The AD feature cannot be observed over all measurements scans, particularly if a small number of antennae are used; therefore, it is essential to integrate the AD feature into the tracking framework in order to accumulate the variance of the received signal across the antennae and to suppress/mark the entire multipath track. It also worth mentioning that using a small number of antennae will reduce the reception of multipath signals. The basic idea of the proposed method is to integrate the measurements in the time domain through the use of the tracking framework in order to make a more accurate decision and to relax some constraints in the space domain such as the large number of antennae that are placed over a large area. The proposed method uses the particle filter, which is essential to resolve tracking problems in nonlinear and/or non-Gaussian case. Particle filter algorithm is given by Algorithm 5.1.

Algorithm 5.1 Particle filter algorithm

1) Initialize the particles.

2) Prediction (Sample particles using the proposal distribution).

3) Measurement update (Compute the importance weights).

4) Resample (Replace unlikely samples by the more likely ones).

5) Iterate from step 2.

The weight calculation in step 3 is given by

$$w_k^{(i)} = w_{k-1}^{(i)} p(y_k | x_k^{(i)}) \tag{5.1}$$

Where i is the index of the particle, $w_{k-1}^{(i)}$ is the previous weight of the particle, and $p(y_k|x_k^{(i)})$ is the probability of the measurement given the state of the particle. Two variants of the TBM approach are proposed, the first one seeks to suppress the multipath track by modifying the weight calculation mechanism of the particle filter to take into account the AD feature. For each object, the variance of the received signal is calculated across the antennae, the larger the variance the more likely that the observed object is a ghost. The new weight calculation mechanism is given by

$$w_k^{(i)} = w_{k-1}^{(i)} p(y_k|x_k^{(i)})/(v+q) \qquad (5.2)$$

Where $q \geq 1$ if the AD featured is observed and $q=1$ otherwise, q is related to the sampling rate and to the required suppression speed. v is the variance of the received signal across the antennae, the larger the variance the smaller the weights of the particles. The weights will decrease in each time the AD featured is observed until the track is completely suppressed. The second variant seeks to mark the entire multipath track without suppressing it, this allows the multipath signals to be used in improving the localisation accuracy. The track will be marked as a multipath track if the sum of the variance v over multiple scans exceeds a threshold t. The first variant of the TBM approach is more suitable when the AD feature can be observed for most of the duration of the multipath signal because the weights of the particles will increase again when the AD feature is no longer observed.

5.6 Results

Computer simulations are performed to evaluate the proposed method. Two antennae are used in this work, the first one is placed at position (0.125m, 0m), and the second one at (0.375m, 0m). Two walls are considered, both walls are 4m from the first antenna. It is assumed that the person is moving in a specific path in the up-right corner, Fig. 5.4 shows the person path on the left side of the wall, while the measurements on the right side of the wall are caused by the multipath effect.

For simplicity, only multipath reflected from the side wall is considered. The person starts moving in the upper part toward the side wall, only the direct signal is received by the antennae for most of the person path, the multipath signal starts arriving at the second antenna before the person makes the first turn and continues for a short time, after that the multipath signal is received by the two antennae.

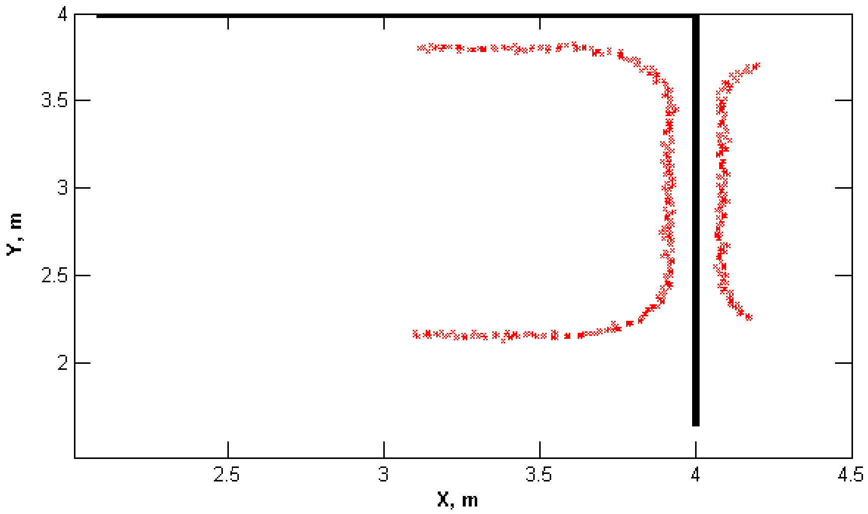

Fig. 5.4 The measurements on the left side of the wall represents the trajectory of the person, while the measurements on the right side of the wall represents a ghost object caused by the multipath effect.

Fig. 5.5 shows the result of using the particle filter, where the multipath ghost appears clearly on the right of the sidewall as a track of a new object. This shows that the particle filter is unable to mitigate the multipath effect.

The method initiates a new track when it starts to receive the multipath measurements. For the first variant of the TBM approach, the weights of the particles of the new track start to decrease when the AD feature is observed until the track is totally suppressed, Fig. 5.6 shows the result of the first variant of the proposed method where the multipath track is suppressed. For the second variant of the TBM approach, when the sum of the variance v over multiple scans exceeds the threshold t, the particles of the new track are only marked for future exploitation

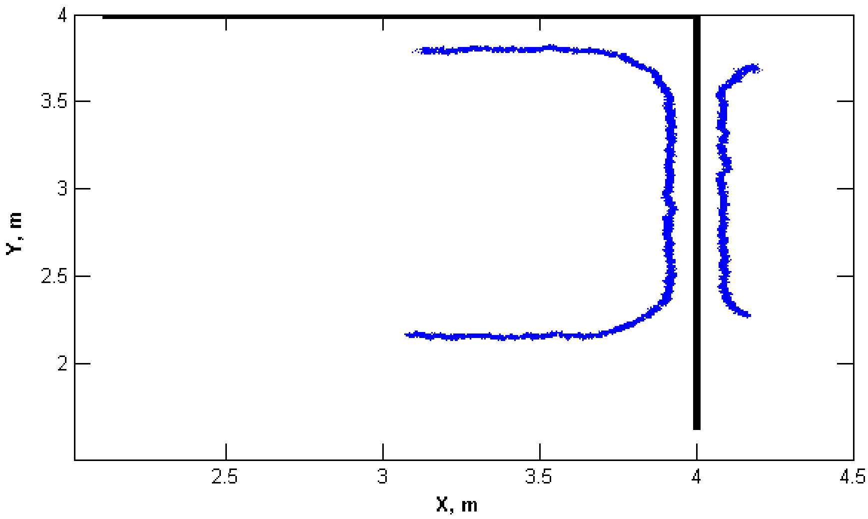

Fig. 5.5 Using the particle filter without any multipath mitigating method

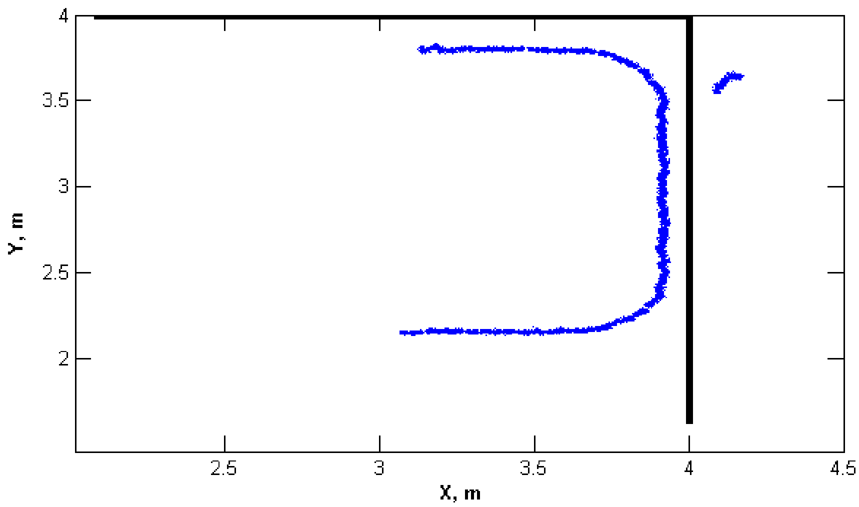

Fig. 5.6 Multipath suppression using the proposed method

Fig. 5.7 shows the result of the second variant of the proposed method where the particles of the multipath track are marked in red.

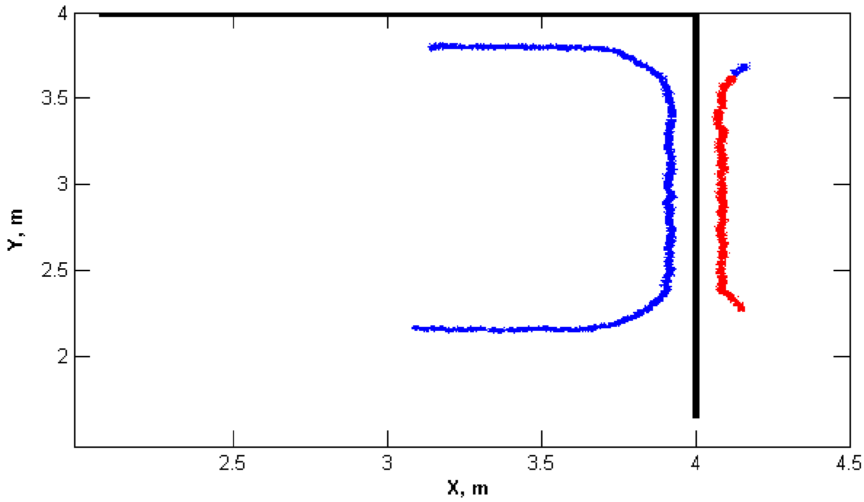

Fig. 5.7 Multipath track marking using the proposed method

One limitation of the proposed method is that it could suffer from a varying amount of delay before it can accurately suppress/mark the multipath track, this delay depends on the movement of the person.

5.7 Conclusion

This chapter has presented an efficient tracking based multipath ghost mitigation method. The basic idea of the proposed method is to use the information available from the tracking stage to improve the performance of the mitigation stage. The use of the tracking framework allows the use of more useful information in the time domain in order to make a more accurate decision and to relax some constraints in the space domain such as the large number of antennae that are placed over a large area. The proposed method integrates the aspect dependence feature of multipath signals into the tracking framework. The proposed method is more accurate, requires less number of antennae, and can suppress/mark the entire multipath track. Simulation results demonstrated the effectiveness of the proposed method. The use of the tracking framework has shown to be very effective in addressing problems in the sensing stage, where it has been used to address the multipath problem, the abrupt motion problem, and the weak signal problem. Future work will investigate using one tracking-based method to address these three challenges simultaneously. Future work will also investigate the use of the tracking framework to address other challenges such as signal occlusion. In the next chapter, the thesis will be concluded and future research directions are discuss.

Chapter 6

Conclusions and Future Work

6.1 Main findings

The main findings of this work can be summarised as follows:

- The research has extensively investigated the use of the Wi-Fi signal for people tracking, which turned out to have strong potential in indoor and outdoor tracking applications, Wi-Fi technology has several important features compared to other sensing techniques, such as relatively high transmitted power, and high availability. The contents of this thesis represent an important step towards the development of reliable Wi-Fi based tracking systems, by bringing them closer to real-world environments, where several challenges facing these systems have been addressed.

- The new formulation of the signal detection problem has been found to be essential to address the weak signal problem.

- The integration of signal shadowing with the conventional reflection approach has been found to significantly improve the detection probability of weak signals.

- The use of deep learning has been found to significantly reduce the computational time and improve the accuracy in comparison with existing methods. The deep learning based technique has shown its ability to adapt to real-world imperfections, which cannot be always captured by analytical models.

- The use of quantum mechanics inspired tracking approach to cope with the uncertainty of abrupt motion has been found to significantly decrease the tracking error and the tracking delay.

- The use of the tracking approach in multipath ghost mitigation has been found to improve the accuracy, decrease the number of required antennae, and provide the ability to suppress/mark the whole track without assuming any prior knowledge about the environment.

6.2 Contributions to knowledge

The novelty of this research and its contribution to knowledge can be summarised as follows:

- An extension of existing compressive sensing detection methods has been proposed to achieve angle of arrival estimation.

- The research has presented a combined reflection-based and shadowing-based weak signal detection method that significantly improve the detection probability of weak signals, where the detection of the weak signal reflected from the person's body is enhanced by taking into account the changes in the signals that are reflected from the surrounding environment.

- The research has presented a deep learning based Wi-Fi localisation technique that significantly improves the accuracy and reduces the runtime in comparison with existing techniques. The proposed approach has shown a high ability to adapt to challenging environments. It has also shown that it is relatively robust to multipath signals, and no additional multipath mitigation techniques are required to be used.

- The research has presented a tracking method that outperforms existing tracking methods when there are abrupt changes in the speed or in the direction. It also reduces the tracking delay when there is abrupt motion.

- The research has presented a tracking based multipath ghost mitigation method that requires a smaller number of antennae in comparison with existing methods, it can accurately suppress/mark the entire multipath track; furthermore, it does not assume any prior knowledge of the environment.

6.3 Limitations of the work

During the course of this research, some assumptions, simplifications, and design choices have been taken to achieve the research aims with the available resources. As a result, some limitations arise which can be summarised below:

- The effectiveness of the weak signal detection method is restricted by the assumptions made on the availability of signals that are reflected from static objects in the surrounding environment.

- The deep learning based localisation technique requires a large number of examples covering different situations during the training stage, collecting that large amount of data could be challenging.

- The proposed multipath ghost mitigation method could suffer from a varying amount of delay before it can accurately suppress/mark the multipath track, this delay depends on the movement of the person.

There are also some inevitable limitations in using the Wi-Fi signal, such as:

- The high power of direct signal interference, which will cause the masking of echoes from objects of interest, therefore; the cancellation of the direct signal is a crucial issue to improve the localisation performance of Wi-Fi based people tracking systems.

- Wi-Fi has limited range resolution in comparison with other sensing technology such as UWB, which could limit the range of applications. When the size of the object becomes close to the wavelength of Wi-Fi signals, which is 12 cm approximately at 2.4 GHz, the interaction of the object with the Wi-Fi signals decreases. This is a fundamental limitation of Wi-Fi based imaging. This fundamental limitation could be addressed using higher Wi-Fi frequencies such as 5 GHz that has a smaller wavelength of 6 cm approximately.

6.4 Suggestions for future work

During the research, a number of new problems and topics, which require further investigation, have been identified. Some of future research directions can be summarised as follows:

- The large number of people in real-world environments poses a real challenge, new methods or extension to existing methods should be developed to take into account this challenge.

- In dense environments, the system should be able to cope with partial occlusion of the wireless signal, new methods or extension to existing methods should be developed to take into account this challenge.

- The use of the tracking framework has shown to be very effective in addressing problems in the sensing stage, where it has been used to address the multipath problem, the abrupt motion problem, and the weak signal problem. Future work will investigate using one tracking-based method to address these three challenges simultaneously. Future work will also investigate the use of the tracking framework to address other challenges such as the occlusion of the wireless signal.

- The sparse nature of the measurement matrix should allow for more computationally efficient reconstruction methods, the development of such methods would be of great interest to the research in this field.

- Bats are known to have very sophisticated tracking capability in challenging environments [313], they are able to track their preys in very cluttered and dense environments. They can also detect a very weak echo from small insects. Proposing bat-inspired tracking strategy could result in significant improvement of tracking systems.

- Pigeons are known for using different cues for navigation [314], these include odours, infrasound, magnetic and vision cues; furthermore, pigeons can adaptively use different cues according to the environment. Using pigeons-inspired fusion methods to combine information from different sensing technology such as vision and sound would result in significant improvement of tracking systems.

- Borrowing from the rich literature in the computer vision community could result in more efficient tracking methods, particularly in occlusion and abrupt motion conditions.

- Using flexible nonparametric density estimation techniques to model the unknown noise and the uncertainty in the user's location would be also an interesting research direction.

- One of the main limitations of the tracking methods is the difficulty in capturing the real motion model of the person. Applying machine-learning techniques that can automatically learn the motion model is also an interesting research direction.

- The application of deep learning in localisation systems represents a promising research direction that is still in its initial stage. Although some recent works have shown promising results, some challenges still need more investigations. Further research must be conducted to propose deep learning architectures that best suit localisation, signal processing, and communication systems. The performance of the neural network highly depends on the used architecture. Current architectures used for signal processing and communication systems are very simple, and they only use conventional architectures. Choosing the right architecture and hyper-parameters are also an important question, which is currently an active research area. One other promising direction is to introduce expert knowledge to the deep learning architecture. Another important question is whether to use the end-to-end approach where the performance of the whole system can be optimized rather than optimizing the performance of each sub-task or using deep learning for each sub-task and hence reduce the curse of dimensionality.

6.5 Availability of the software

The code of the proposed techniques can be requested by contacting the author using the following email: a.m.khalili@outlook.com

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