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Accuracy Assessment of UWB RTLS for Tracking Resources on Construction Sites

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Accuracy Assessment of UWB RTLS for Tracking Resources on Construction Sites

by

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Abstract

The evolution of positioning technologies such as Ultra-Wide Band (UWB) has created an opportunity to improve the construction in various aspects. Enhanced situational awareness can be used to improve the level of safety and productivity of the construction. Providing information about situational awareness of static and moving objects on a construction site is feasible with applying positioning awareness. In order to apply positioning methods and technologies efficiently, they should be evaluated and assessed in different situations. The positioning performance changes when the dynamic parameters such as speed changes. In this study, two experiments are designed and carried out on the dynamic performance of UWB positioning. The result of the experiments and the evaluation of the results are stated in details.

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List of Abbreviations

Abbreviations	Definition
AASHTO	American Association of State Highway and Transportation Officials
AOA	Angle of Arrival
BIM	Building Information Model
BLS	Bureau of Labor Statistics
CAD	Computer Aided Design
CEP	Circular Error Probability
CI	Confidence Interval
DRMS	Distance Root Mean Squared
GDP	Gross Domestic Product
GIS	Geographical Information Systems
GPS	Global Positioning System
GPR	Ground Penetrating Radar
HSE	Health and Safety Executive
ILO	International Labor Organization
LOS	Line-of-Sight
MRSE	Mean Radial Spherical Error
NLOS	None-Line-of-Sight
OR	Object Radius
OSHA	Occupational Health and Safety Administration
PA	Positioning Accuracy

PDF	Probability Density Function
PI	Prediction Interval
POE	Power over Ethernet
PPE	Personal Protective Equipment
RCC	Remote Control Car
RFID	Radio Frequency Identification
RPRT	Relocation in Perception and Reaction Time
RSS	Received Signal Strength
RTLS	Real Time Location System
RTS	Robotic Total Station
SD	Standard Deviation
TDOA	Time Difference Of Arrival
TOA	Time Of Arrival
UWB	Ultra Wide-Band
VR	Virtual Reality
WCB	Wireless Location Area Network
WLAN	Work Compensation Board
WSN	Wireless Sensor Networks

List of Symbols

Symbols	Definition
cm	Centimeter
d_{PA}	Positioning accuracy factor
d_{RPRT}	Relocation in perception reaction time
D_f	Degree of freedom
E	Error
E_x	Error in x direction
E_y	Error in y direction
Km/h	Kilometer per hour
m	Meter
r_o	Object radius
R^2	R-squared
S	Speed
Sxx	Sum of the squares of the x data
SS_E	Sum of square of the errors
SS_T	Total sum of squares of the response variable y
t_i	Moments of location estimation
x_{mean}	Average of x

Chapter One: INTRODUCTION

1.1 Background

Construction is one of the largest industries in many countries by making up a large proportion of Gross Domestic Product (GDP). For example, construction comprises ten (10) percent of the GDP in Japan (Stat. Japan 2014) and seven (7) percent in Canada in 2014 (Stat. Canada 2014). The growth rate of construction industry's GDP in last four years in Canada is shown in Table 1.1 (Stat. Canada 2014). In Canada, the only industry exceeds from construction in GDP is manufacturing with a GDP of $173,442B comprising 10 percent of the total GDP in 2014 (Stat. Canada 2014).

Table 1.1 Growth rate of GDP in construction in Canada

Year	GDP Annual Growth
2011	3.68%
2012	6.50%
2013	1.90%
2014	0.59%

While the construction industry is a remarkable contributor to Canada's GDP, it is also considered to be one of the most dangerous industries as per the number of reported annual fatal injuries. For example in 2010, workers in the construction industry were three (3) times more likely to die from work-related collisions compared to the workers in other dangerous industries such as mining and agriculture (Cambraia et al. 2010, Ruff and Holden 2003). In 2010, approximately 108,000 workers lost their lives in the construction industry, comprising one third of all fatal occupational injuries worldwide (Stat. Canada 2010). In Alberta, while only approximately 18 percent of person-year worked is in the construction industry, 28 percent of days-lost due to injury among all industries are reported in construction (WCB 2010).

Besides the health and safety issues, injuries and work-related accidents have other major consequences such as financial losses and unpredicted project delays. Therefore, a considerable amount of resources has been put forth towards improving construction safety and reduce the number of injuries. As such, the safety management procedures, safety regulations, and developed tools such as personal protective equipment (PPE) have improved greatly in the recent years. For example, as shown in Table 1.2, the number of fatal injuries in the United States is on a decreasing trend since 2003 (BLS 2014). Similarly, Canada reports an improved rate of fatal injuries in the last decade (Stat. Canada, 2011). No doubt, today's construction industry can be considered safer than ever. However, it is still an unsafe industry.

Table 1.2 Construction fatalities in United States by year (BLS 2014)

Year	Fatalities
2003	1131
2004	1272
2005	1224
2006	1226
2007	1204
2008	969
2009	607
2010	816
2011	751
2012	775
2013	796

Despite significant efforts, the construction industry is still suffering from poor safety records (HSE 2012, Hinze and Teizer 2011). Construction workers are exposed to a variety of hazards. The major two causes for construction fatalities and injuries are falling from heights and collisions (OSHA 2012). Therefore, reducing the number of collisions on the construction sites can have significant financial and, more important, human safety benefits.

The evolution of positioning technologies in recent decades can provide an opportunity to improve safety in the construction in both indoor and outdoor jobsites. Among various ways to improve safety, situational awareness has been suggested as a means that could have significant potential (Teizer et al. 2008b). Providing precise real-time position of moving objects on construction sites such as labourers and equipment on a construction jobsite is shown to have high potential for identifying and avoiding unsafe situations (Razavi and Haas 2010). Positioning can help to predict, detect, and prevent the collisions construction sites (Cheng and Teizer 2012). Ultra wide-band (UWB) tracking, as a wireless RF-based Real Time Location System (RTLS) is gaining more attention and been used in numerous practical applications (Cheng et al. 2011). UWB is considered as a low-range wireless positioning technology as its range is limited to 160 m (Ubisense 2010). The increased attention to the potential of UWB RTLS in various industries, in construction industry in particular, has led to examination of its application in construction industry.

Performance assessment of UWB tracking is important as it relates to how it can be used and the way it can help to improve safety on construction sites. The accuracy of UWB RTLS changes when the dynamic parameters such as speed or acceleration change (Cheng and Teizer 2012). In order to apply positioning methods and technologies effectively, the accuracy and performance of such technologies is required to be assessed. Such an assessment can help in defining safety boundaries for collision detection and safety management models. Previous studies have mainly analyzed the accuracy of UWB RTLS focusing on static resource tracking. Few studies have focused on the accuracy of UWB RTLS in tracking dynamic resources. However, the impact of speed and acceleration on the accuracy of the UWB RTLS has not been assessed to date.

1.2 Research Motivation

Among various applications, using positioning technologies for improving the safety of construction sites has been proposed in previous studies (Oloufa et al. 2003, Cheng and Teizer 2012, Sadeghpour 2006). For example, applying positioning technologies in monitoring and improving behaviour of the construction equipment drivers has also been examined in previous studies (Hammad and Zhang 2011). Positioning technologies, in addition to location estimation, has also been used for acquiring the speed of equipment on a construction site. The application which enables alerting or warning when a driver exceeds the speed limit or enters an unsafe situation (Wang and Razavi 2015, Chae and Yoshida 2010).

The combination of using a robust alerting system and a reliable tracking technology can be invaluable for increasing the construction job-site safety levels and significantly reducing the number of collisions. In order to make a connection between a tracking and alerting system, object safety boundaries are used (Hwang 2012, Taubig et al. 2012). A safety boundary entails an area, commonly a circle, that covers a moving object equipped with positioning tags. The overlap of safety boundaries of two different objects can be defined as an unsafe situation or an on-site collision.

In order to accurately define a safety boundary, the accuracy of the positioning system in both static and dynamic tracking is required. Tracking static and dynamic resources are, respectively, referred to as static and dynamic tracking. A safety boundary is considered more efficient if it entails a “dynamic safety boundary”. The radius of the dynamic safety boundary can be obtained by considering three factors: the smallest circle that entirely covers the moving object, minimum stopping distance of the moving object, and the accuracy of the positioning technology. The radius of the circumvent circle is constant, the minimum stopping distance and the performance of the positioning technologies are functions of speed. In consequence, the radius of a dynamic safety boundary can be calculated as a function of speed.

In Equation 1.1 and Figure 1.1, three factors are implemented for obtaining the radius of the safety boundary. These are referred to as: 1) object radius (r_o); 2) minimum stopping distance (S); and 3) positioning accuracy (d_{PA}) respectively.

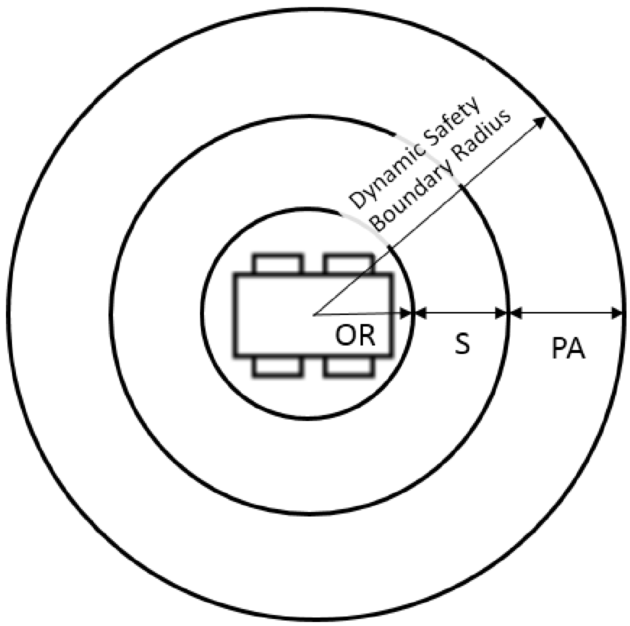

Figure 1.1 Dynamic safety boundary parameters

Safety boundary Radius = $r_o + S + d_{PA}$ (1.1)

To further define the different acronyms, r_o is the object radius, S stands for the minimum stopping distance, and d_{PA} stands for positioning accuracy.

Additionally, the radius of the smallest circle that entirely covers the moving object can be easily obtained.

The minimum stopping distance (S) is function of speed of the moving object and the perception and reaction time of the driver of the moving object (Roger et al. 1992). This factor can be obtained using the following equation:

$$S=S_{pr}+S_b \tag{1.2}$$

where S_{pr} is the relocation of the moving object during the perception-reaction time of the driver and S_b is the distance that the moving object travels while decelerating from the initial travelling speed to zero. S_{pr} and S_b can be calculated, respectively, using the following equations:

$$S_{pr}=\frac{v_0}{3.6\times t_{pr}} \tag{1.3}$$

$$S_b=\frac{v_0^2}{254\times f} \tag{1.4}$$

where V_0 is the initial speed of the moving object in km/hr, t_{pr} is the perception-reaction time in second, and f is the coefficient of longitudinal friction (see APPENDIX A). The perception-reaction time (t_{pr}) was matter of studies and experiments in different environments and situations (Alm and Nilsson 1995, Jurecki et al. 2014, Green 2000).

The findings of these measurements in this study can be applied and utilized in obtaining the third factor of the radius of the dynamic safety boundary (d_{PA}).

1.3 Research Objectives and Scope

The overall goal of this study is to evaluate the accuracy of UWB RTLS in tracking moving resources such as equipment and labourers in construction projects. The specific objective of this study is to examine the effect of *speed* and *acceleration* on the accuracy of UWB RTLS in dynamic tracking on construction sites. The findings of this study can be used for defining dynamic safety boundaries, as defined in the previous section, to reduce work related injuries and, in consequence, increasing the safety level of construction jobsites. The scope of this study is to examine the performance of UWB RTLS in an indoor lab environment that is similar to an indoor construction jobsite.

1.4 Methodology

Two sets of experiments are conducted to assess the accuracy of UWB RTLS in tracking dynamic resources. In these experiments, the actual position of the UWB tag is compared with the estimated position. In the first set of experiments, the accuracy of UWB RTLS in tracking dynamic resources is evaluated while a tagged mobile object accelerates over a defined path. Analyzing the results raised the question that if acceleration had an impact on the accuracy of UWB tracking. Therefore, the second set of experiments were designed in an identical method, except that the acceleration was eliminated. In this experiment, the mobile object moves over its path with a constant speed and is observed at several observation points that are defined on the path.

The performance of UWB tracking from the two experiments are compared using the accuracy measures, namely: offset, DRMS, and precision at various speeds allowed on construction sites. The confidence interval (CI) and prediction interval (PI) for the error of the data are calculated. The CI is used to obtain accuracy measures such as DRMS, precision, and offset. The PI can be used for defining the dynamic safety boundary for moving objects as described in section 1.2.

1.5 Organization of Thesis

This dissertation is organized as follows: in the second chapter, studies regarding the performance of several tracking technologies such as GPS, WLAN, and UWB in different environments for different applications are reviewed. In the third chapter, the accuracy of UWB RTLS in tracking dynamic resources is tested and discussed with different speeds. In the fourth chapter, an experiment is conducted to assess whether acceleration affects the accuracy of the UWB RTLS in tracking dynamic resources. Conclusions, summaries, and recommendations for future research are discussed in the final chapter.

Chapter Two: LITERATURE REVIEW

In this chapter, studies conducted on increasing the safety level of construction sites are reviewed. Because collisions are the main cause of most work-related serious and fatal injuries, this chapter focuses on studies related to collisions in construction. The reviewed studies are categorized into groups: collision detection and prediction models, collision warning approaches, and the reason for collisions. Positioning has shown a great potential to reduce the number of accidents. Therefore, studies conducted on assessing the performance of different positioning technologies are discussed and compared.

2.1 Safety Approaches in Construction

There are several categories of research on safety in construction sites at different phases of progression of a project such as design and process. In these studies, new software, methodologies, and hardware are applied in designing safer construction environment, training the people involved in the construction, and improving the safety of the workers during the construction.

The main focus of one category is at the design level of a construction project and the impact of design on construction safety. It is mainly engaged with practitioners who develop and sustain a safe construction environment. In this research, time and energy are mainly focused on using databases, Building Information Modeling (BIM), and 4D Computer Aided Design (CAD) in different construction phases (Zhou et al. 2012). Different tools are developed to improve the safety of projects. These tools are taking advantage of online databases, such as Geographical Information Systems (GIS) 4D CAD and BIM, for site hazard avoidance. These tools are used in different phases of construction projects (Yu 2009).

At the process level, online databases are mostly used for enabling project safety information queries and communication between companies. At the process level, significant efforts have been dedicated to improving safety as well. Most of these efforts take advantage of 4D CAD to enable safe project delivery. The integration of GIS and BIM with 4D CAD has resulted in a better understanding of construction safety (Zhou et al. 2012). Two main tools in this category are ToolSHeD (Cooke et al. 2008) and a knowledge-based safety design analysis prototype (Davison 2003). Their main advantage, respectively, is being suitable for multi-party collaboration and being integrated with design information. ToolSHeD is a web-based tool designed for assessing the risk of falling during building maintenance. The importance of this tool is shown in the UK's Health and Safety Executive report: by using this tool, researchers discovered that falling from buildings on construction sites during maintenance is the main cause of accidents in the UK (Cambraia et al. 2010).

There are some studies that assess the impact of training of labourers on safety (Bouchlaghem 2005, Carbonari et al. 2011). The method of teaching and training for increasing safety is referred to as “proactive”. Virtual Reality (VR) is a term used for the combination of hardware technologies and software and it is used for developing 3D and real-time tools in a virtual environment such as computers or phone applications (Woo et al. 2011). The developed computer applications are used to train labourers in a virtual construction site. The main advantage of virtual training, e.g. Building Management Simulation Centre De Vries et al. 2004), is getting trained in a risk-free environment.

In another branch of research, taking advantage of location estimation technologies is considered to be a solution for improving safety (Oloufa et al. 2003). In these studies, the researchers conduct experiments to determine the efficiency and reliability of the positioning technologies on reducing the number of collisions, falls, and labourers get stuck by heavy machinery. The performance of the location estimation technologies, such as GPS, RFID, WLAN, and UWB, is evaluated in various construction environments, indoor and outdoor. (Khoury et al. 2009, Riaz et al. 2006, Maalek and Sadeghpour 2013).

2.2 Collision in Construction

Collisions have always been an important issue in different fields, especially in the construction industry, which has a high number of collisions reduce the safety level of this industry. Construction sites are known as complex environments and have equipment, materials, tools, and workers in continuous interrelation. The nature of construction sites, and the interrelation of the moving objects, endanger the health of the labourers in this industry (Teizer et al. 2010b). Collisions cause major monetary and time losses, and, most importantly, serious and fatal injuries. Some of these accidents are attributed to the dynamic environment in which the workers and equipment operate too closely together (Behzadan et al. 2008). The significant number of accidents has resulted in more studies being conducted on the issue of collisions from different perspectives. The main goal of these studies is reducing the number of accidents and losses with focusing on *collision detection*, *collision prediction*, and *collision warning* as will be explained in this section.

2.2.1 Collision Detection and Prediction

Earlier research on reducing the number of collisions was focused on warning labourers when collisions were about to occur. In these models, detecting collisions that are about to occur is referred to as “collision detection”. Collision detection methods are categorized into two major groups: broad-phase and narrow-phase (Kockara et al. 2007, Cheng and Teizer 2012, Jiménez et al. 2001). In most of the collision detection models, both the broad-phase and narrow-phase methods are used. In the broad-phase methods, the possibility of a collision between pairs of moving objects is examined by approximating the volume of the involved objects. In the narrow-phase method, further inspection and calculation is conducted for each pair that demonstrated the possibility of collision, as detected in the broad-phase (Moore and Williams 1988, Lin and Canny 1991, Mirtich 1998, Ehmann and Lin 2000). In the narrow-phase methods, the model concentrates on the shape and geometry of the objects to detect the probability of a collision occurring. In computer modeling and simulations, the position of the moving objects and their orientation can be extrapolated from the specification of parameters using the narrow-phase method (Steketee and Badler 1985).

Another branch of research related to collision focuses on collision response, which is mainly implemented in computer animation (Moore and Williams 1988). Researchers are using the assumption of zero elasticity to use momentum equations that use an angular velocity vector for each object and an impulse vector. Improving the collision detection models and systems on construction sites reduces fatalities and injuries. This advancement will save time, money, and increase the safety of the conditions for construction workers.

2.2.2 Collision Warning Approaches

Alerting labourers to the possibility of an imminent crash or dangerous situation is referred to as a "collision warning". The approaches used for warnings are divided into two groups: reactive and proactive. The reactive approach in most cases takes advantage of video cameras or time-lapse photography for data collection in real-time (Teizer et al. 2010b). Converting the data into useful real-time data and then sending warning messages to the labourers takes time and effort, which makes it nearly impossible to warn the operators in danger (Jog et al. 2011, Teizer and Vela 2009, Yang et al. 2010). In the proactive safety approach, the workers are alerted once they are in danger of collision (Fullerton et al. 2009). In this approach, the safety system can collect data for detecting hazardous situations (Hinze and Teizer 2011).

The most common proactive safety approach is the sensor-based proximity warning system, which detects objects and alerts the drivers. The main disadvantage of this approach is object discrimination (Bliss and Acton 2003). Object discrimination (recognition) is the ability to identify or perceive the objects' physical properties, such as colour and shape; the user does not have any understanding or experience of the detected object while using a sensor-based technology. Radar-based technologies are also used on construction sites for object detection (Porsani et al 2010). Due to the lack of visual information, it has been proposed to integrate visual monitoring methods with radar-based technologies to increase the reliability of the alerts (Ruff 2006). However, this integration does not have enough precision in large-scale and complicated construction environments because the performance of long-range detection is limited in the current technologies (Wu et al. 2013).

New forms of spatial awareness in construction sites are being developed using advances in information, sensing, and visualization technologies (Teizer et al. 2005, Weingarten et al. 2004, Choe et al. 2013). Considering the shortcomings of the mentioned technologies and approaches for collision warning, taking advantage of an appropriate positioning technology can be a giant leap forward in increasing safety in the construction industry. Positioning can improve safety by applying them in modeling, detecting, and tracking objects in hazardous zones (Teizer et al. 2007a).

An automated obstacle avoidance support system has been developed and studied to navigate and operate machines safely (McLaughlin 2004). Radio Frequency Identification (RFID) (Song et al. 2006), Ultra Wide-Band (UWB) (Fontana 2004), Video rate range imaging (Teizer and Vela 2009), and Global Positioning System (GPS) (Navon 2005 and Caldas et al. 2006) are applicable technologies for tracking and locating the stationary and moving objects on a construction site. Experimental studies on tracking technologies demonstrated that the estimated position, dimension, direction, and speed have a reliable level of accuracy; they are compatible with the requirements of safety features of proactive approaches for construction environments. Hence, these technologies are able to be used for proactive warnings in dynamic and dangerous environments in construction sites. These active warning systems have the advantage of generating warnings and feedback to labourers when risks may occur close to them.

The practicality of using real-time warning systems integrated with location estimation technologies in regular construction sites has been studied (Teizer et al. 2010b). However, the application of these technologies has various weaknesses. This study focuses on assessing the performance of UWB in tracking dynamic objects in conditions that are most common on construction sites. The results of this experiment will be used to estimate the variables required for defining safety zones. "Safety zone" is a definition used to define a collision or being in a dangerous situation.

2.2.3 Collision in Construction

Studying collision detection and prevention has been matter of attention in different fields such as computer graphics (Kim and Rosignac 2003), robotics (Gonzalez et al. 2002), and unmanned vehicles on the road (Sakkila et al. 2010). Although common goals and problems are shared between these fields and construction, there are significant differences in terms of context and environment. The concept of studying collisions on construction sites is relatively new with only a few studies previously conducted. These studies can be categorized as follows: 1. Equipment-to-people collision (Sakilla et al. 2010, Gonzalez et al. 2002), 2. Equipment-to-equipment collisions (Kim and Rossignac 2003), and 3. Equipment-to-facility collisions (Pratt et al. 2001, Teizer et al. 2005a). It is accepted that the techniques applied for collision detection in the above studies should satisfy sufficient geometric information, location of obstacles, and collection of missing data in real-time by the location estimation system. The third requirement highlights the necessity of continuous collision detection followed by collision prediction (i.e. assessment of the potential for a collision in advance). This study focuses on assessing the performance of UWB in tracking dynamic objects in conditions that are common on construction sites. The results of this experiments will be used to estimate the variables required to define a safety zone.

2.3 Applications of Positioning in Construction

Advancements in sensing technology and communication has resulted in the automation of field management in the construction industry. Acquiring data from construction processes has become automated more than ever before and it is still increasing. GPS, RFID, UWB, and WLAN are technologies that are used in construction automation (Bohn et al. 2009). The potential of automating construction projects in different phases using the location estimation technologies is high because they can be implemented in several applications, for example, project control, safety control, progress monitoring, and quality control. Automation in construction is an important factor that is able to increase the reliability of the construction environment where heavy equipment play an irreplaceable role because location estimation technologies can be used for several purposes such as collision detection (Esmaeilnejad and Sadeghpour 2014, Andolfo and Sadeghpour 2015), security (Choe et al. 2014), safety (Giretti et al. 2009), and productivity (Grau et al. 2009 and Sacks et al. 2003).

Esmaeilnejad and Sadeghpour (2014) developed a simulation for collision detection. The simulation was able to generate random trajectories for the moving objects on a construction site. In the collision detection model the number of warned collisions and real collisions were compared to obtain the efficiency of the model. This model was a simple model which only considered moving objects such as labourers and equipment. Andolfo and Sadeghpour (2015) developed and evaluated a collision detection model detecting the moving objects in danger situations. In this study the feasibility and efficiency of the model was assessed by considering the process time for the model using several frequencies for data acquisition.

Using these technologies has been helpful in improving the quality, efficiency, and outcome of construction projects. The impact of equipping labourers, materials, tools, and equipment with location estimation tags has been assessed independently (Torrent et al. 2009, Grau et al. 2009). For security, some studies evaluate the trustworthiness and practicality of using positioning. In these studies, avoiding theft and loss of materials and tools on construction sites is assessed (Khoury et al. 2009, Riaz et al 2006).

Further, equipment collisions are playing a significant role in damages and harms with serious health and monetary consequences. Collision detection is one of the most important applications of positioning technologies, which can help to reduce these losses (Teizer et al. 2010b). Therefore, collision detection is matter of attention to several studies from different perspectives. For instance, some of them focus on the cause of the collision on a construction site (Hinze and Teizer 2011); some other studies attempt to recognize and alleviate the source of accidents such as blind spots in reverse movements (Teizer et al. 2010a).

2.3.1 Positioning for Safety in Construction

The methodology of applying location estimation technologies on construction sites has an important impact on their efficiency. Some studies develop new methodologies while others focus on improving old ones (Li et al. 2013). For evaluation, the newer ones are compared with the previous ones. The methodologies focus on different phases of using the positioning technologies. In several studies, which focus on changing the methodology, collision detection, dangerous situation warning, and location estimation algorithms are major parts that captured great attention of the studies.

A wide range of applications of tracking technologies in the construction industry resulted in studies focusing on their performance in both static and dynamic situations (Maalek and Sadeghpour 2013, Hwang 2012). In most of the accuracy assessment studies, either the static or dynamic performance is studied (Teizer et al. 2007b, and Maalek and Sadeghpour 2013, Saidi et al. 2011, Cheng et al. 2011, and Cho et al. 2008); the combination of these two modes was also researched (Cho et al. 2010, Jiang et al. 2010). The accuracy assessment experiments are categorized into two major classes: indoor and outdoor. The reason for this classification is that there are different factors in the environments that impact the performance of the tracking technologies. These parameters are considered and discussed in some of the studies (Saidi et al. 2011). Other studies focus on the effect of construction progress on the accuracy of the tracking systems (Shahi et al. 2012). In these studies, the estimated position of the tags, while static, during the construction of the project, are recorded during several construction phases. The performance of the technology is compared in different construction phases using the recorded data and obtained results.

2.3.2 Positioning in Collision Detection

Other studies pertaining to tracking in collision detection and prediction have recognized and evaluated the main specifications of location estimation technologies that affect their performance (Maalek and Sadeghpour 2013, Navon 2005, and Niu and Ma 2011). Several alternatives are available for tracking in collision detection and prevention. They differ in their cost, size, response time, reliability, and effective operational range. Different studies for location estimation technologies in construction sites are carried out using GPS, RFID, WLAN, and UWB (Khoury et al. 2009, Maalek and Sadeghpour 2013, and Riaz et al. 2006). Their performance in collision detection in real-time including of line-of-sight, cost, response time, reliability and operation range are evaluated and compared in several studies. (Maalek and Sadeghpour 2013, Khoury et al. 2009).

Usage of ultrasound technology is constrained within line-of-sight arrangements of transmitters across the construction sites (Hightower and Borriello 2001). Ultrasound performance is poor in sunlight (Shahi et al. 2012). Further, only objects within a short range can be detected. These shortcomings make ultrasound less efficient for real-time location estimation in construction sites. Vision tracking is associated with line-of-sight and, similar to ultrasound, this property is a disadvantage because the Line-Of-Sight (LOS) can be blocked, for example, by materials and heavy equipment, easily and frequently in such environments.

Image-based vision technology is becoming more popular in path-finding and navigation (Sim and Dudek 2003, Kim et al. 2003). Advanced technologies have been used for tracking and locating objects and people. GPS is known to be accurate and practical in a construction environment. However, its implementation cost is higher in comparison with other alternatives (Hightower and Boriello 2001, and Liu et al. 2007), and GPS does not work properly in indoor environments, which is considered a highly restrictive feature. Some studies discuss the implementation of a combination of the two aforementioned positioning technologies with the goal of improving the performance of RTLS (Costin et al. 2012). RFID + GPS, RFID + ultrasound, and RFID + wireless LAN are some of these combinations (Viani et al. 2012, Teizer and Castro-Lacouture 2007, and Jiang et al. 2010). They demonstrated limitations in terms of scalability and reliability (Riaz et al. 2006).

2.4 Remote RF-based Positioning

Positioning technologies in the literature are Global Positioning System (GPS), Radio Frequency Identification (RFID), Wireless Local Area Network (WLAN), and Ultra-wide Band (UWB). Each of the positioning technologies has its own specifications and capabilities (see APPENDIX B). These technologies are introduced and compared in order to identify the best option for location estimation in the construction sites.

2.4.1 Global Positioning System (GPS)

The Global Positioning System (GPS) is a satellite-based navigation system. This positioning technology is made up of 24 satellites placed into orbit of earth with known positions. In order to perform the positioning in 3D four (4) satellites with LOS signals are required (three position coordinates and the deviation of the receiver clock from satellite time) (Lu et al. 2007, Su et al. 2014).

GPS is known as an accurate and economical positioning technology. However, it does not work accurate in indoor places such as indoor construction jobsites because of signal attenuation caused by NLOS situations from the satellites (Lu et al. 2007).

2.4.2 Wireless Local Area Network (WLAN)

Wireless local area network (WLAN) is commonly used for communication and data transfer over short distances using RF. WLAN is a very good alternative for traditional cabling. WLAN are made up with access points (AP) connected to the edge of the wired network.

WLAN is also referred to as a Wireless Sensor Network (WSN) compatible with IEEE 802.11 standard which is able to transfer relatively high amount of data. WLAN is widely used for transferring data, such as internet access points (Sugano et al. 2006). Therefore, there are some studies performed on using WLAN as an economical solution for indoor tracking (Retscher et al. 2006).

WLAN can be used for location estimation. In the case of having enough information and data about the WLAN antennas involved received signal strength can be used for positioning by applying finger printing method. In order to be able to use the finger printing method, a database form the APs' RSS at different location in the area of interest is required. In addition, the data acquired from WLAN are commonly used for improving the positioning of A-GPS in the cell phones.

2.4.3 Radio Frequency Identification (RFID)

RFID is a technology that can be used for location estimation. This technology consists of two parts: reader and tags. Each tag has an identification code stored within the tag (Lu, et al., 2007). RFID tags vary based on their specifications: power source, carrier frequency, read range and rates, etc. As power source dictates other characteristics RFID tags are classified into two major groups: active and passive. Both kinds of tags communicate via radio frequency. The difference between passive and active tags is that active ones have internal batteries. The reader acquire the identification code of a tag while the tag is in the coverage range of the reader. The conventional RFID was known as a suitable alternative for barcodes (Lee and Seo 2005, Lee and Ju 2007). The reason is that RFID is able to work with a higher range, works in NLOS and harsh environments, and able to save more data. To be able to use RFID for positioning different methods can be used: finger printing, received signal strength (RSS), angle of arrival (AOA), and proximity methods.

2.4.4 Ultra-wide Band (UWB)

UWB has a large bandwidth that enables this positioning technology to use TOA and AOA of the LOS signals for accurate location estimation. Moreover, the signal frequencies are well suited for penetrating through objects (Fernandez-Madrigal et al., 2007, Zhang et al. 2006). This characteristic of UWB makes it a very good alternative for positioning in the indoor construction jobsites where GPS does not perform accurate due to signal attenuation caused by NLOS condition. Positioning methods used by UWB are: AOA, TOA, and TDOA.

There are two types of UWB signals: Impulse-based and Multicarrier-based. In the Multicarrier-based systems differentiating the LOS and multipath signals are performed by higher accuracy (Reed, 2005). However, the Multicarrier-based systems perform in lower ranges (5 – 10 m). Consequently, a Multicarrier-based UWB can provide better accuracy in lower range positioning.

2.4.5 Comparison of RF-based Positioning Technologies

Some studies analyzed and compared remote sensing technologies (e.g. GPS, RFID, WLAN, and UWB) considering different factors such as installation cost or number of receivers required for covering the area of interest (Retscher et al. 2006, Ciurana et al. 2006, Muthukrishnan and Hazas 2009, Welch et al. 2002). These studies are performed on the accuracy for tracking of the positioning technologies in both stationary and moving objects (labourers, equipment, tools, and materials) in different situations. Comparing the result of these studies shows that UWB is the best option considering the advantages and disadvantages of possible RF-based sensor options such as the accuracy, cost, maintainability, durability and the ability of working in harsh environments (Khoury and Kamat 2009, Maalek and Sadeghpour 2011).

Results of studies on UWB show that UWB technology, in different construction environments, achieves the accuracy of 35 cm (Liu et al. 2007, and Maalek and Sadeghpour 2013).

UWB can be implemented in indoor environments and it has a superior response time and reliability compared to other location estimation technologies; UWB also has the same or less cost of installation and implementation. Considering different factors such as durability, maintainability, cost, accuracy, response time, and reliability; UWB RTLS has great potential of getting implemented in dynamic and cluttered construction environments for collision detection amongst possible RF-based sensor technologies (Maalek and Sadeghpour 2011).

2.5 Ultra-Wide Band (UWB) in Construction

Previous studies have shown that there is a high potential of using location estimation technologies in the construction industry. Most of these studies are mainly focused on tracking and locating the labourers and materials within a construction site (Lee et al. 2006, Song et al. 2006, and Yagi et al. 2005). There are various studies performed on the UWB RTLS focusing on its static accuracy in different indoor and outdoor environments, but fewer ones focused on the accuracy of tracking dynamic resources. The studies focused on dynamic performance are concerned with tracking and locating people (Teizer et al. 2008b and Venugopal et al. 2010). This technology can be used to improve the safety level on a construction site. UWB has been studied and successfully applied in different fields.

UWB performance in the construction industry has been evaluated in several studies. These studies can be categorized in the following domains: real-time 3D construction resource tracking and positioning, on-site real-time safety management, robot equipped with UWB positioning system, pavement and railroad non-destructive evaluation, and application for localization in mining.

2.5.1 Resource Tracking and Positioning

Real-time decision making is an indispensable factor for a construction project. Resource status assessment and work task performance should be performed quickly and efficiently to have a fast decision making system. This condition can be satisfied with using a real-time 3D location estimation system (Teizer et al. 2008). UWB technology performance for resource tracking and positioning in a construction environment is tested in different studies (Teizer et al. 2008b). Another branch of studies focuses on the performance of UWB in a dynamic environment because construction sites are dynamic and have a high probability of signal blockage.

In this group of studies, the ability of signals to penetrate different materials is a matter of attention. Giretti et al. assessed the accuracy of UWB during the progression of a project (2009). The results state that single layer cellular blocks do not have considerable impact on signal penetration strength, but double layer concrete walls with insulation weaken the signal penetration strength. Another researcher evaluated the impact of wood and metal on UWB signal strength. In this study, tags are placed in boxes made of wood and metal (Shahi et al. 2012). This study revealed that wood does not have a tangible influence on UWB signal strength while the metal boxes changed the average accuracy of the system by 200 percent. Another study tested signal penetration strength through the human body (Welch et al. 2002). The result of this study demonstrates considerable signal attenuation after passing human body.

2.5.2 Safety Management

Construction safety is a major concern in the industry. The industry is suffering from various aspects of safety issues, such as health, monetary, and time delay concerns. Location estimation combined with an efficient alerting system has been considered as a solution for many years. A consistent model needs to be developed and studied to prevent probable consequences (Oloufa et al. 2002).

Recognizing travel patterns of moving objects on a construction site can also lead to advancements in increasing safety. Travel pattern recognition requires accurate, real-time information regarding the speed, location, and trajectory of different equipment. In a study using UWB for positioning, an algorithm for locating and identifying the obstacles is developed and evaluated (Teizer et al. 2008a). In addition, this algorithm can be used in safe path planning studies.

A very important factor in these models for on-site, real-time safety management is the continuity and sustainability of the system. The sustainability of UWB is evaluated in an environment similar to a construction site (Giretti et al. 2009). The size of a UWB tag is an advantage of this technology because they are small and, therefore, do not interfere with ongoing activities. The impact of the elevation of the tags relative to the readers' elevation on the performance is assessed in some studies in both indoor and outdoor places (Saidi et al. 2011 and Cho et al. 2010). The results of these studies state that the higher the elevation of the tags, the higher the accuracy in location estimation.

2.5.3 Robots

A robot should be able to perform effectively and independently (Cho and Youn 2006). The performance of a path planning model integrated with UWB is evaluated in a study by Cho and Youn (2006). They used autonomous mobile robots to improve the navigation functions in indoor environments such as warehouses, office buildings, manufacturing facilities, and various construction sites. The architecture of this model is shown in Figure 2.1. UWB is used for the tracking for robot navigation. The acquired data are visualized to provide a better understanding of the performance of the designed system for indoor path planning (Cho and Youn 2006).

2.5.4 Non-destructive Evaluation of Pavement and Railroad

In some experiments, part of a material is required to be taken apart to find out how it works. But sometimes it is hard or impossible to put it back together with the same condition. Time and money would be saved if the pavements get evaluated in a non-destructive manner after construction. A study is carried out to assess the combination of a ground penetrating radar (GPR) system with UWB (Lee et al. 2004 and Al-Qadi et al. 2010). The evaluation is performed by measuring the thickness and relative permittivity of samples taken from the pavement. This branch of studies considers the fact that the energy of UWB transmitted signals is highly dependent on the frequency and transmission medium. The result of the studies show that the scattering patterns of the received signals can be used to recognize the air void volume in the ballast of the railroad.

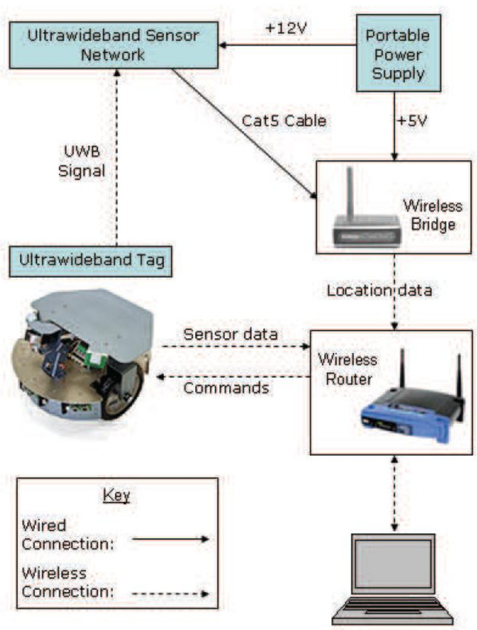

Figure 2.1 UWB integrated mobile robot tracking system architecture (Cho et al. 2008)

2.5.5 Localization in Mining

Mining is an underground process and, therefore, this industry is hazardous due to several factors such as poor visibility, poor ventilation, dangerous rock falls, and toxic gases. Using wireless communication technologies can be beneficial in this industry, particularly in emergency situations. The goal of this study is to locate the mining equipment and miners during normal operations. UWB has the ability to penetrate obstacles in a cluttered environment and delivers a high performance compared to other available Wireless Sensor Networks (WSN); as a result, it was selected for in this study (Chehri et al. 2009). UWB positioning also has low complexity, excellent time domain, and low cost. WSN offers several advantages such as security, larger area coverage, and elimination of costly wires compared to traditional sensor networks.

2.6 Accuracy Assessment of UWB

Among the studies held on UWB tracking technology, there are some that have similar goals to our study. In this section, these studies are discussed in detail. The methodology and the results of these studies are reviewed to find an area where the UWB RTLS has not been studied and has the potential of being evaluated.

Maalek and Sadeghpour (2013), performed six (6) different experiments on UWB performance in stationary modes; dynamic modes were not tested (Maalek and Sadeghpour 2013). These experiments were designed to assess the performance reliability of UWB in certain situations; the performance reliability was influenced by several factors that affected the performance of the positioning process such as the multipath effect, signal blockage, existence of a metal surface, removing the timing cable, number of tags, and number of receivers. In the real world, these factors are usually occur in a construction environment.

The first experiment in this study is considered as the base experiment to identify the impact of the imposed changes on the experiment environment area. To be able to analyze the collected data, control points, points that we know their actual position using surveying tools, are used. The (x, y, z) coordinates of the control points are recorded for two minutes. In this time period, 1000 location estimation data control points were collected. Distance Root Mean Squared (DRMS) is a parameter used in this study for comparing the 2D accuracy of the control points.

The multipath effect in this study is modeled by putting tags below a metal table elevation. The result showed that the performance decreased almost 70 percent and 89 percent in 2D and 3D, respectively, compared to the base experiment. The signal blockage was modeled with turning off the closest receiver to the control point. The result of this designed experiment was a decrease in the performance, 21 cm in 2D and 38 cm in 3D. The experiment on the existence of metal surface in the lab resulted in almost the same result compared to base experiment. Removing the timing cables simulates the situation that position acquiring is only performed by Angle-of-Arrival (AOA) equations (see APPENDIX B). Therefore, the result of this experiment compares the location estimation performance of the method only applying AOA with the method applies both the AOA and Time-Difference-of-Arrival (TDOA) methods (see APPENDIX B). Applying this change to the system resulted in a decrease in accuracy: approximately 12 cm in 2D and 7 cm in 3D.

The impact of number of the tags on the performance is assessed by increasing the number of tags by one in each subsequent experiment. The result demonstrated that the decrease in the performance is meaningful up to nine tags, but, with ten or more tags, the performance changes gradually as the number of tags increases. Thirteen settings out of 246 possible settings were experimented to find out the impact of the number of receivers on the location estimation performance. These thirteen settings, with two to seven receivers (readers), were discovered to be the worst out of the possible settings, in terms of LOS. The result of this study showed that the performance of UWB worsened when the number of receivers decreased. The average accuracy of location estimation was 14 cm in 2D and 26 cm in 3D. The results of this study are shown in Table 2.1.

Table 2.1 Result of the study by Maalek and Sadeghpour 2013

	Average Accuracy (cm)		Minimal Accuracy (cm)	
	2D	3D	2D	3D
Experiment 1: Base experiment	16	34	41	79
Experiment 2: Multipath effect	24	60	67	146
Experiment 3: Signal blockage	33	65	52	68
Experiment 4: Metal surface	15	30	47	69
Experiment 5: Removing timing cable	27	37	53	63
Experiment 6: Number of tags	34	60	34	77
Experiment 7: Number of receivers	14	26	54	76

Saidi et al. conducted an experiment to evaluate the static and dynamic performance of UWB in free space and realistic construction environments using six receivers (readers) (Saidi et al. 2011). In this study, there are about 23 factors that potentially affect the UWB positioning performance. One of the factors, the impact of geometry (alignment) of the receivers on the static performance of UWB, is tested. The time interval for collecting the location estimation data is one minute with the frequency of 1 Hz. For each controlling point, 60 positioning datum are collected.

The experiment was designed to enable the evaluation of two characteristic of the UWB: 1) The error in 3D and 2) the sensitivity of the performance of UWB to the accuracy of measuring the position of the readers. Each set of experiment is conducted twice; once with knowing the receiver position by ±1 mm accuracy, called "ideal setup," and the second time with ±20 cm accuracy, called "GPS setup." The position of the sensors are acquired using a total station and the second time with a differential GPS with the accuracy ranging between 20 cm to 30 cm to obtain the position coordination with the mentioned accuracies. The static performance assessment is performed in an open, grass-covered field with an area of 20 m × 10 m. The dynamic performance evaluation is conducted in a lay down yard zone, which was part of a construction site that included several construction machines and workers. The maximum mean error of the system was 77 percent and 12 percent higher in the GPS setup compared to the ideal setup in 2D and 3D, respectively. The result of the accuracy assessment in open space is shown in Table 2.2.

Table 2.2 Open space accuracy assessment result (Saidi et al. 2011)

	Average Accuracy (m)	
	Mean	Standard Deviation
2D	0.087	0.010
3D	0.466	0.040

The results of the experiments in the construction yard is presented in another way. 47 percent of the collected data were less than 1.25 m and 87 percent were less than 2.5 m. In addition, different elevation of the tags are tested in this study. On average, tags at lower elevations have more errors. The error for the tags with elevation of 1 m to 3 m is in the range of 7 mm to 348 mm in 2D. This study does not take into account the magnitude of the mean and the standard deviation of the location estimation accuracy in the dynamic mode. In addition, regarding dynamic movement, there is no detail such as elevation of the tags.

Cheng et al. carried out an experiment with the goal of evaluating the performance of the UWB technology in outdoor harsh construction environments (Cheng et al. 2011). In this study, four receivers cover the area of the experiment. A Robotic Total Station (RTS) is utilized for measuring the ground truth of the control points. The study is carried out in three different environments, one controlled environment wherein static performance is assessed, and two real-world construction sites where the dynamic location estimation performance of UWB is assessed. One of the construction sites was a construction pit and one was a lay down yard for placing the steel materials.

A new factor tested in this study is the frequency of the tags. The frequency that a tag transmits signals to the readers and can be set by the UWB software. Tags are set to frequencies of 1 Hz, 15 Hz, 30 Hz, and 60 Hz. The results demonstrate the static accuracy of UWB, with implementing a tag with the frequency of 1 Hz, is less than 2 m. The result of the accuracy assessment in the last two environments are shown in Table 2.3.

Table 2.3 Result of accuracy assessment of Cheng et al. 2011

	Average Accuracy (m)			
	1 Hz		60 Hz	
	Raw Data	Filtered Data	Raw Data	Filtered Data
Experiment 2: Construction Pit	0.48	0.40	0.36	0.34
Experiment 3: Lay Down Yard	1.82	1.26	1.64	1.23

The relationship between the speed of the moving objects and the accuracy of the location estimation is not analyzed. In addition, speed is not considered as a continuous variable and it is broken down into workers' walking speed and speed of the machines. The considered data in this experiment is filtered for further analysis, but the method of filtering the data is not explained.

Giretti et al. performed a study consisting of three different experiments designed for checking the UWB performance in an indoor and outdoor construction site (Giretti et al. 2009). The experiments were designed for simulating the tracking performance of a UWB system in three different phases of a six-storey building construction: 1) during the excavation, 2) after the completion of the concrete frame, and 3) after the erection of the walls. The method of implementing the experiments enables one to assess the performance of the UWB during the construction of a building. The area of the construction site is about 500 m^2. The evaluation of UWB performance resulted in less than 0.3 m accuracy in different construction phases. The results showed that the performance of UWB remained constant during the different phases of the construction project. Therefore, the UWB system setup can stay untouched during this period of construction. The performance of UWB for different moving objects with various speeds, which is an important factors for the performance assessment, is not taken into consideration in this study.

Cho et al. conducted a study on various location estimation technologies such as WLAN, RFID, and UWB in both indoor and outdoor locations (Cho et al. 2008). Four receivers were mounted on tripods to cover an indoor space with an area of 400 m^2. The position of the receivers were acquired using a total station. The result of the experiments in the open space is depicted in Table 2.4.

Table 2.4 Result of UWB performance experiment in an indoor space (Cho et al. 2008)

	Average Accuracy (cm)	
Tag Elevation	Center Points	Outermost Points
Floor Level	7.9	30
Raised 35 cm	6.2	13.8

The author concluded that at least three receivers should have a clear LOS for a tag to achieve a high and desirable performance. In addition, the elevation of the receivers is important and it is recommended that they be as high as possible. The experiment in the closed space was the same as first experiment with slight differences, namely the elevation of the tags. The elevation of the tags in this experiment was 104 cm. The accuracy of the tags on the floor level was 40 cm and 48 cm for the elevated tags. The decrease in accuracy was attributed to presence of human subjects in the closed space test area. Similar experiments are carried out on WLAN and RFID. The average accuracy of these experiments according to this study is shown in Table 2.5.

Table 2.5 RFID, WLAN, and UWB performance evaluation results

Location estimation technology	Average accuracy (cm)
WLAN	0.93
RFID	1.0 - 1.2
UWB	0.45

2.7 Summary

This chapter reviewed statistics regarding some of the problems resulting in losses in the construction industry in Canada. These statistics demonstrate the necessity and importance of improving the safety level of the construction industry. The previous related studies performed on two categories of collision reduction and applying RF-based technologies to increase the safety level in the construction industry are discussed. The studies conducted on collisions to improve the safety conditions in the construction industry (e.g. reasons, detection methods) are interpreted and compared. The advantages and disadvantages of the mentioned models are listed and explained as well. In addition, some of the proposed solutions are discussed. Among the proposed solutions, utilizing the RF-based technologies for tracking moving objects was found to be promising and more efficient considering the specifications and potentials of such technologies.

Moreover, some of the studies carried out on the applicable remote sensing technologies (e.g. GPS, RFID, WLAN, and UWB) are explained and compared. The studies on their performance for tracking both stationary and moving objects (labourers, equipment, tools, and materials) in different situations in construction jobsites is reviewed and discussed as well. UWB is the best option considering the advantages and disadvantages of possible RF-based sensor options such as the accuracy, cost, maintainability, durability and the ability of working in harsh environments (Maalek and Sadeghpour 2011).

Therefore, UWB is considered the most suitable alternative for tracking objects on construction sites with the aim of increasing the safety because of factors such as installation price, maintenance cost, and accuracy. Therefore, research that was reviewed focused on the studies performed on UWB mainly in the construction sites.

In addition, some studies with the similar goals, methodology, or experiments to ours are discussed. The shortcomings and the potential for future research are listed in the following section. Based on discussions on previous studies, there is lack of experiments on determining the effect of speed on the performance of the UWB RTLS. Therefore, the experiments in this study are designed to address this question. The results are stated in detail and evaluated in the following chapters of this dissertation.

Chapter Three: IMPACT OF SPEED ON THE ACCURACY OF UWB TRACKING FOR DYNAMIC RESOURCES

3.1 Overview

There are two (2) sets of experiments performed in this study. The first one is explained in this chapter. As mentioned in the previous chapter, the impact of speed on the performance of the UWB RTLS in an indoor construction environment has not been studied in detail. Therefore, the objective of the designed experiment in this chapter is evaluating the impact of speed on accuracy of UWB RTLS.

In the following sections of this chapter, the UWB RTLS system is described in detail. It is followed by explanations and information regarding the test area and the experiment methodology (designing and performing). The next section provides an explanation of accuracy measures used for calculations and analyses. The application of the explained measures, analyses, results, and discussion of the results comprise the next sections.

3.2 Real-time Location Estimation with UWB

UWB RTLS consists of four components: the central processor or location estimation platform, readers (sensors or receivers) (Figure 3.1a), tags (Figure 3.1b), and a communication system between the readers and the central processor.

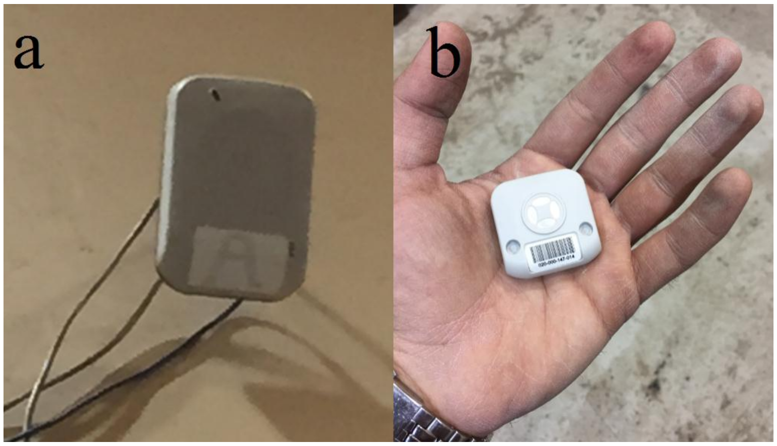

Figure 3.1 a) UWB reader (sensor) and b) UWB tag

The readers receive signals transmitted from the tags. The received signals are sent to the central processor where data are processed into spatial information. There are different ways of conveying data from readers to the central system such as Wi-Fi access points, Cat5e Shield cables, and Ethernet switches. In this study, the received signals are conveyed to the central system via Cat5e shield cables. The synchronization of the readers, enabled with timing cables, helps to improve the performance of the tracking process (Saeed et al. 2006). The readers were synchronized in the first step of installing and running the system. The power of the receivers is provided by Power over Ethernet (POE) switch. The Ethernet cables connect each of the readers to the POE switch and both convey the power to the sensors and transfer the raw data collected by the readers to the positioning platform. One of the readers is assigned as the “Master Receiver” and the rest of the readers are called “Slave Receivers”. Both kinds of readers receive the signals from tags. In addition to receiving signals, the master receiver is also responsible for sending commands to the tags (see Figure 3.2).

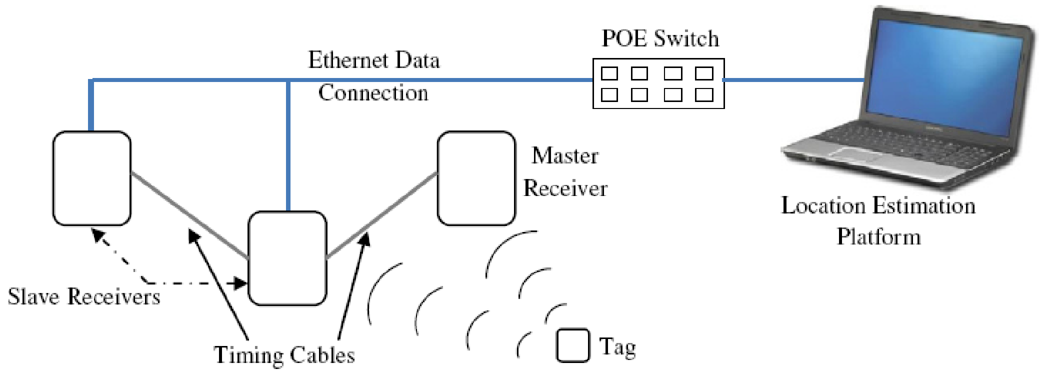

Figure 3.2 Data collection using UWB (Maalek and Sadeghpour 2013)

UWB uses different methods to track the tags: Angle-Of-Arrival (AOA), Received-Signal-Strength (RSS), Time-Of-Arrival (TOA), and Time-Difference-Of-Arrival (TDOA). In the AOA method, the angle between a given tag and number of reference nodes (readers) are used in the positioning. In the RSS method, the distance between the given tag and the sensors are calculated by measuring the strength of the received signal. In this method at least three (3) readers are required. In the TOA and TDOA methods, the distance between the given tag and the readers is calculated using the travel times of signals between the tags and each of the readers. One of the advantages of UWB RTLS by Ubisense which is used in this study, is that it uses both TDOA and AOA methods for positioning (Ubisense 2010). In addition, the UWB by Ubisense is able to estimate the position of a tag in 3D using only two readers. This feature is very important in a construction environment where there is a high probability of signal blockage from the tags and sensors.

The UWB Real-Time Locating System (RTLS) used in this study is manufactured by Ubisense. The UWB by Ubisense works in the frequency bandwidth of 6 to 8 GHz. The high bandwidth decreases the probability of error caused by the misidentification of multi-path and line-of-sight (LOS) signals. The best temperature range for the performance of UWB RTLS is 0 to 60 degrees with the humidity of up to 95 percent. The reading range mentioned in the manual is 160 m with an accuracy better than 15 cm in static tracking.

3.3 Experiment Design and Setup

In this experiment, a remote control car (RCC) equipped with an UWB tag was moved along on a predetermined path. This path was prepared in a way to pass a benchmark (observation) point. The benchmark was used for evaluating the estimated location of the UWB tag while passing this point. Since the precise location of this point was surveyed by a total station, the difference between the actual location and estimated location of the tag at this point can be measured. The speed of the RCC varied from 0 – 40 km/h. The estimated position of the RCC and its speed while passing the benchmark point are obtained by, respectively, using the recorded log file by Ubisense hub and the recordings from a camera installed on the scene. The experiment was repeated several times to collect the data in different speeds. Each run of this experiment was compromised of the following main steps:

1. The RCC was moved along (operated) on the predetermined path.
2. The video of the RCC while passing the benchmark point was recorded by a camera installed on the scene.
3. The position log file of the tag located on the RCC was acquired by the UWB RTLS location estimation platform.
4. The actual and estimated coordination (x, y, z) of the closest point to the benchmark point are obtained using the recording and the acquired log file.
5. The speed of the RCC was obtained by the recording.

The details regarding the mobile object (RCC), experiment test area, selection of the benchmark point, and the data collection will be explained in sections 3.3.1 through 3.3.5.

3.3.1 The Mobile Object

A remote control car (RCC) was used in this study to play the role of the mobile object that was being tracked by the UWB. The RCC used in this study had a maximum speed of 48 km/h according on its manual. The RCC had a length of 39.1 cm, width of 33.4 cm, and axles spacing of 27.1 cm. This RCC was equipped with an UWB tag (Figure 3.3). The acquired position of the UWB tag while the RCC was passing the benchmark point was recorded. The recorded log file was used for data collection as it will be explained in section 3.3.5.

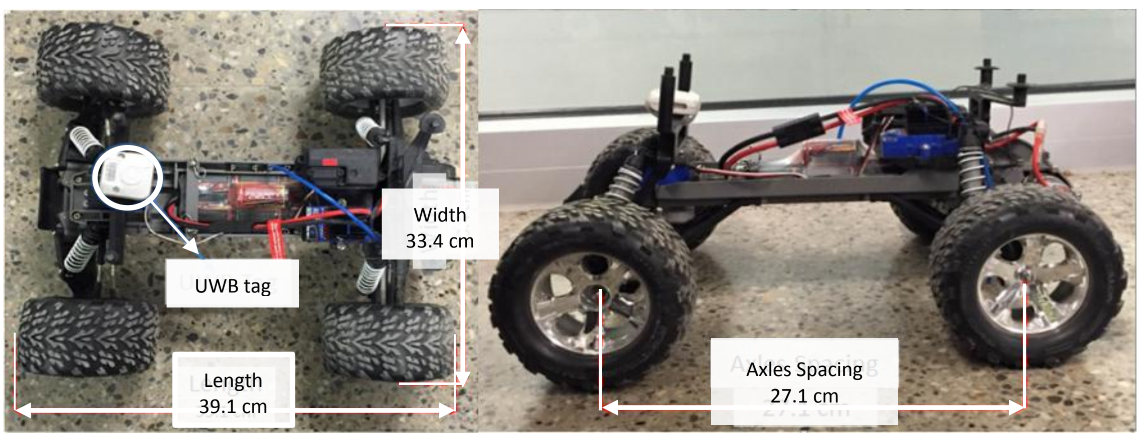

Figure 3.3 RCC dimension and axles spacing

3.3.2 Experiment Environment

The experiment was conducted in the structural laboratory of the Civil Engineering department in the Schulich School of Engineering at the University of Calgary (see Figure 3.4). Due to the existence of concrete blocks, steel profiles, and wooden materials, the environment in the lab was similar to an indoor construction jobsite, and, therefore, it was suitable for conducting the experiment. The area of the laboratory, where the experiments are conducted, was 30×10 m^2

(Figure 3.5). This area was covered by eight UWB readers. The location of eight (8) UWB readers used in this study are shown in Figure 3.5. The precise local position of the readers in the lab are brought in Table 3.1. In Figure 3.5, the guiderails (steel bars), benchmark point, and the alternatives for the single benchmark (observation) point are demonstrated.

Figure 3.4 Experiment environment: department of civil engineering, structural laboratory

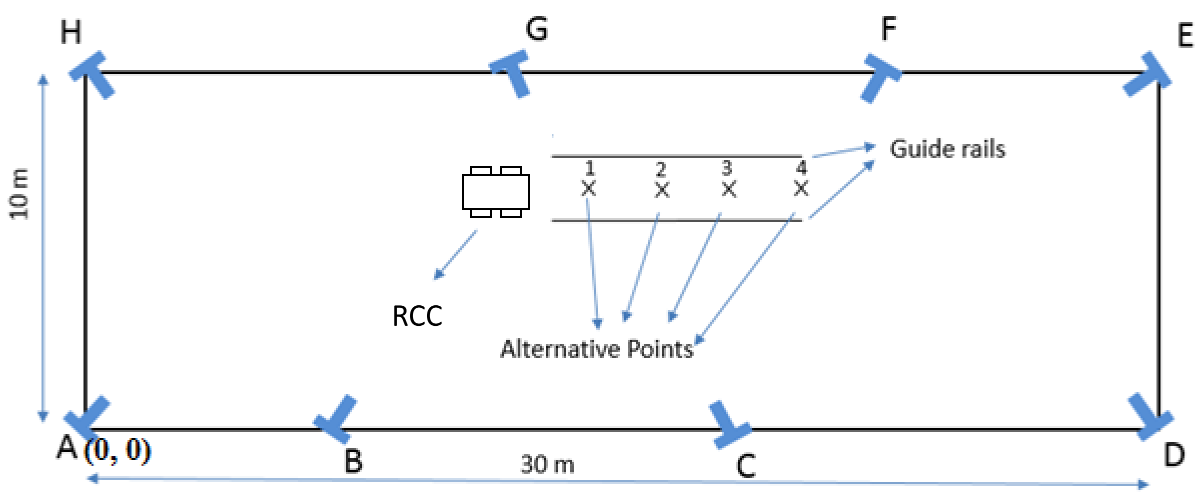

Figure 3.5 Layout of the test area

Table 3.1 Local (x, y, z) coordination of the readers

	Readers							
Coordination	A	B	C	D	E	F	G	H
X (m)	0.00	5.95	17.85	29.54	29.80	22.81	11.87	-0.04
Y (m)	0.00	0.04	0.05	0.04	9.78	9.57	9.81	9.84
Z (m)	5.34	5.37	5.35	5.36	5.36	5.35	5.33	5.33

3.3.3 Benchmark Point

The area in the lab for performing the experiment was required to be large enough to operate the RCC to meet the considered speed. In addition, this area should have an acceptable level of coverage of the readers. The result of a previous study on the accuracy assessment of the UWB RTLS (Maalek and Sadeghpour 2013) that was conducted in the same lab was used to make the decision for the approximate location of the test area. The results of the previous study are used to assign four alternative points for choosing the benchmark point. These points are selected in the zones where the assessed performance of UWB was high in the previous study. To identify the most accurate alternative point to be used as the benchmark, an accuracy assessment experiment on the four (4) alternative points was performed. The accuracy of the points is demonstrated using Distance Root Mean Squared (DRMS), a circular accuracy measure. The point with the highest DRMS was selected as the benchmark point. The result of the accuracy assessment experiment is shown in Table 3.2. The third alternative point was selected as the benchmark point as it has the highest accuracy with the lowest DRMS.

Table 3.2 Accuracy of the acquired position of the alternative points

	Alternative Point 1	Alternative Point 2	Alternative Point 3	Alternative Point 4
DRMS (cm)	19.54	24.33	**15.07**	19.68

3.3.4 Experiment Test Area

To prepare the lab for the experiment, a path was prepared for operating the RCC. The path was confined with steel bars to work as “guide rails” (see Figure 3.6). These bars were high and heavy enough to not let the car go off the path. Further, the concrete flooring of the lab was not suitable for operating the RCC as it causes the RCC to drift and not reach the higher speeds. Therefore, the confined path was covered by carpet, fixed to the concrete flooring, to avoid drifting of the RCC.

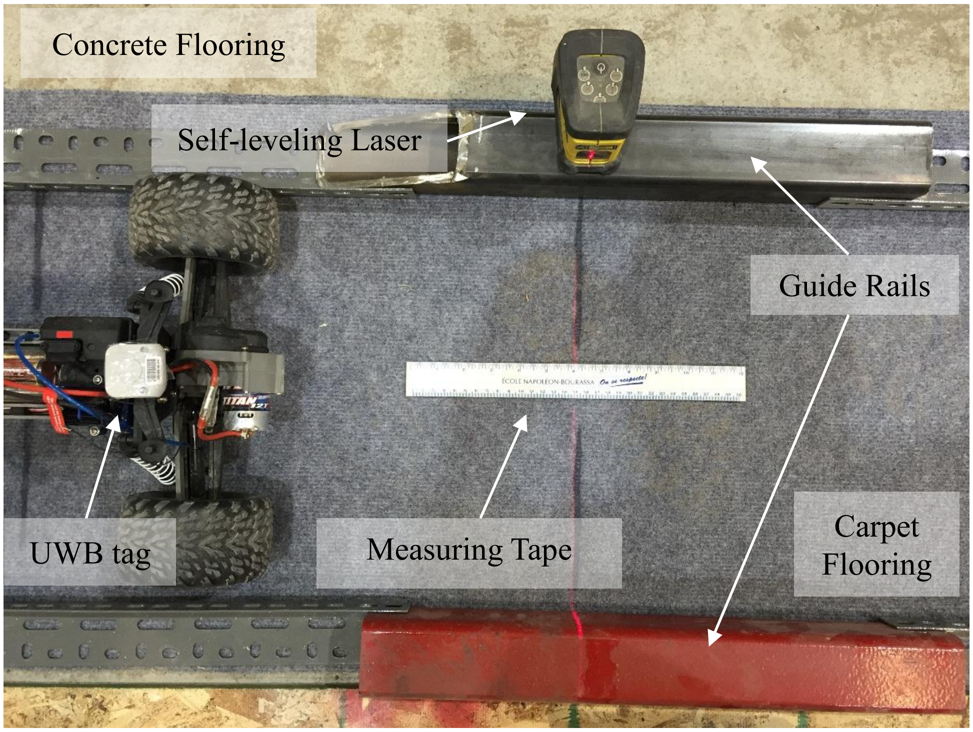

Figure 3.6 Experiment path improved with steel profile bars and carpet flooring

A self-leveling laser was used to set up the center of the camera lens along the benchmark line to decrease the probability of optical illusion. In addition, the self-leveling laser was used to ensure that the origin (0) of the measuring tape was perpendicularly on the benchmark line (see Figure 3.7).

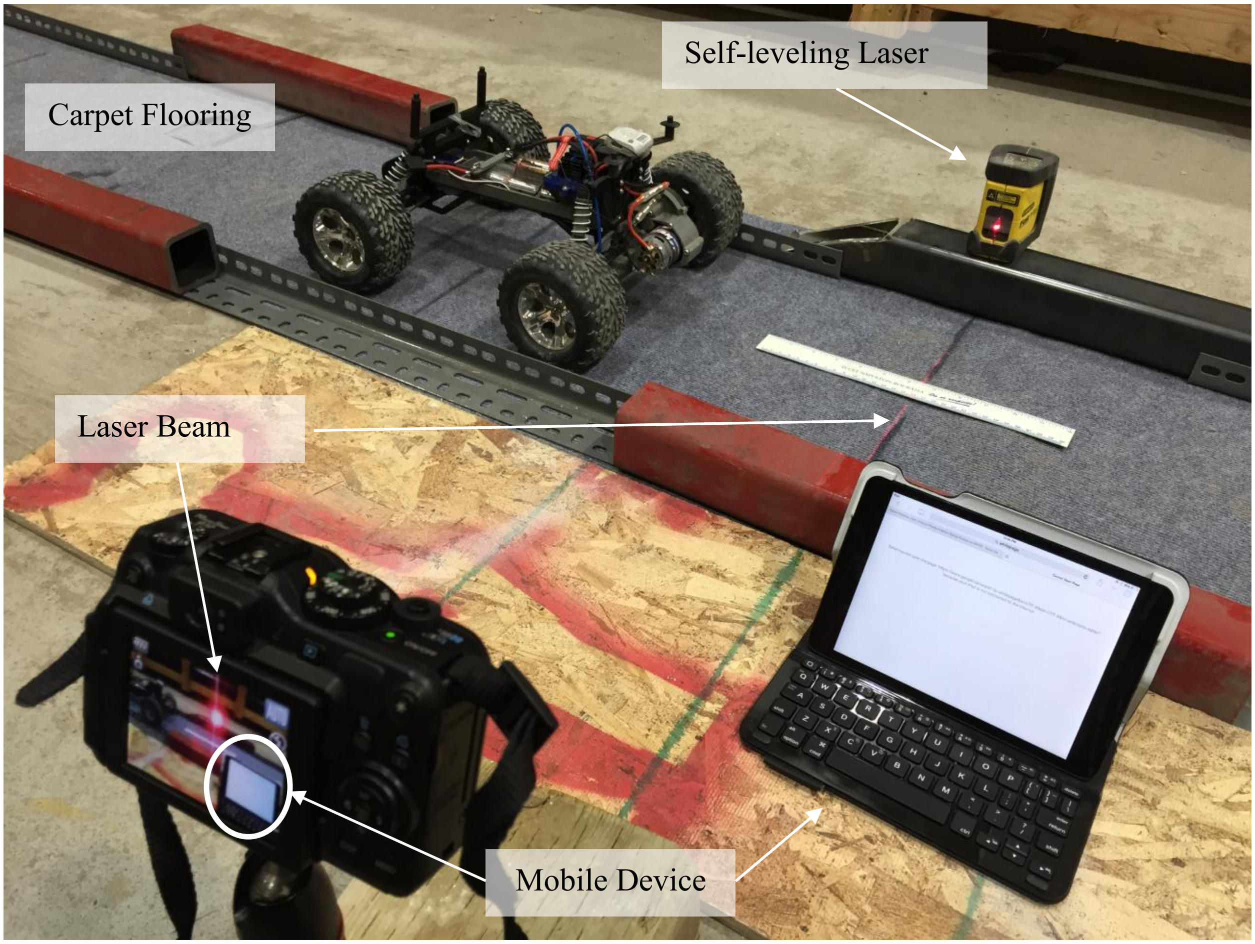

Figure 3.7 Experiment setup for data collection

3.3.5 Data Collection

In order to assess the impact of speed on the accuracy of UWB in dynamic tracking, the speed of the moving object was required in the data collection. Therefore, the collected data for each run included the coordination of the actual position and estimated of the tag and the speed of the RCC while passing the benchmark line. The experiment was repeated for 1087 times in speed range of 0 – 40 km/h as explained in detail below.

3.3.5.1 Obtaining Estimated and Actual Locations

While the RCC was approaching the benchmark line, the estimated position of the tag provided by the UWB system in the log file was constantly checked. The benchmark line was the line which was both perpendicular to the path and passes through the benchmark point. The estimated position by the UWB is not continuous; it is discrete. Therefore, the probability of getting an UWB position estimation for the position of the tag when it was exactly on the benchmark line was zero. Consequently, instead of aiming to acquire the estimated position of the benchmark point, it was aimed to acquire the actual location of the tag where the position estimation was provided by UWB.

The UWB platform provides and displays the estimated location of the tag in real-time which were recognized with the time slot number saved while recording the data. So the comparison could be easily conducted, if the actual location of the tag could be obtained at the moments of location estimation. To enable the comparison and matching the actual and estimated locations of the tag, a mobile device (cell phone, laptop, or a tablet) duplicating the UWB location estimation platform display was set up at the test area (Figure 3.8). This mobile device was placed close and within the camera to identify the exact points in time (t_i) where the estimated location was acquired. Since the camera vision was set up at the benchmark line as well (see Figure 3.7). Consequently, the actual locations of the tag at the times where the location estimation was acquired (t_i) can be obtained using the known location of the benchmark point and the measuring tape set on the test area.

Figure 3.8 Mobile device (cell phone) showing the UWB hub display

The perpendicular distance of the tag from the benchmark line (Δx_i) was measured at t_i. Among different estimated locations that were acquired close to the benchmark line the point with the minimum Δx_i- the closest estimated position to the benchmark line- was used as the true or actual point for each run (see Figure 3.9). In order to find the point with the minimum Δx_i, the two points from either side of the benchmark line were identified and the one with the smaller Δx_i was used for the comparison purposes for that run. The acquired actual and estimated locations of the tag coordinates were used for measuring the accuracy of UWB in dynamic tracking.

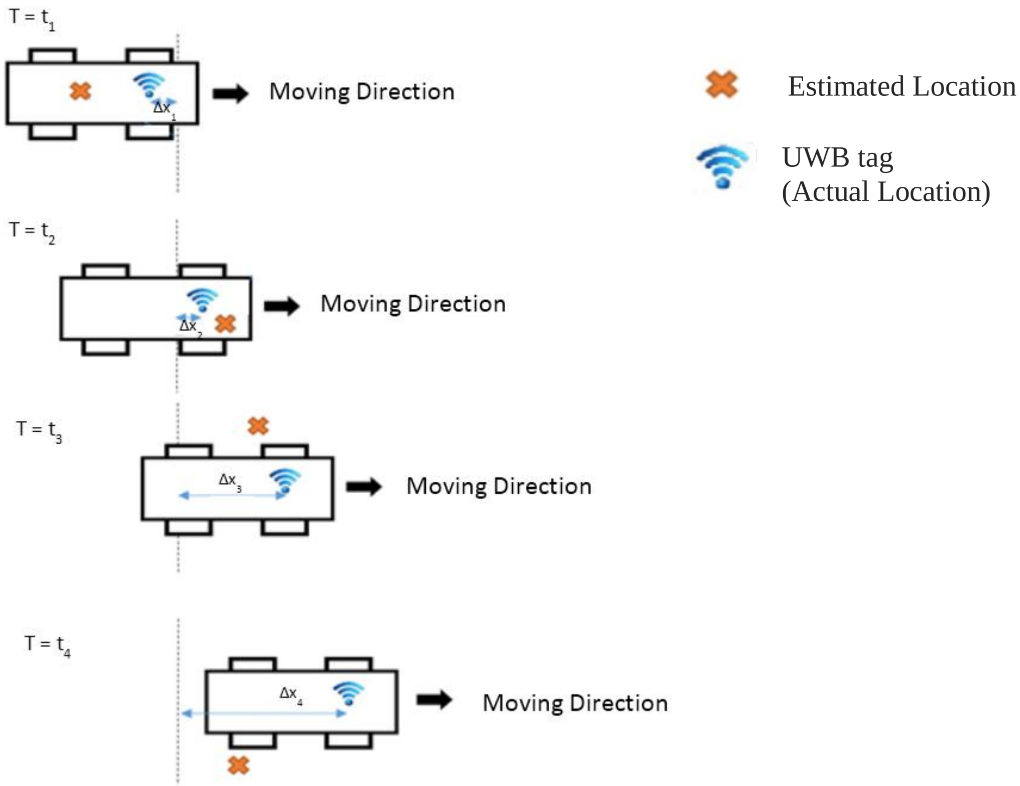

Figure 3.9 Obtaining RCC position coordinates

3.3.5.2 Calculating the Speed

The speed of the RCC in each run was obtained from the recordings. The spacing of the axles (see Figure 3.3 and Figure 3.10) and the time lapse between the front and rear axles passing over the benchmark line were used to calculate the speed of the RCC (Equation 3.1 and Figure 3.10).

$$\text{Speed} = \frac{d_{\text{axles}}}{\mathrm{t_e} - \mathrm{t_s}} \tag{3.1}$$

where d_{axles} is the axle spacing in (m), t_e, and t_s are the moments that, respectively, rear and front axles pass the benchmark line in second. The axles spacing was obtained from the user manual of the RCC and double checked by a computer drawing software. The t_e and t_s were obtained by getting advantage of the recordings of the camera set up at the experiment test area.

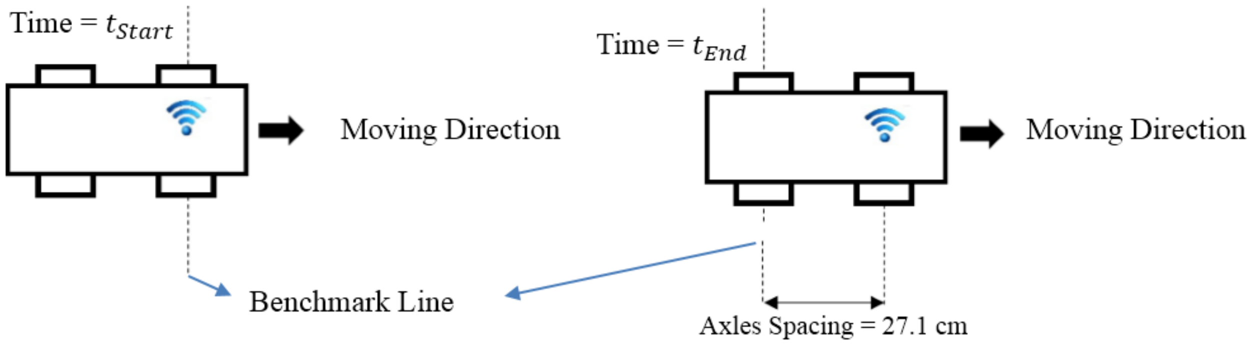

Figure 3.10 Calculating the speed of the RCC

3.4 Accuracy Assessment Measures

Accuracy measures were used in this study to represent and discuss the UWB RTLS dynamic tracking performance: 1. error, 2. DRMS, 3. offset, and 4. precision. The accuracy measures used in this study are all in 2D. In the following section these accuracy measures are explained and differentiated.

3.4.1 Error (E)

The distance of a single collected datum (estimated location) in 2D from the true point (actual location) is referred to as Error (E) (Chapra 2012). For such errors, the relationship between the true value and the observation value can be formulated as follows:

Error = True Value – Observation Value (3.2)

The true error is customarily defined as the absolute value of the error and referred to as the absolute error. Error in 2D can be calculated using equation 3.3:

$$\text{Error} = \sqrt{(x - x_{True})^2 + (y - y_{True})^2} \quad (3.3)$$

where (x, y) are the coordinates of the estimated location, and (x_{True}, y_{True}) are the coordinates of the true point.

3.4.2 Precision

Precision is the standard deviation of data showing the congestion of the collected data. The smaller value for precision means that the precision of the collected data is higher. Precision is a parameter that reflects the random error in positioning and calculated using equation 3.5 (Leick 2013):

$$\text{Precision} = \sqrt{\frac{\sum_{i=1}^{n} (x_i - x_{Mean})^2}{n} + \frac{\sum_{i=1}^{n} (y_i - y_{Mean})^2}{n}} \quad (3.4)$$

where (x, y) are the coordinates of the estimated location, and (x_{Mean}, y_{Mean}) are the average of the coordinates of estimated locations, respectively, in x and y direction.

3.4.3 Offset (Trueness)

Offset is the distance of the average of collected data from the true point in the horizontal plain. The offset can be calculated as follows:

$$\text{Offset} = \sqrt{(x_{True} - x_{Mean})^2 + (y_{True} - y_{Mean})^2} \quad (3.5)$$

where (x_{True}, y_{True}) are the coordinates of the true point, and (x_{Mean}, y_{Mean}) are the average of the coordinates of estimated locations, respectively, in x and y direction.

3.4.4 DRMS

Distance Root Mean Squared (DRMS), is used to measure the 2D performance of UWB tracking in this study. DRMS is an accuracy measure that expresses accuracy with a single number. The standard errors (σ) from the known location or zone are required in the direction of the coordinate axis to calculate the DRMS. In other words, the square root of the average of the square errors is referred to as DRMS and calculated using equation 3.6 (Leick 2013):

$$\text{DRMS} = \sqrt{\frac{\sum_{i=1}^{n} (x_i - x_{True})^2}{n} + \frac{\sum_{i=1}^{n} (y_i - y_{True})^2}{n}} \quad (3.6)$$

where n is number of readings, (x_i, y_i) are the coordinates of the estimated location of the ith run out of n runs, and (x_{True}, y_{True}) are the coordinates of the actual location for each run (Leick 2013). DRMS is a value which is the simplification of error ellipse. The value of DRMS is equal to the average radius of the error ellipse. In 2D, the difference between variance in x direction and y direction defines the closeness of DRMS to the error ellipse (see APPENDIX C).

The relationship between DRMS, precision, and offset is shown with equation 3.7. This equation helps to calculate the DRMS using offset and precision. The relationship between the accuracy measurements is visualized in Figure 3.11. In this figure, the true point is the center point of the concentric circles.

$$\mathrm{DRMS} = \sqrt{\mathrm{Offset}^2 + \mathrm{Precision}^2} \tag{3.7}$$

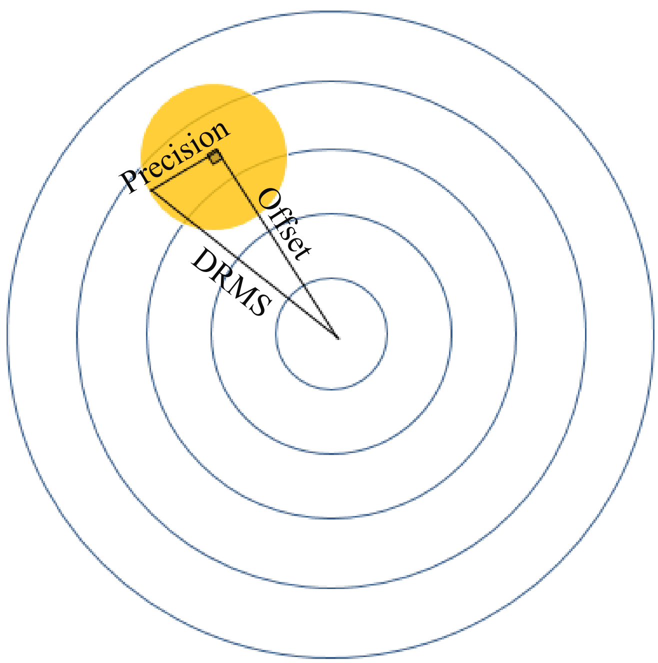

Figure 3.11 Relationship between DRMS, precision, and offset

Figure 3.12 and Figure 3.13 differentiate the concept of the offset and the precision of the collected data. Offset can be defined as the difference of the average of the data from the true value (point), while the precision is the closeness and congestion of the collected data. In Figure 3.13, the true point is the center point of the concentric circles. The more the measurements (red points) are congested, the more precise the measurements (collected data) are, which results in the smaller magnitude for precision.

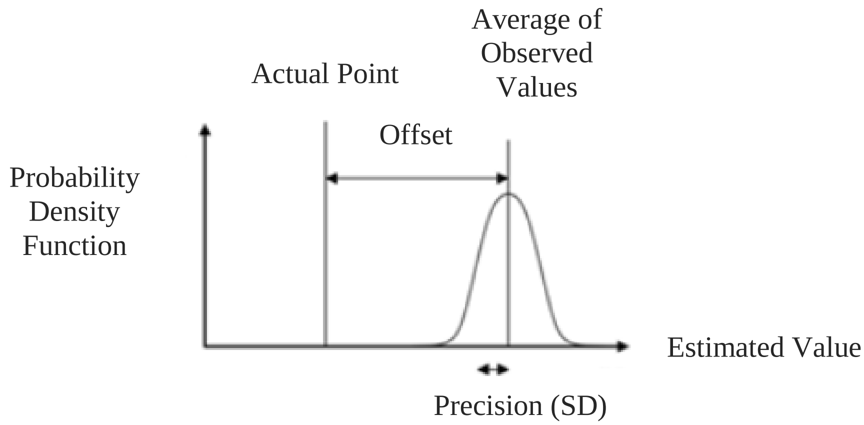

Figure 3.12 Relationship between offset and precision

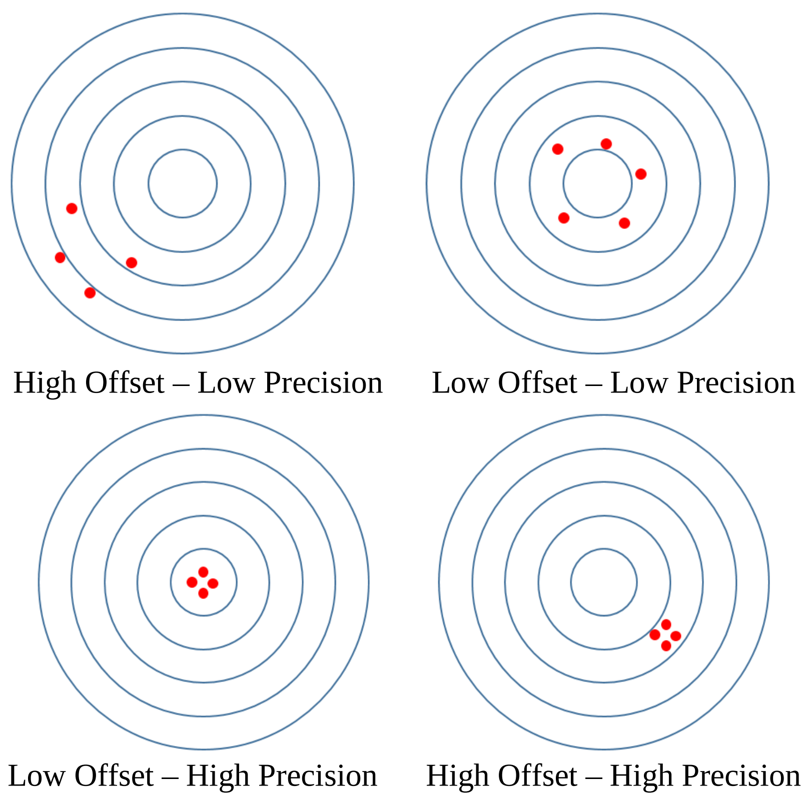

Figure 3.13 An example of illustrating the concept of offset and precision

3.4.5 Offset, Precision, and DRMS for Dynamic Positioning

In order to obtain the accuracy measures (DRMS, offset, and precision) in different speeds, the collected data can be categorized into speed intervals. For example, the speed range of 0 – 40 km/h can be categorized into four (4) speed intervals with the span of 10 km/h. Then, the accuracy measures will be calculated for each speed interval. After that, an estimation function can be obtained with the calculated values of the accuracy measures. The major problem with this method is that the calculated accuracy measures are not continuous in the speed range.

Instead, it is proposed to obtain the error of the entire collected data as a function of speed without clustering them into groups. Using this approach allows to calculate continuous equations for accuracy measures (offset, precision, and DRMS) explained follow:

- Offset is in fact the mean of the estimated location data in 2D from the true point. Therefore, the continuous equation of the offset can be obtained by calculating the mean regression line of the error.
- Precision, as explained in section 3.4.2, is the standard deviation of the data with two degrees of freedom in this study. In order to obtain a continuous equation for precision, confidence interval (CI) of the mean regression line of the error is required. For two (2) degrees of freedom and the confidence level of 95%, the difference between the CI and the mean regression line is 5.99 times of the standard deviation (see APPENDIX E).
- The DRMS can be easily derived from equation 3.7 after calculating the precision and offset.

3.5 Experiment Results

This section presents the results of the experiment by showing the calculated accuracy measures (error, offset, precision, and DRMS) of the collected data, as proposed above. In the second part of this section the effect of time latency of the UWB system is discussed and compared to the first set of results.

3.5.1 Error as a Function of Speed

The designed experiments were repeated in 1087 runs in the speed range of 0 – 40 km/h. The error of the collected data is illustrated in a scatter plot in Figure 3.14. Several types of mean regression lines (linear, exponential, and polynomial) were tried to fit to the error. Based on R-squared (R^2), calculated for each type of mean regression line, and considering that over-fitting of the mean regression line can cause large errors, the mean regression line was selected (see APPENDIX D). The best-fit mean regression line selected for the error as a function of speed (including the outliers) is a polynomial of the fourth order. The polynomial equation with order of four (4) as the estimation function (regression line) with the R^2 of 0.8071 is brought as equation 3.8 and shown in Figure 3.14.

$$y = 2\times10^{-06}\, S^4 - 9\times10^{-05}\, S^3 + 0.0002\, S^2 + 0.0543\, S + 0.1498 \qquad (3.8)$$

where error is in meter and S is the speed in km/h.

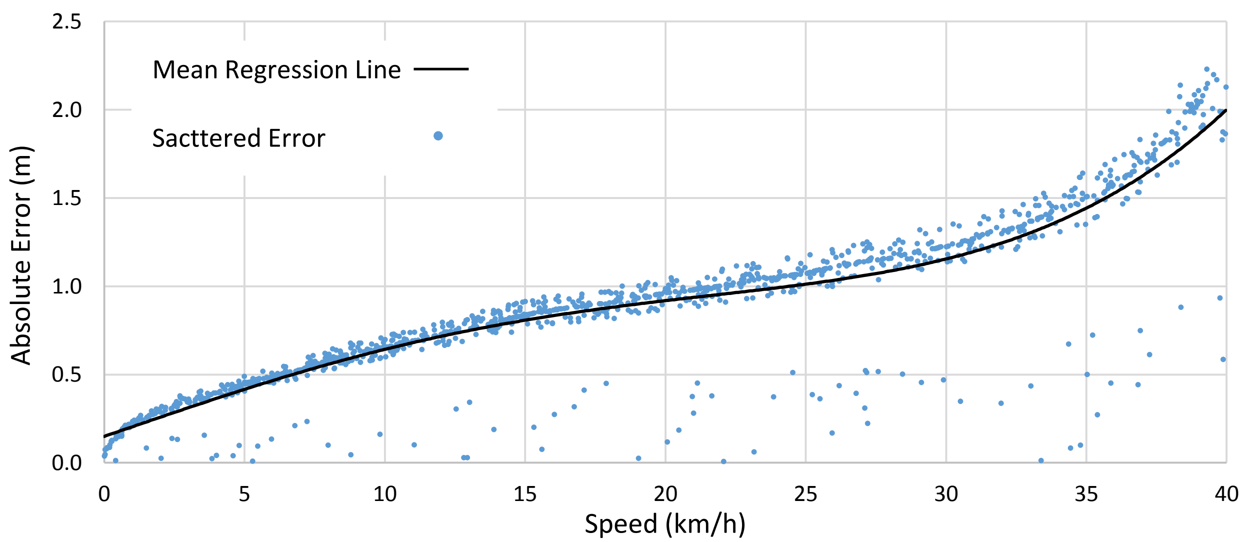

Figure 3.14 Observed error as a function of speed including outliers

The error has an S-shape pattern instead of a noise pattern. The reason of having such pattern can be explained by a bias caused by the time latency of the UWB system, systematic error of the positioning system, or errors deriving from the methodology of performing the experiment. The mentioned reasons are studied and examined in this chapter.

3.5.2 Elimination of Time Latency

The collected data includes the time latency impact. This issue occurs in the experiments conducted for studying the dynamic performance of the tracking systems. The reason is that UWB RTLS, same as other positioning technologies, has a small delay in displaying or saving the estimated position compared to real-time. Several factors have impact on the time latency of a positioning system such as the strength of the computer processor used as the hub, the strength, length, and material used for the cables. The problem is that the data including time latency cannot be used for generalizing the accuracy of UWB. Therefore, the time latency was tried to be eliminated from the data.

Ubisense personal communication document indicate that the system has a time latency of 5 to 27 ms, from receiving signals from the tags to showing the position result on the display (UWB RTLS by Ubisense 2010). In general, the time latency of positioning systems can be calculated experimentally and statistically. In our case, the time latency could not be calculated experimentally for the UWB RTLS because: 1. there was no access to the time of receiving the signals by the readers from the tags and 2. the time of recorded position data has the precision of a second. Consequently, the time latency was calculated statistically in this study.

In order to calculate the time latency, a linear line was fitted to the error of the data as a function of speed. The slope of the fitted linear mean regression line can be used as the value of time latency (see Figure 3.15).

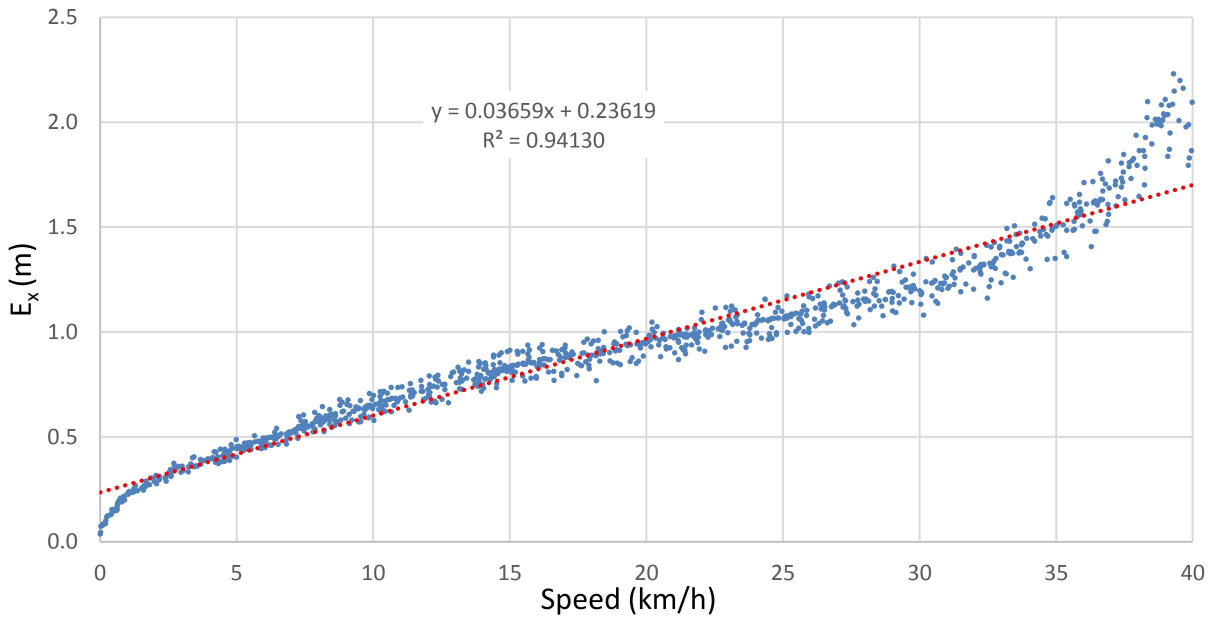

Figure 3.15 Fitting the linear mean regression line to the error in x-direction

The slope of the linear mean regression line is 0.03659. The unit of the slope is (hr/1000). Therefore, after changing the unit of the slope, the time latency value was equal to 0.01016 sec. The calculated value for time latency is within the range of 5 – 27 ms (the range of time latency in the manual of UWB by Ubisense). Therefore, the impact of time latency from the data was eliminated with shifting the position data for each run against the x direction equal to the relocation of the moving object in 10.16 ms of time latency. After shifting the x dimension of position data (for each run), the error of the collected data was calculated and plotted to see the pattern of the error (see Figure 3.16). The pattern of error after elimination of time latency is S-shape. The reason why the error has a S-shape pattern is discussed in section 3.5.3 in more detail.

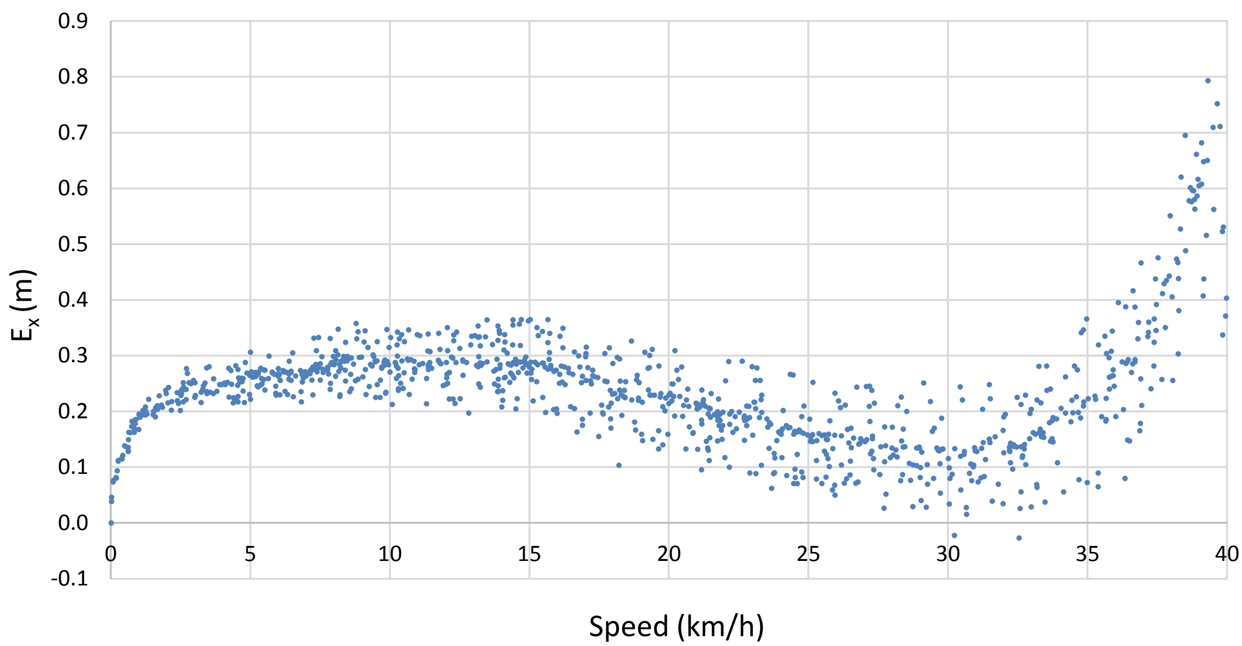

Figure 3.16 Observed error excluding time latency as a function of speed

3.5.3 Pattern of Error

It was noticed that the error of both the raw data and the data after elimination of time latency impact (Figure 3.16) have a S-shape pattern. It can be inferred that the error of the raw data is biased by one or more factors. In such cases if the bias source could be identified and eliminated correctly, the pattern of the data transforms to a noise by elimination of bias impact. In this study, it was noticed that one source of bias was the time latency of the UWB system in displaying the acquired position. The value of this factor was calculated by the assumption that the time latency of the system was constant. The error still had a S-shape pattern after elimination of time latency impact (Figure 3.16). It was inferred that there was another source of bias in the data.

After performing the data analysis, it was noticed that another source of bias in the error of the data was in the methodology of the experiment. In order to obtain the actual location of the UWB tag in each run, the recordings prepared by a camera were used. The center of the lens of the camera was set up along the benchmark line perpendicular to the path. In order to obtain the actual location of the RCC, the images from the recordings were used. The problem of this methodology is that when the RCC goes further from the benchmark line number of pixels in the image does not change proportional to the distance. This error is systematically biased by tangent (Martin and Pongratz 1974). Unfortunately, the value of this bias cannot be obtained as the distance of the camera from the center of the path was not obtained in each run of the experiment.

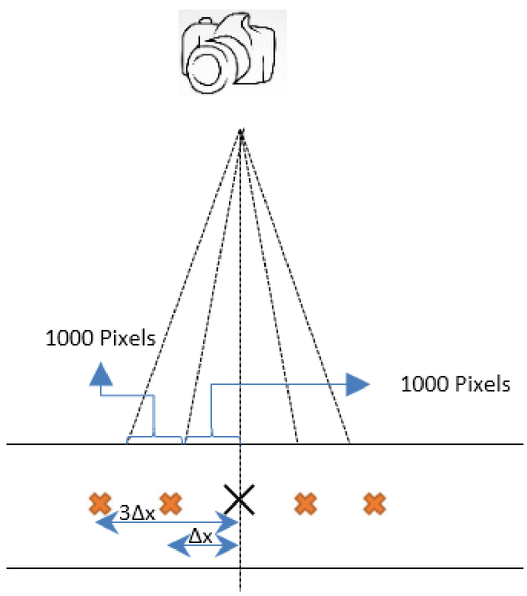

Figure 3.17 Angular vision of the camera towards the moving object

3.5.4 Using error in y direction (E_y) to calculate the accuracy measures

In order to calculate the accuracy measures, the error in y direction was used. The reason of using the data in y direction was that, the prepared path was parallel with the x-axis and the collected data in the accuracy of positioning in y direction was independent from the time latency. As a result of the experiment setup there was no bias caused by lens focal in acquiring the position in y direction. The error in y direction (E_y) as a function of speed is plotted in Figure 3.18 to see if the pattern of the E_y was like a noise and suitable for calculating the accuracy measures.

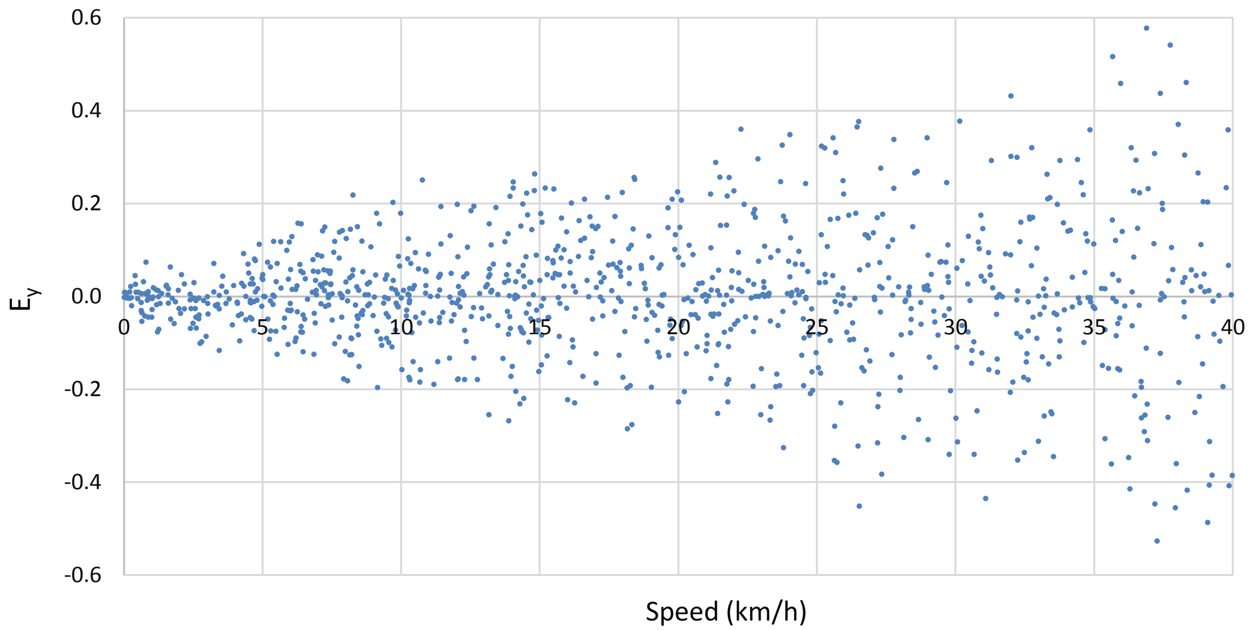

Figure 3.18 Error in y direction as a function of speed

E_y has a noise pattern and can be used for calculating the accuracy measures. Figure 3.18 demonstrates that the congestion of the E_y, as expected earlier, decreases as the speed increases. In order to be elucidate the impact of speed on the accuracy of UWB system, the accuracy measures (offset, precision, and DRMS) were calculated.

In order to be able to calculate the accuracy measures, the collected data should be categorized into smaller groups. It was considered that the number of data in each group is required to be enough for performing the data analysis (at least 35). In this study, the speed range (0 – 40 km/h) was broken down into ten (10) speed intervals. In consequence, the span of each speed interval was 4 km/h (see Table 3.3).

Table 3.3 Accuracy measures for each speed group

Speed Group (km/h)	**No. Data**	**Average Speed (km/h)**	**Offset (cm)**	**Precision (cm)**	**DRMS (cm)**
0 – 4	95	1.78	1.06	3.53	3.68
4 – 8	128	6.09	0.98	6.69	6.76
8 – 12	120	9.81	1.20	9.05	9.13
12 – 16	127	14.08	1.50	11.59	11.69
16 – 20	97	18.02	1.84	12.25	12.38
20 – 24	109	21.98	1.67	13.66	13.76
24 – 28	122	26.35	1.78	17.33	17.42
28 – 32	61	30.48	2.02	16.58	16.71
32 – 36	90	33.94	1.99	17.67	17.78
36 – 40	81	37.93	2.58	25.38	25.51

Table 3.3 is comprised of six (6) columns. The columns one through three, respectively, demonstrate the speed intervals, the number of data in each interval, and the average speed of the data in each interval. The last three columns shows the calculated accuracy measures for each interval. The accuracy measures are plotted in Figure 3.19 through Figure 3.21 as a function of speed.

The offset as a function of speed is plotted in Figure 3.19. The offset varies in the range of 1 to 2.5 cm in the speed range of 0 – 40 km/h. Based on the definition of the offset (see section 3.4.3), the distance of average value of collected data from the true point varies from 1 to 2.5 cm in the speed range of 0 – 40 km/h.

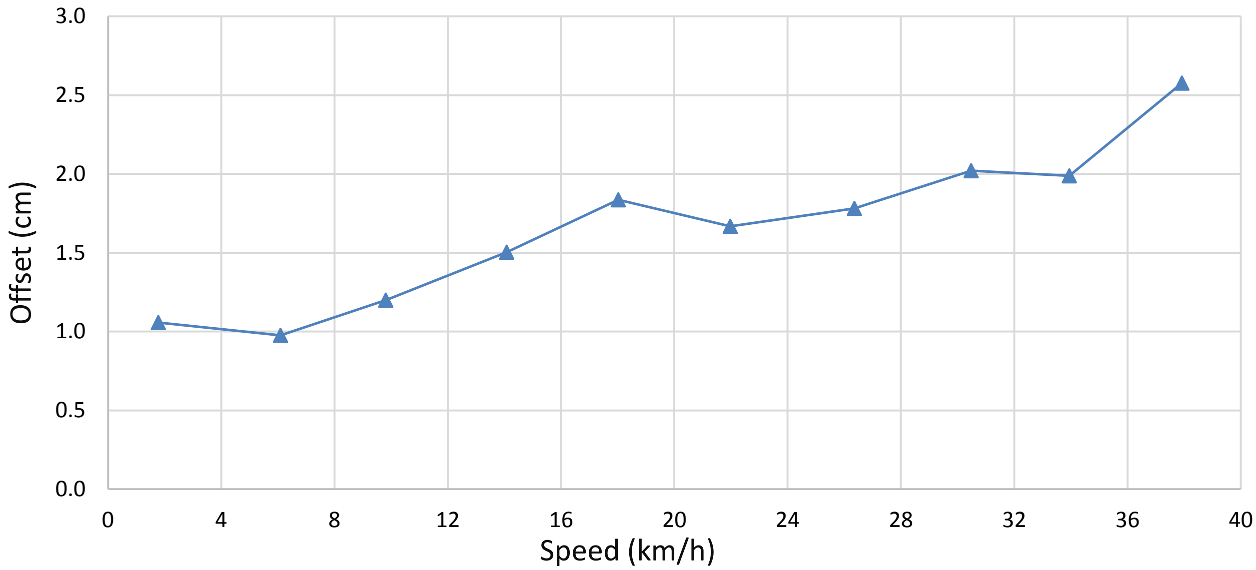

Figure 3.19 Offset of the data as a function of speed

The precision as a function of speed is plotted in Figure 3.20. The precision varies in the range of 4 to 25 cm in the speed range of 0 – 40 km/h. Based on the definition of the precision (see section 3.4.2), 67 percent of the data acquired by UWB is in a circle with the radius of 25 cm and the true point as the center point in the speed range of 0 – 40 km/h.

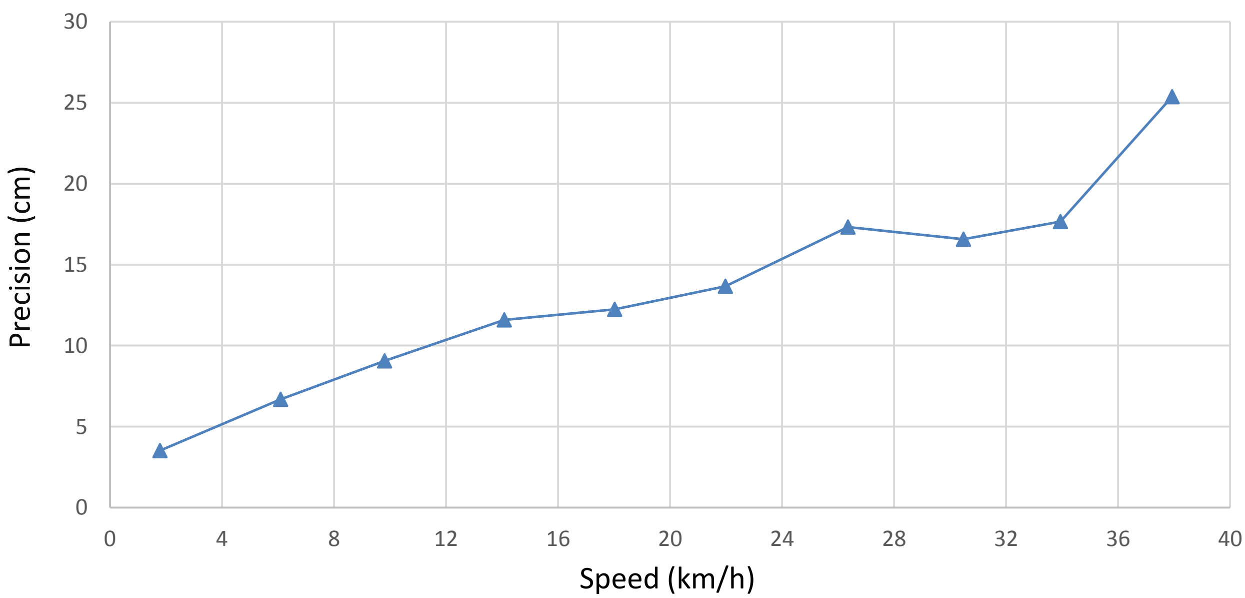

Figure 3.20 Precision as a function of speed

The DRMS as a function of speed is plotted in Figure 3.20. The DRMS varies in the range of 4 to 25 cm in the speed range of 0 – 40 km/h. The DRMS is almost equal with the value of precision. The reason is that precision value is ten times larger than the offset in the same speeds (see equation 3.7)

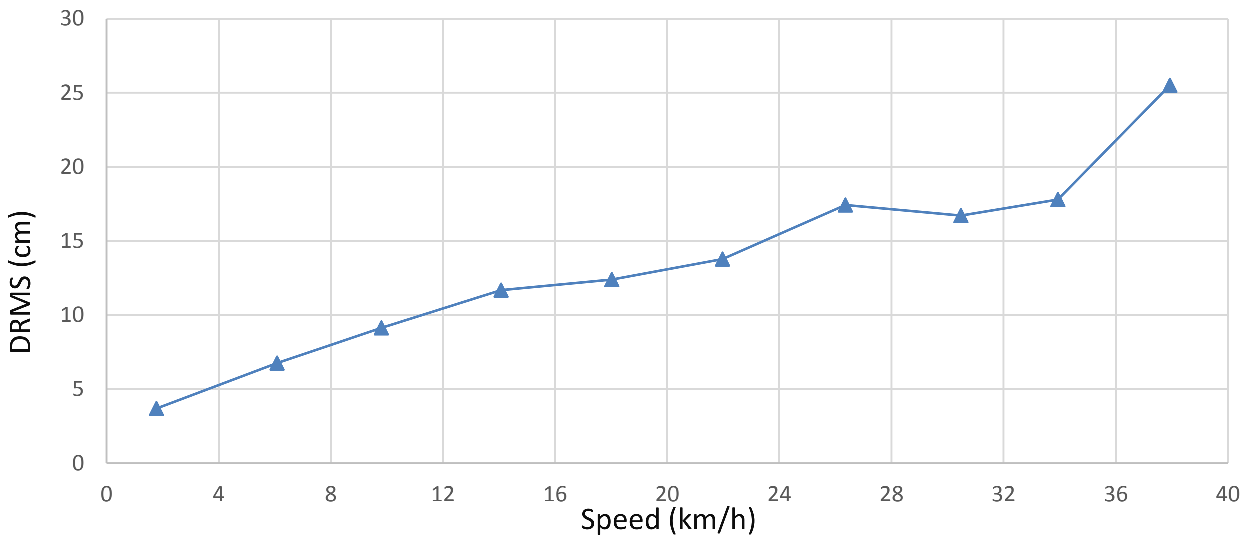

Figure 3.21 DRMS as a function of speed

3.6 Conclusion and Discussion

In this chapter the error of the collected data as a function of speed was plotted. The error had a S-shape pattern instead of a noise pattern. The time latency of the UWB was identified as the source of bias in the error. Two methods were used for estimating the time latency and eliminating the impact of the time latency from the error. Both methods resulted in error with a S-shape pattern. It was noticed that another source of error was in the methodology of the data collection. Closer examination of the methodology revealed that error derived by the focal length of the camera lens used for recording in data collection. This error is systematically biased by tangent. In order to eliminate this bias from the results the distance of the camera from the path for each run was required. Unfortunately, this value was not acquired during the experiments.

Therefore, the data in the y direction, which was independent from the time latency and systematic error caused by the camera, was used for calculating the accuracy measures.

In order to calculate the accuracy measures, a group of data is required. In order to be able to calculate the accuracy measures, the collected data are categorized into smaller groups with breaking down the speed range into smaller speed intervals. The speed interval size considered for breaking down the speed range was 4 km/h.

It was noticed that the offset changes in the range of 1 – 2.5 cm. It can be inferred that the offset value is independent from changes in speed. The value of offset demonstrates that the distance of the average of the collected data from the true point is less or equal with 2.5 cm in the speed range of 0 – 40 km/h.

In these experiments, the offset value of the UWB is shown to be very small compared to the precision. The precision value at each speed is almost ten times larger of the offset at the same speed. It can be inferred that while positioning with single data might not be accurate, having more data for acquiring a position results in having a better accuracy. Higher number of data can obtained by increasing the frequency of data collection or increasing the time interval for positioning. In addition, it was noticed that the value of DRMS was almost equal to the precision value in different speeds. The reason was that the DRMS is the square root of summation of squared offset and squared precision (see equation 3.7). Since the value of offset compared to precision is negligible in this experiment, DRMS will be almost equal to the precision.

Chapter Four: IMPACT OF ACCELERATION ON THE ACCURACY OF UWB TRACKING FOR DYNAMIC RESOURCES

4.1 Overview

The experiment discussed in chapter three (3) was conducted to assess impact of speed on the accuracy of UWB RTLS in tracking dynamic resources. While analyzing the results of this experiment, the question raised if the acceleration has effect on the performance of UWB RTLS. Therefore, another experiment similar to the first experiment was designed. In the second experiment, the acceleration was eliminated from moving pattern of the mobile object.

In this chapter, the methodology (designing and performing), calculations, and the results of the second experiment are discussed.

4.2 Experiment Design and Setup

As previously mentioned, the second experiment in this study has slight differences compared to the first one. This experiment consists of two major parts: data collection and data analysis. The data in this experiment was collected in dynamic tracking while changes in speed was minimal. In other words, it was tried to eliminate acceleration from the moving pattern of the mobile object. In order to have enough data for analysis, the experiment was repeated for 83 times. Each repetition of the experiment is called a run.

Same as the first experiment, the RCC equipped with an UWB tag was operated on a straight path to generate data for dynamic tracking. In this experiment, four (4) benchmark points in a line were considered for data collection. Four (4) cameras recorded the RCC while passing the benchmark points. The data was collected while the RCC was traveling at approximate speeds of 5 km/h, 10 km/h, and 15 km/h. In other words, the collected data were categorized into three speed groups (5, 10, and 15 km/h). The following steps were followed to perform each run:

1. The RCC was moved along (operated) on the predetermined path.
2. The video of the RCC while passing the benchmark point was recorded by a camera installed on the scene.
3. The position log file of the tag located on the RCC was acquired by the UWB RTLS location estimation platform.
4. The actual and estimated coordination (x, y, z) of the points close to each of the benchmark points were obtained using the recordings and the log file.
5. The speed of the RCC was obtained by the recordings.

The mobile object specifications, the experiment environment, the benchmark points, and the data collection for each run in this experiment are explained in the following sections.

4.2.1 The Mobile Object

The mobile object used for this experiment was the same RCC used in the previous experiment. The specifications and setup of this RCC were the same as the first experiment (explained in section 3.3.1).

4.2.2 Experiment Environment

The environment of the second experiment was the same as the previous experiment. However, the number of benchmark points and, consequently, the cameras was increased from one (1) to four (4) (see Figure 4.1). The position and orientation of the receivers, the calibration of the system, and the test area of the experiment were the same as the first experiment.

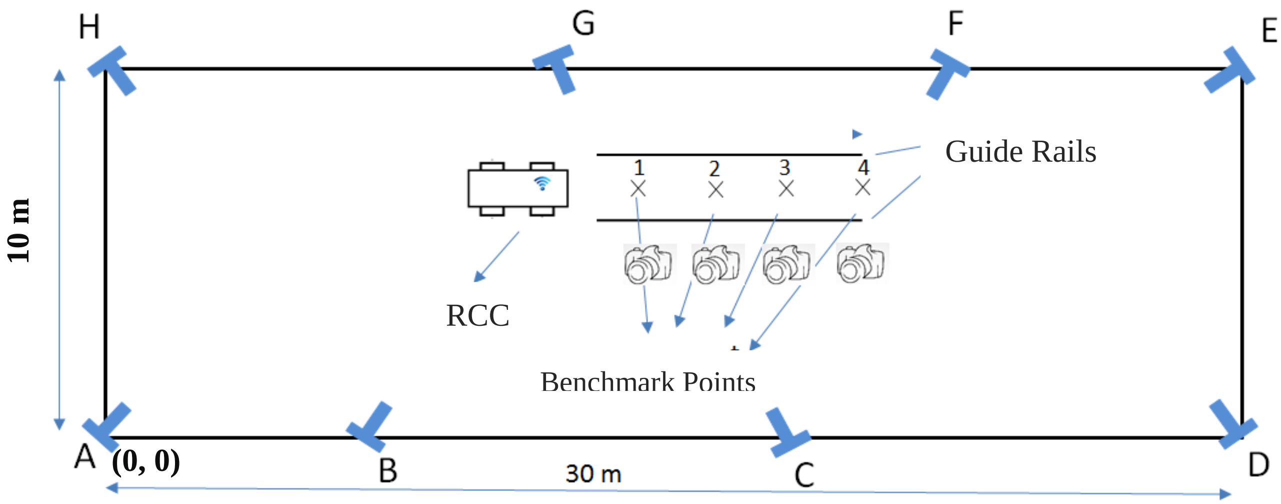

Figure 4.1 Experiment test bed

4.2.3 Benchmark Points

The major difference between the first and the second experiments was the number of benchmark points. In the second experiment, there were four benchmark points. These points were selected on a line parallel with the local x-axis. As such, the y-coordinates of the benchmark points were equal. As a result, the load of work for data collection was reduced.

The DRMS of the benchmark points were presented in Table 4.1. Points 2 and 4 are the same points as, respectively, considered as alternative points 1 and 3 in in the first experiment (see Table 3.2). Although the experiment test area and UWB system setup was the same, the DRMS of these points were increased in Table 4.1. The reason is that the collected data for the calculating the DRMS in Table 4.1 was performed with a new computer with new calibration. Comparing the obtained DRMS in two sets of data collection states the importance of accuracy in system calibration. The higher accuracy in calibration the better performance of the UWB system in location estimation.

Table 4.1 DRMS of observation points

	Point 1	Point 2	Point 3	Point 4
DRMS (cm)	23.72	25.16	24.42	23.39

As the data collection for the second experiment was performed with the first computer, the DRMS shown in Table 4.1 was only used for comparing the performance of UWB RTLS close to the benchmark points.

4.2.4 Experiment Testbed

The predetermined path was similar to the previous experiment (explained in section 3.3.4).

4.2.5 Data Collection

The data collection method performed for this experiment was almost the same as previous experiment (explained in section 3.3.5). The only difference in data collection, compared to the first experiment, was that there were four benchmark points and four cameras in the second experiment. Consequently, obtaining the coordinates and speed were performed four times for each run.

4.3 Accuracy Measures

The accuracy measure used for analysis and evaluation of the collected data, same as the first experiment, were error, offset, precision, and the DRMS. These measures are explained and illustrated in detail in section 3.4.

4.4 Results

The error of the collected data as a function of speed for the second experiment is presented in Figure 4.2. The data in this figure were categorized into three (3) groups. The red indicators show the error of the collected data for the runs with approximate speed of 5 km/h. The green and the blue indicators show the error of the collected data for the runs with speeds close to 10 km/h and 15 km/h, respectively.

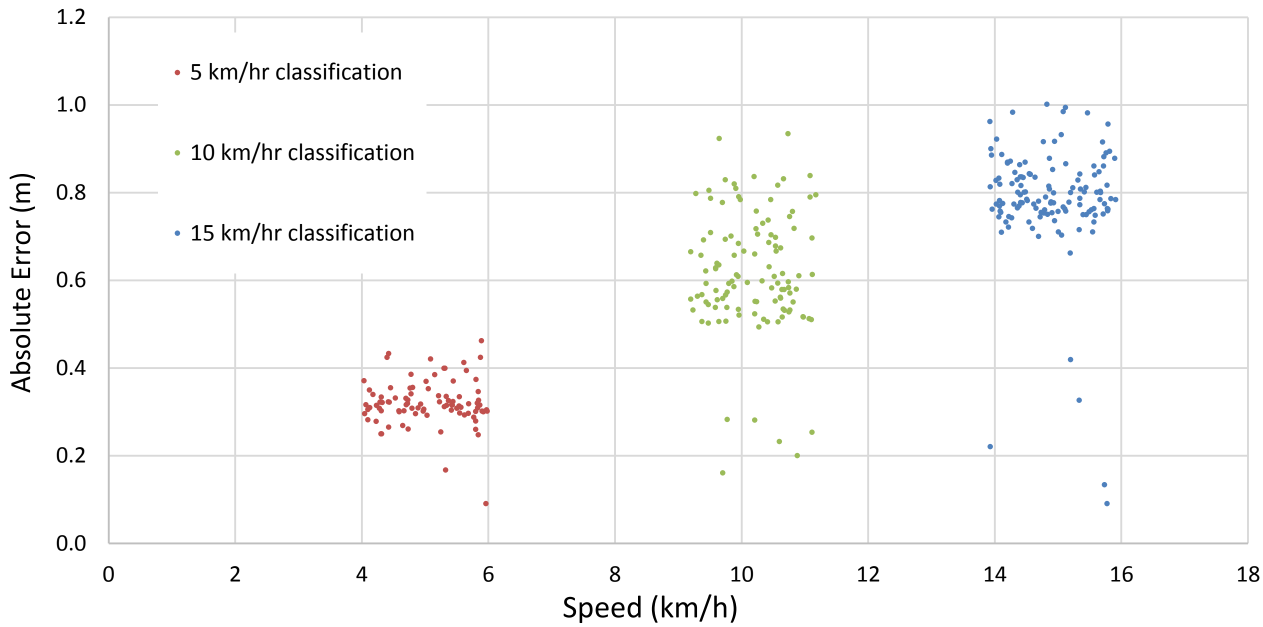

Figure 4.2 Absolute observed error as a function of speed

The details regarding each category of data collection are brought in Table 4.2. In each run, four sets of data were collected and used for the analysis. For example, the 23 runs performed at 5 km/h category yielded 92 sets of data.

Table 4.2 Information pertaining to the second experiment

	Speed Classifications		
	5 km/h	10 km/h	15 km/h
Number of Runs	23	28	32
Speed Average (km/h)	5.06	10.18	14.88
Standard Deviation of the Speed	0.61	0.55	0.60

The number of collected data, average speed, and the standard deviation (SD) of the speed for each speed group are brought in Table 4.2. The average speed helps knowing the value of speed for comparing the accuracy measures with other experiments and the standard deviation elucidates the closeness and similarity of the collected data in each group. The smaller the standard deviation in value, the closer the collected data to each other. The SD of the speed for all three data groups is about 0.6. Therefore, it can be assumed that the speed was constant in performing the experiments and the acceleration was eliminated in a good level.

4.5 Discussion

In this study, two sets of experiments were performed (including and excluding acceleration in the moving pattern of the mobile object). The data from these two experiments are compared in this section to find out the effect of acceleration on the performance of UWB RTLS tracking. In order to facilitate the discussion, the data, from both of the experiments, are shown with the same format.

4.5.1 Absolute Error as a Function of Speed

The absolute error of the collected data from the second experiment is plotted in Figure 4.3. The 95% confidence interval (CI) calculated in the first experiment for the error is illustrated in the same figure to enable comparing the data of both of the experiments (see Figure 4.3). The data plotted in Figure 4.3, from first and second experiment, is before eliminating the impact of time latency. In Figure 4.3, the black line is the mean regression line, the blue and red lines are, respectively, the upper and lower boundaries of CI.

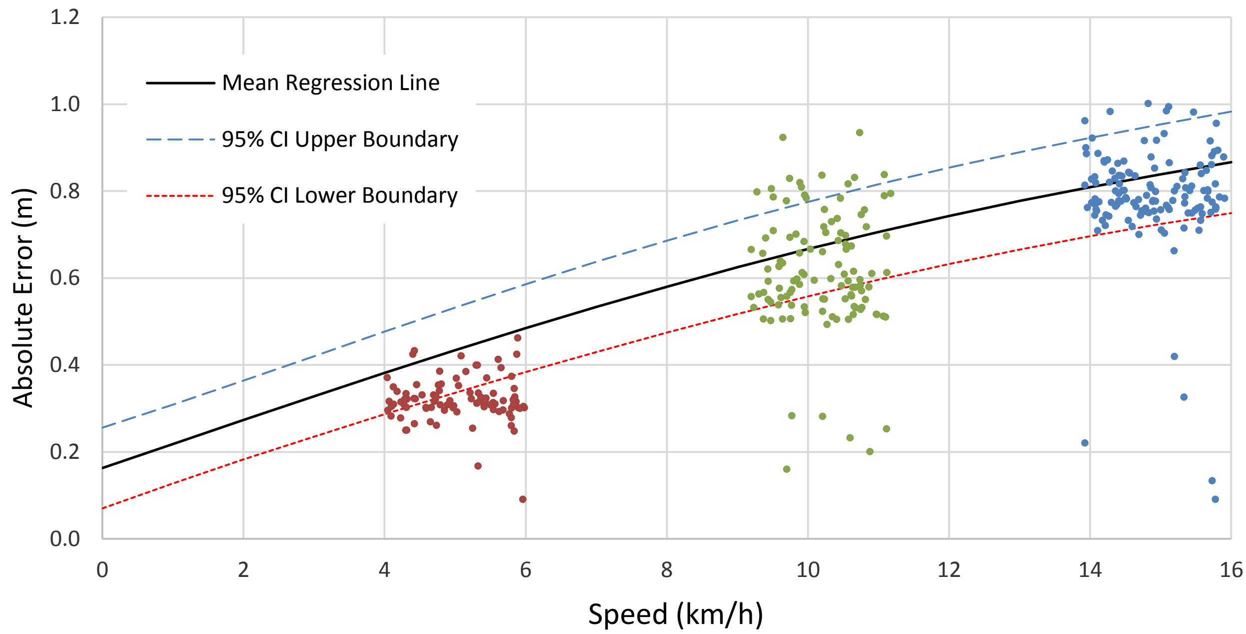

Figure 4.3 Absolute observed error of second experiment, the mean regression line and the 95% confidence interval (CI) of the of the mean regression line of the error of the first experiment

As shown in Figure 4.3, the distribution of the error of the collected data in the second experiment for speed groups of 10 km/h and 15 km/h are the same as the first experiment. While most of the error at 5 km/h is below the mean regression line and outside of the confined area of the 95% CI. It can be inferred that in lower speeds the acceleration decreases the accuracy of UWB RTLS. In addition, it can be inferred that the impact of acceleration compared to other sources that have impact on the accuracy of UWB positioning is negligible in the higher speeds.

In Figure 4.3, there are some data that has less absolute error compared to the rest of the collected data. In order to find out the reason, the data collected close to each of the benchmark points were categorized by color (see Figure 4.4).

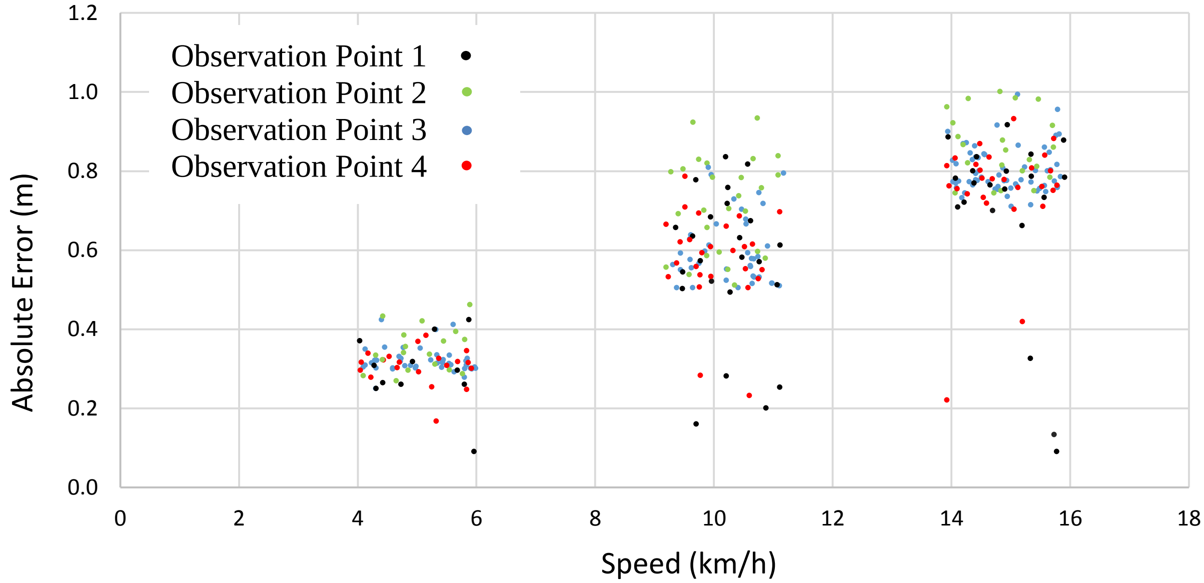

Figure 4.4 Absolute observed error classified with color – second experiment

In Figure 4.4, the collected data close to observation points one through four are shown, respectively, with black, green, blue, and red indicators. Most of the indicators with lower absolute error are allocated to observation point one (1) and four (4). Both of the points, one and four, has better DRMS compared to the other points (see Table 4.1). It can be inferred that the coverage of area has a meaningful impact on the accuracy and performance of UWB positioning.

4.5.2 Ex as a function of speed

The error in the x direction (E_x), as a function of speed, after elimination of time latency bias impact, for both experiments are illustrated, respectively, in Figure 4.5 and Figure 4.6 with color classification. It is worth mentioning that the x direction was along the prepared path for data collection in the data collection. The indicators for both experiments are almost identical. It can be inferred that the acceleration does not have a meaningful impact on the accuracy of UWB positioning. However, it can be noticed that the congestion of the data is decreased after elimination of the acceleration from moving pattern of the mobile object. It can be justified by different performance of UWB in the four observation points used for the second experiment.

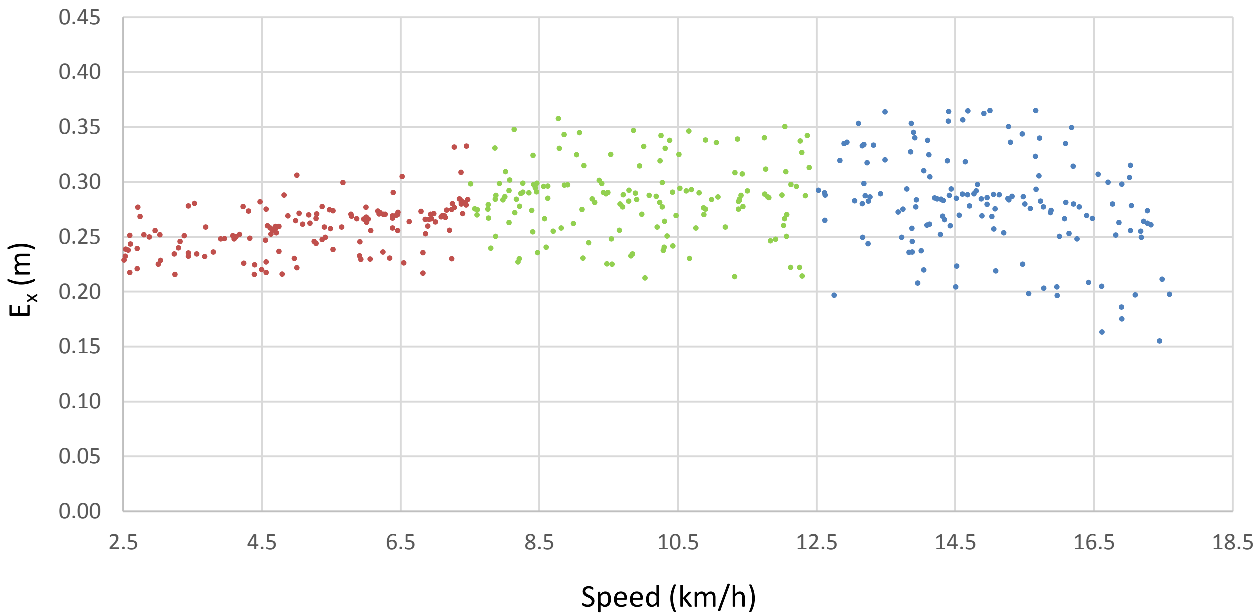

Figure 4.5 E_x as a function of speed with color classification - first experiment

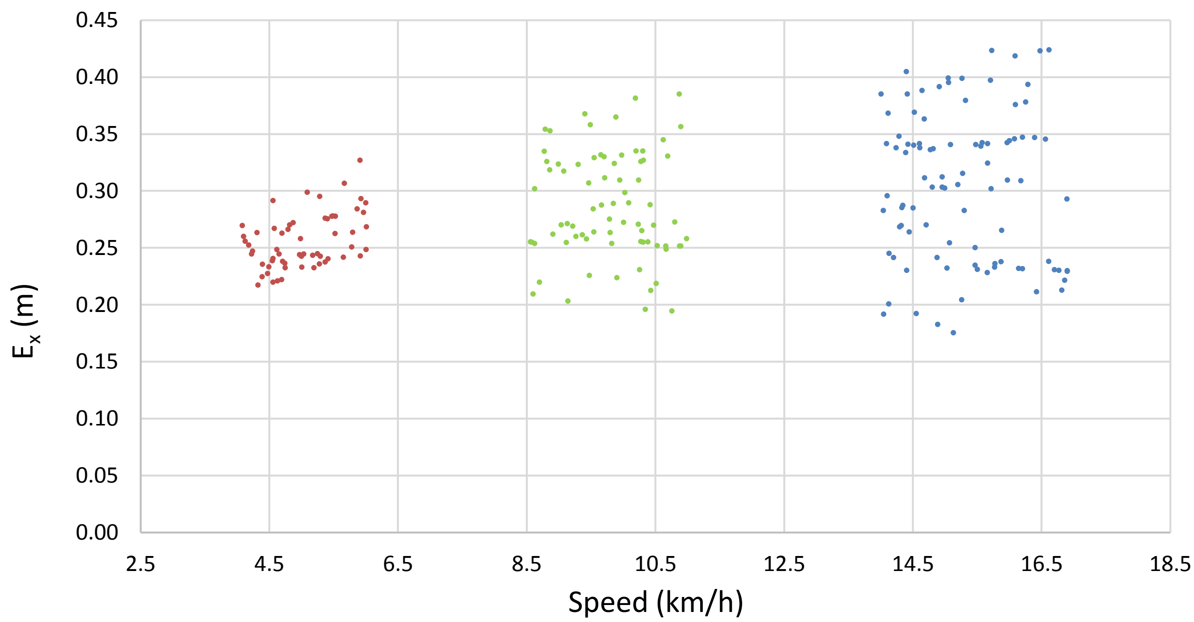

Figure 4.6 E_x as a function of speed with color classification - second experiment

4.5.3 Ey as a Function of Speed

The error in the y direction (E_y) as a function of speed for both experiments are illustrated in Figure 4.7 and Figure 4.8. It can be seen that the error of the data collected in the direction perpendicular to the moving direction did not sensibly change when the mobile object accelerated. However, in the second experiment, the E_y is larger compared to the first experiment. It can be justified by considering that different observation points with different coverage and static accuracy were used in the second experiment.

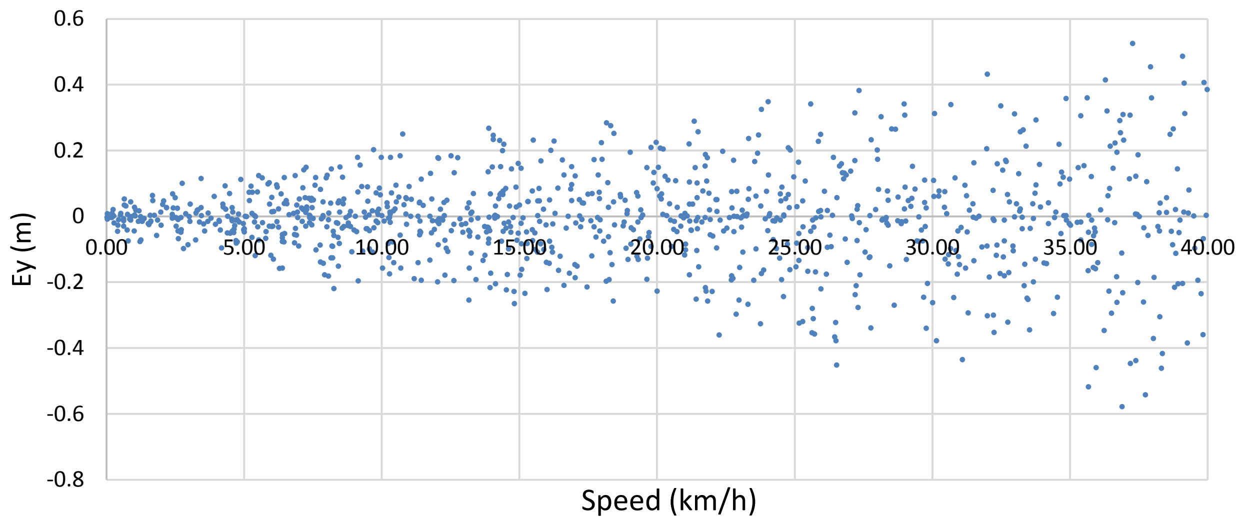

Figure 4.7 E_y as a function of speed - first experiment

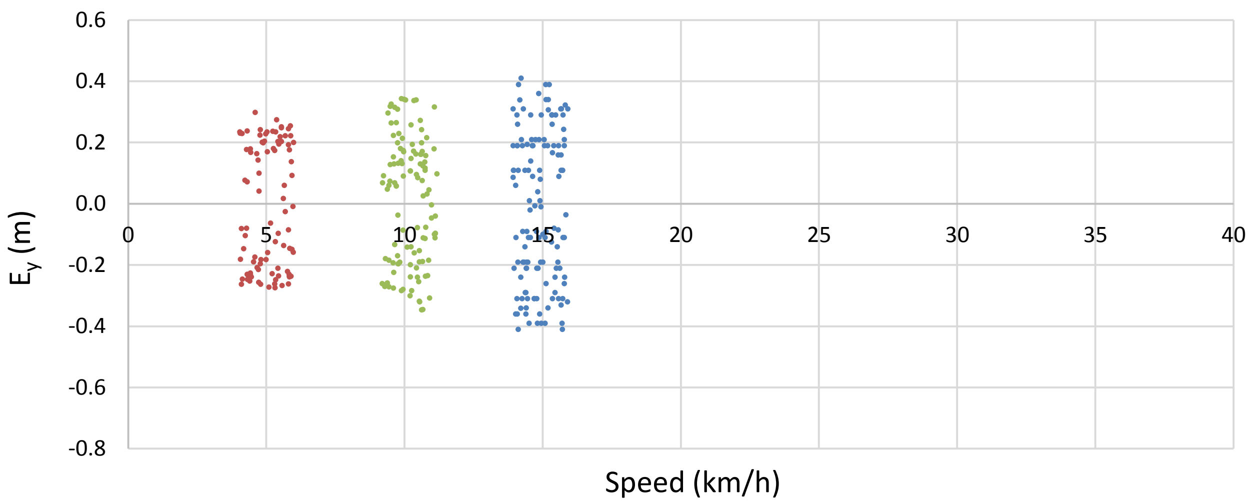

Figure 4.8 E_y as function of speed - second experiment

4.5.4 Ex as a Function of Ey

The error in the y direction (E_y) is pictured as a function of error in the x direction (E_x) in Figure 4.9 and Figure 4.10, respectively, for the first and the second experiment. The indicators from the first experiment were classified with colors (Figure 4.9a). Then, the indicator for the higher speeds in the first experiment was omitted (Figure 4.9b) to make the comparison and discussion easier. The indicators in Figure 4.9b and Figure 4.10 for the three speed classifications are in red, green, and blue colors. The color classification helps to show how the indicators for E_y as a function of E_x were distributes with the increase in speed. Comparing Figure 4.9b and Figure 4.10 shows that the error in the moving direction increases faster than the direction perpendicular to the moving direction.

It is worth mentioning that Figure 4.9 and Figure 4.10 show the pattern of the collected data in the both experiments. Color classification of the data reveals that the error pattern in both experiments are the same. However, there is minor difference between the error patterns of the experiments. But this slight difference can be justified by the unequal performance of the observation points. Pattern of the data is a very important factor to see if a factor has impact on the data. Therefore, it can be inferred that the acceleration did not have meaningful impact on the pattern of the collected data.

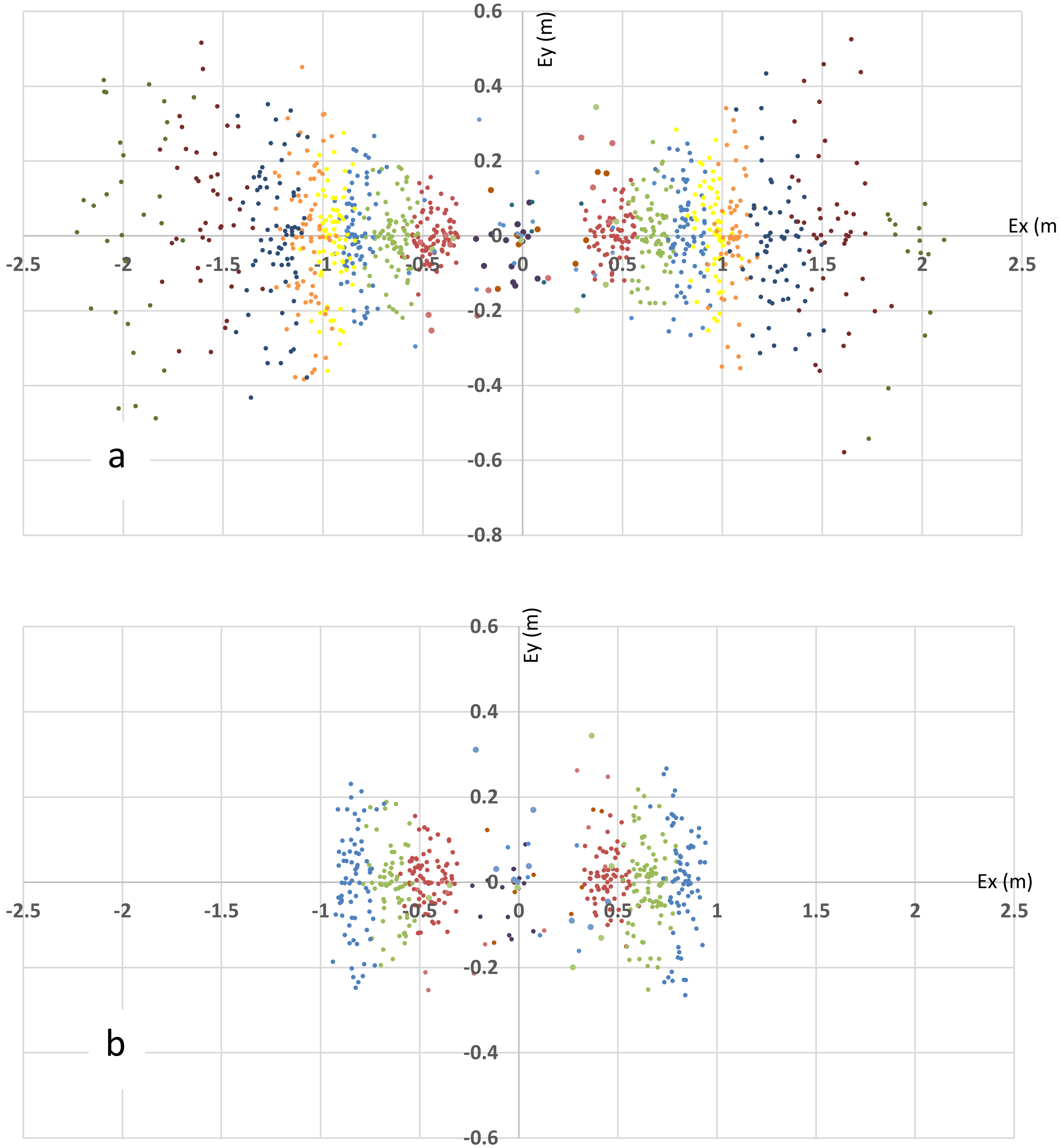

Figure 4.9 E_y as a function of E_x – first experiment a) with color classification b) with color classification and omission of the higher speeds groups

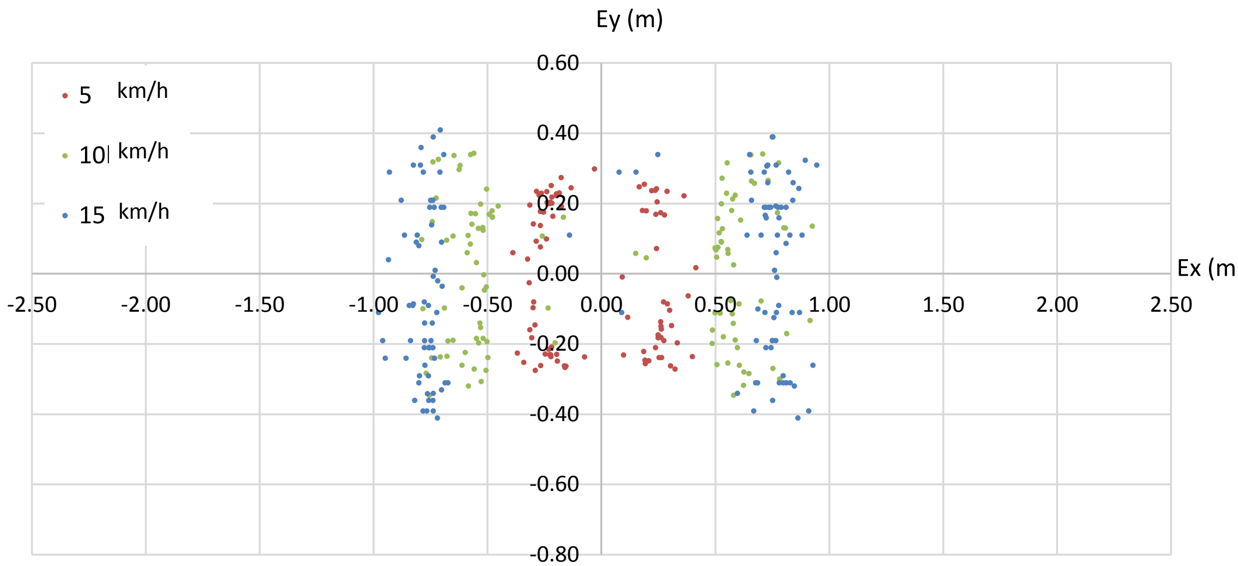

Figure 4.10 E_y as a function of E_x - second experiment

4.5.5 Ex and Ey

The mean and the standard deviation of the error of the collected data in the second experiment is presented in Table 4.3.

Table 4.3 The average and the standard deviation of the E_x and E_y - second experiment

	Error of the Collected Data					
	5 km/h		10 km/h		15 km/h	
	E_x	E_y	E_x	E_y	E_x	E_y
Average (m)	0.25	0.19	0.37	0.20	0.74	0.22
Standard Deviation (SD)	0.07	0.07	0.15	0.13	0.24	0.11

The average and the standard deviation of E_y is almost the same in all speed categories. It can be inferred that as E_y is the error perpendicular to the moving direction, the offset (average) and the precision (standard deviation) of the positioning are almost independent from the speed of the moving object and excluding the bias caused by time latency or other source of biases which are result of the moving direction of the mobile object.

In addition, at lower speed, the average and the standard deviation of E_x and E_y are close. It can be inferred that when the moving object does not accelerate the error in both directions are almost equal. In addition, the average and the standard deviation of E_x increases with the increase in speed. It can be inferred that the error in positioning is mainly caused by the E_x which is the error in the moving direction of the mobile object.

4.6 Conclusion

Comparing the result of the two experiments showed that acceleration has more impact on the UWB performance in lower speeds. In addition, the standard deviation of the E_x and E_y in 2D was shown to be independent from acceleration. In other words, the findings suggest that acceleration does not significantly impact the precision of the UWB RTLS.

Illustrating the 2D pattern of collected data with color classification revealed that the acceleration does not have meaningful impact on the pattern of the collected data. In addition, it was inferred that the decrease in the congestion of the collected data was mainly caused by the scattering of the data in the moving direction of the mobile objects.

By comparing the E_x and E_y from the same speed groups, it was inferred that the error in positioning is mainly caused by the E_x which is error in the moving direction of the mobile object in this study. In addition, it was noticed that the moving direction of the mobile object does not influence the precision as the precision in both directions were almost equal.

Chapter Five: SUMMARY AND DISCUSSION

A summary of the results of the experiments conducted in this study is brought in this chapter. The discussion on the results, contributions, limitations in conducting the experiments, and the recommendations for the future works are brought in the following sections.

5.1 Summary

The primary objective of this study was to assess the accuracy of UWB RTLS in dynamic tracking. In order to conduct this study, two sets of experiment are performed. The first experiment aimed to evaluate the impact of speed on the accuracy of UWB in dynamic tracking. This experiment conducted utilizing a remote control car (RCC) equipped with an UWB tag. The UWB-equipped RCC was operated on a prepared path in the speed range of 0 – 40 km/h. A specific benchmark point was selected and the estimated position of the mobile object while passing the benchmark point was compared with the actual coordinates of that point. This experiment was repeated 1087 times to increase the reliability of the analyses.

Similar to other positioning systems, the UWB RTLS has latency in presenting its estimated position. The time latency of the UWB RTLS in dynamic tracking was identified to be 5.6 ms by comparing the deviation of average of the error from zero. Time latency brings bias in the data in addition to other source of bias in data collection in the x direction (along the moving path). Therefore, the position data collected in y direction- safe from the biases in the moving direction- was used for calculating the accuracy measures (DRMS, precision, and offset) as a function of speed.

The abovementioned accuracy measures for the data when the time latency error is included can be referred to as *real-time* accuracy measures and the ones excluding the time latency can be referred to as *dynamic* accuracy measures. Consequently, the calculated accuracy measures are considered as dynamic accuracy measures as the time latency effect is not included in the data in the y direction.

The offset in the speed range of 0 – 40 km/h increased gradually from 1 to 2.5 cm as the speed increased. The R^2 of the linear mean regression line fitted to the offset was equal to 0.89. Therefor it could be inferred that the offset had a linear correlation with the speed.

The precision in the speed range of 0 – 40 km/h varied from 4 – 25 cm. Similar to the offset, the precision had a linear positive correlation with the speed as the R^2 of the mean regression line fitted to the precision was equal to 0.93.

The DRMS is equal to square root of summation of squares of precision and offset (see equation 3.7). As the offset was small in value compared to precision (particularly in the higher speeds), the DRMS was almost equal to precision and varied from 4 cm to 25 cm.

In analyzing the results and values from the first experiment, it was noticed that the moving object had acceleration while passing the benchmark line. At this point, another research question was raised to verify if acceleration had an effect on the accuracy of UWB RTLS. Consequently, the second experiment was designed and performed with the goal of eliminating acceleration from the moving pattern of the RCC and examining the effect. In order to minimize and eliminate the effect of acceleration in the second experiment, four (4) benchmark points were assigned.

The UWB-equipped RCC was operated as it remained in speeds close to 5, 10, and 15 km/h when passing through all benchmark points. A total of 83 runs, generating 332 data sets, were conducted. The generated data and results from both abovementioned experiments are separately presented in absolute error, error in x direction (E_x), and error in y direction (E_y) as function of speed and E_x as a function of E_y.

Comparing the result of the two experiments showed that acceleration has more impact on the UWB performance in the lower speeds. In addition, the standard deviation of the error in both x and y directions in 2D was shown to be independent from acceleration. In other words, the findings suggest that acceleration does not significantly impact the precision of the UWB RTLS.

5.2 Discussion

- In the dynamic safety boundary defined in section 1.2, two factors are required. The first parameter is function of size of the moving object. The second parameter is the minimum stopping distance which is function of speed, friction ratio, and the perception-reaction time (tpr). The tpr is a constant which is required to be identified based on the different factors in the place of using the safety management model. Based on the earlier studies, as the construction environment is a complex environment where the operators and labourers are alerted while working the tpr can considered to be 1.5 sec. The third factor for defining a dynamic safety boundary is the accuracy of positioning. Defining of this factor requires a coefficient level which depends on the application of the safety management model. In order to bring an example, the coefficient level is considered to be equal to 95 percent. Therefore, in order to cover the 95 percent of the collected data the offset (average) of the collected is required to be summed up with precision (SD) times 5.99.
- The error of the collected data in the x direction (along with the direction of the moving object) was biased instead of having a noise pattern. Two sources of error were identified in the collected data: time latency and camera lens focal used for preparing the recordings. The time latency resulted in a linear bias in the error pattern. However, the focal of the camera lens biased the data with tangent which resulted in having a zero-mean S-shape error pattern. The first source of bias could be eliminated by calculating the time latency. As there was not enough

data recorded from the experiment setup, the bias from the second source could not be eliminated from the data. Two sources of bias only had impact on the collected data along to the moving direction which was x direction. Therefore, the error of the data in the y direction was double-checked to have a noise pattern and used for calculating the accuracy of the UWB in dynamic tracking. In the case that the pattern of the error of the data was acceptable and the bias was result of UWB positioning system performance, the value of upper boundary of prediction interval (PI) in each speed could be implemented in defining the third parameter of the dynamic safety boundary which is positioning accuracy (PA). The coefficient level for calculating the PI depends on the application.

- In the case that the time latency was not eliminated for the calculating the accuracy measures the obtained accuracy was referred to as real-time accuracy. However, when the time latency is excluded from the data the accuracy is referred to as dynamic accuracy. Therefore, the accuracy measures calculated in this study are dynamic accuracy measures. Each of these accuracy measures, real-time and dynamic, has different values and applications. For example, in order to use the UWB in a construction environment for safety management systems such as collision detection, the real-time accuracy will be implemented. In contrast, the dynamic accuracy measures are more suitable when the positioning data is going to be used for identifying moving patterns of the labourers or equipment, which can be used for planning safer site layouts. Consequently, in defining the third factor of the dynamic safety boundary, the dynamic accuracy measures are required to be implemented and the impact of time latency on the accuracy of UWB positioning is required to be considered.
- Two sets of experiments were conducted in this study in order to assess the impact of speed and acceleration on the accuracy of the UWB positioning. It was shown that as the speed increases

the value of the accuracy measures increase. However, comparing the result of the two experiments showed that acceleration has more impact on the UWB performance in the lower speeds. It can be inferred that when the speed increases the impact of acceleration compared to other sources of error is negligible. Therefore, it can be inferred that the acceleration did not have meaningful impact on the value of the accuracy measures calculated in the speed range of 0 – 40 km/h. Based on the results it can be guessed that in the speeds higher than 40 km/h the result would be the same. However, it needs performing new experiments for assessing the impact of acceleration in the higher speeds.

- Illustrating the 2D error pattern of the data revealed that that the decrease in the congestion of the collected data was mainly caused by the scattering of the data in the moving direction of the mobile objects (x direction). In other words, the precision in the moving direction of a mobile object is less than this value in the direction perpendicular to the moving direction. Therefore, in order to define a more efficient dynamic safety boundary, the precision in moving direction can be considered larger than this value in the perpendicular direction.

5.3 Research Contributions

The main contributions of this study can be listed as follow:

- Assessing the impact of speed and acceleration on the accuracy of UWB in tracking dynamic resources within indoor construction jobsites in speed range of 0 – 40 km/h.
- Providing a methodology for calculating the "positioning accuracy" (PA) factor of the dynamic safety boundary zone (as described in section 1.2) using the accuracy measures
- A set of recommendations -derived from the results of each experiment- were provided for effective utilization of UWB resource tracking on construction sites.

5.4 Limitations

There are several factors affecting the accuracy of the UWB RTLS in tracking dynamic resources. These factors include coverage of the readers, numbers of the readers, alignment of the readers, installation and calibration, and the experiment environment. This study only focused on assessing the impact of speed and acceleration on the accuracy of UWB in tracking dynamic resources. Further studies is required to assess the effect of other factors on the performance and accuracy of UWB in dynamic tracking.

5.5 Recommendations for Future Work

The following future researches can be considered imminent to the presented study and are recommended:

- Assessing the impact of relative elevation of the UWB tag to the readers on the accuracy of the dynamic tracking.
- Applying the result of this study and proposed dynamic safety boundary in safety management systems such as collision detection models.
- Assessing the impact of coverage area, alignment, and geometry of the UWB RTLS readers on the accuracy of UWB RTLS in tracking dynamic resources.
- Assessing the number of UWB tags in simultaneous tracking on the accuracy of the UWB RTLS in tracking dynamic resources.
- Assessing the impact of the UWB tag frequency on the accuracy of UWB RTLS in dynamic tracking.

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APPENDIX A: PERCEPTION-REACTION TIME

In order to calculate the perception-reaction time (t_{pr}) for a driver, generally four factors are considered: perception, intellection, emotion, and volition. Perception is the time to see an object, intellection is the time to understand the implication of the object, emotion is the time to decide how to react, and volition is the time to initiate the action.

Perception-reaction time is defined for design and operations or control (AASHTO 2004). t_{pr} is obtained to be 2.5 sec and 1.0 sec, respectively, for design and control. These numbers are obtained based on the behaviour of the 85th percentile of the drivers observed in their study. The 2.5 sec for perception-reaction time is examined in some studies (Gazis et al. 1960, Wortman and Matthaas 1983, Chang et al. 1985, Sivak et al. 1982). The result of these studies demonstrated the maximums perception-reaction time of 1.9 sec and 2.5 sec, respectively, for the 85th percentile and the 95th percentile of the observations.

In obtaining the t_{pr}, the alertness of the drivers considered and experimented in other studies (Wortman and Mathias 1983). In the situations that the drivers are alerted t_{pr} is obtained to be 0.9 sec while t_{pr} is equal to 1.3 sec in the surprised situations. Similar to the AASHTO, these numbers are obtained based on the behaviour of the 85th percentile of the drivers observed in their study.

In addition, the complexity of the traffic conditions was suggested to be considered in the perception-reaction time (Sivak et al. 1982). The result of this study showed the minimum of 1.5 sec and the maximum of 3.0 sec for $t_{pr,}$ respectively, for the low and high complexity conditions for the traffic.

APPENDIX B: LOCATION ESTIMATION METHODS FOR REMOTE SENSING

Remote sensing is defined as acquisition of information from an object without making physical contact. Remote sensing technologies enable positioning using the acquired information. Different methods can be applied for performing the location estimation, namely, received signal strength indication (RSSI), angle of arrival (AOA), time of arrival (TOA), and time difference of arrival (TDOA).

Location estimation technologies which use electromagnetic and sound waves for the data acquisition mostly consist of a transmitter and a receiver. The transmitter emits the signals and the receiver collects the transmitted signals. The signals that travel the straight path between the transmitter and the receiver is called the Line-of-Sight (LOS) signal and the signals that had reflection with the surrounding in their travel are called multipath signals. The reflections cause signal attenuation which is called multipath fading.

Using the data acquired by LOS signals, the relative location estimation can be performed. In other words, the LOS signals transmitted by a tag (transmitter) and received by the receivers can be used in positioning methods.

B.1 Received Signal Strength Indication (RSSI)

The receivers measure the strength of the received signal. This method does not have high ability of differentiating the LOS signals from the multipath ones. Positioning by RSSI is performed by fingerprinting. In the fingerprinting method, a number of sample points are used to make a correlation between the RSS measures and the actual locations. Therefore, the accuracy of positioning highly depends on the accuracy of the collected data in the calibration of the system.

In addition, any changes in the surroundings result in changes in the RSSI that affects the accuracy of positioning.

B.2 Time of Arrival (TOA)

The time of receiving the LOS signals by the receivers is measured. Therefore, knowing the time of emitting the signal by the transmitter and the time of receiving the signal enables calculating the travel time of the LOS signals. The travel time times the speed of the electromagnetic waves the distance of the tag from the receivers can be easily obtained.

In this method, the one-way and two- way travel time of the signals can be used for calculating the distance of the tag from the readers. Commonly, calculating the two-way method is easier as a lower precision clock can be used in the transmitter. In this method, LOS and multi-path signals are required to be differentiated by the positioning technology (Dardari et al. 2009).

B.3 Time Difference of Arrival (TDOA)

This method is similar to TOA with the advantage of not requiring synchronization between the transmitter and the receivers. It means that a transmitted signal from a tag does not require having any information about the time of transmitting a signal. Instead, this method requires synchronization of the receivers which can be easily fulfilled using timing cables (Dardari et al. 2009).

B.4 Angle of Arrival (AOA)

In this positioning method, the angle of the received LOS signals by the receivers is measured. In the environments that the chance of signal multipath is high (like construction work environments), applying this method requires accurate calculations for differentiating the LOS signals from the reflected ones (Liu et al. 2007). Commonly, the angle of the signal with the highest strength, recognized as the LOS signal, is used for positioning calculations. The accuracy in installation of the receivers in this method is important as highly affects the accuracy of positioning.

APPENDIX C: 2D ERROR ELLIPSE

Error ellipse is an accuracy measure that can be used for addressing the accuracy and distribution of positioning data. In order to calculate and draw the error ellipse, variance in both x and y directions (σ_x,σ_y) and the covariance (σ_{xy}) are required. In 2D, the required elements can be obtained by calculating the covariance two-by-two matrix. The parameters of a general equation for defining an error ellipse can be obtained using following equations:

$$a = \sqrt{(\frac{1}{2} \times \left(\sigma_x{}^2 + \sigma_y{}^2\right) + \sqrt{\left(\frac{1}{4} \times (\sigma_x{}^2 - \sigma_y{}^2)^2 + \sigma_{xy}{}^2\right)}} \tag{C.1}$$

$$b = \sqrt{(\frac{1}{2} \times \left(\sigma_x{}^2 + \sigma_y{}^2\right) - \sqrt{\left(\frac{1}{4} \times (\sigma_x{}^2 - \sigma_y{}^2)^2 + \sigma_{xy}{}^2\right)}} \tag{C.2}$$

$$\theta = 0.5 \arctan(\frac{2\sigma_{xy}}{\sigma_x{}^2 - \sigma_y{}^2}) \tag{C.3}$$

where 2a and 2b are, respectively, the length of the major and the minor axis of the error ellipse centered at the origin and θ is the azimuth of the major axis (see Figure C.1).

Generally, the equation of an error ellipse aligned with an axis (no orientation) is defined by the following equation:

$$\left(\frac{x}{\sigma_x}\right)^2 + \left(\frac{y}{\sigma_y}\right)^2 = s \tag{C.4}$$

where s is the scale of the error ellipse which defines the confidence level of this accuracy measure. The confidence level of the error ellipse states the percentage of the data covered by the ellipse. For example, the 99 percent confidence interval corresponds to s=9.210. The s value corresponding to the confidence interval of the error ellipse can be obtained using the chi-squared table.

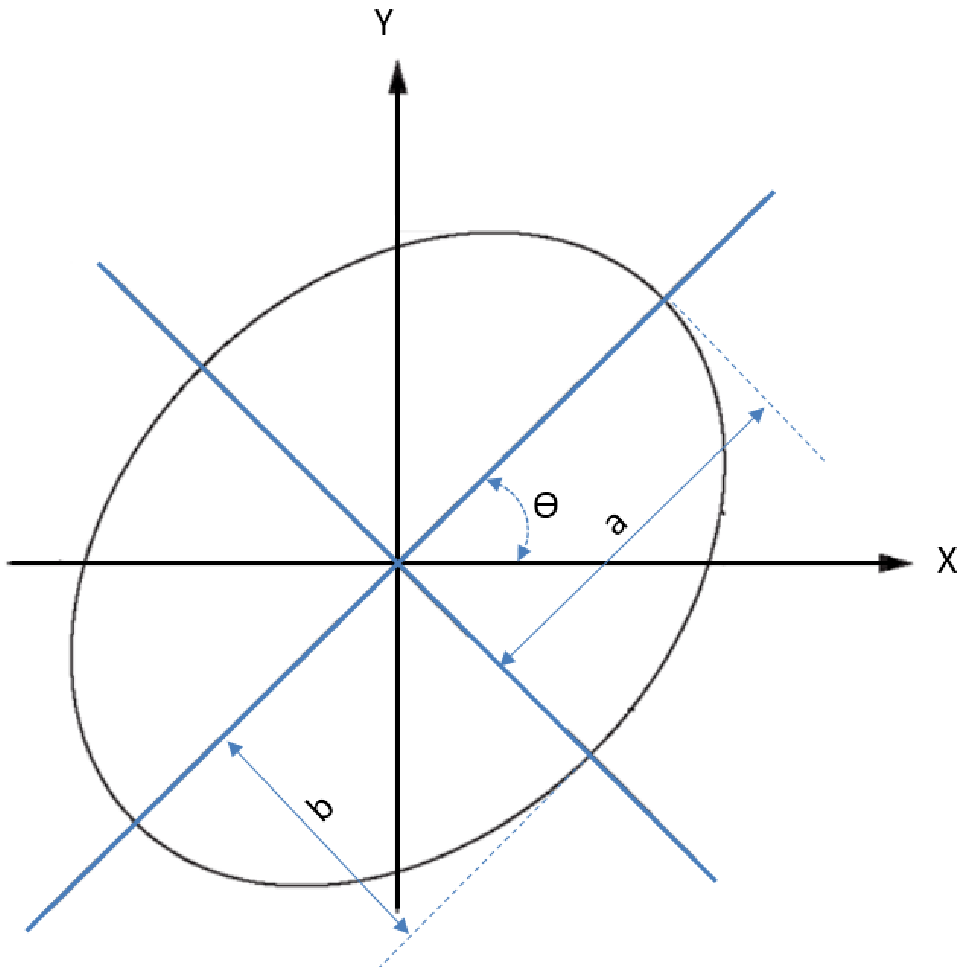

Figure C.1 2D Error ellipse elements

The orientation of the error ellipse in 2D is defined by the direction in which the data varies the most. The direction of the error ellipse can be calculated by the covariance matrix. In order to obtain the orientation of the error ellipse towards the x-axis, the angle of the largest eigenvector towards the x-axis is calculated using the following equation:

$$\alpha = \arctan\frac{V_1\,(y)}{V_1\,(x)} \tag{C.5}$$

where V_1 is the eigenvector of the covariance matrix corresponding to the largest eigenvalue.

APPENDIX D: REGRESSION ANALYSIS

Statistical techniques are applied to find and model a mathematical relationship between the mean value of a variable and the other corresponding variables based on the available data or observations. There are different kinds of regression models and analyses such as linear, multiple, and non-linear regressions.

D.1 Polynomial Regression

If the scatter plot of the observations shows that there is at least one relative minimum or maximum value, a polynomial function may satisfy the approximation for the true regression function (Montgomery and Runger 2014). The k^{th}- degree polynomial parametric regression equation is:

$$Y=a_0 + a_1x^1 + \ldots + a_kx^k + e \tag{D.1}$$

where "a" is a parameter and "e" is the error of the estimation model, which is, customarily, a distributed random variable. Therefore, the regression equation or the estimation function is shown as follows:

$$\mu_{Y.x} = a_0 + a_1x^1 + \ldots + a_kx^k \tag{D.2}$$

In the regression equation calculations, the observed values (x_1, y_1) through (x_n, y_n) are assumed to be generated or collected independently from the regression model equation.

D.2 Calculation of Parameters

Parameters are calculated by minimizing the difference between the estimation function and the observations. Therefore, a trial regression function is considered, such as equation D.3, and the fit of this equation can be calculated by equation D.4.

$$y = a_0 + a_1x^1 + \ldots + a_kx^k \tag{D.3}$$

$$f(a_0, a_1, \ldots, a_k) = \sum_{i=1}^{n}\left(y_i - \left(a_0 + a_1x_i + \cdots + a_kx_i^k\right)\right)^2 \tag{D.4}$$

If the regression equation is well fitted to the observation, then the sum of the squared deviations has a low magnitude. The number of equations is equal to the number of observations. Consequently, the number of observations should be at least one more than the order of the regression model equation. The k+1 partial derivatives of the equations over the parameters are calculated and equated to 0 to find the value of the parameters that minimize equation D.4. The derivation over the parameters results in k+1 normal linear equations as shown in equation D.5. The equation can be solved easily by a linear least square method.

$$a_0 n + a_1 \sum x_i + a_2 \sum x_i^2 + \cdots + a_k \sum x_i^k = \sum y_i \tag{D.5}$$

$$a_0 \sum x_i + a_1 \sum x_i^2 + a_2 \sum x_i^3 + \cdots + a_k \sum x_i^{k+1} = \sum x_i y_i$$

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$$a_0 \sum x_i^k + a_1 \sum x_i^{k+1} + \cdots + a_k \sum x_i^{2k} = \sum x_i^k y_i$$

D.3 Adequacy of the Regression Models

In fitting a regression model, several assumptions are made. For example, the mean of the errors is zero and has a constant variance, and the error is an uncorrelated random variable. The order of the model is always assumed to be correct. Therefore, after fitting a regression model, the correctness of the assumptions should be checked.

D.3.1 Residual Analysis

The residuals in each model are calculated in a similar method as the error for each observation. The difference between the estimation of the regression model and the observation is called a residual. The residuals might be standardized if they are expected to have a normal distributed error for an estimation model. The residuals outside this interval can be considered as outliers. An outlier is an observation which is not a typical of the data for fitting a model. There are several methods for omitting the outliers; however, they can give important information about the experiment and, therefore, they should not be discarded automatically. Drawing the residuals is a way to see their pattern. Based on the pattern of the residuals, in the case that they do not have constant variance, there are transformations that can be applied. The transformation allows the model to have better conditions based on the assumptions explained earlier in this section.

D.3.2 Coefficient of Determination (R^2)

The coefficient of determination (R^2) is a common measurement for checking the regression models. R^2 is a ratio of the sum of the square of the errors; it is calculated using the following equation:

$$R^2 = 1 - \frac{SS_E}{SS_T} \tag{D.6}$$

where SS_E is the sum of square of the errors of the estimation values compared to the observed values and SS_T is the total sum of squares of the response variable y.

R^2 ranges from zero to one ($0 \leq R^2 \leq 1$). If the value of R^2 is closer to one, the model is more accurately fitted to the data. This variable should be used with care because there is the possibility of making R^2 equal to one by adding new terms to the model. For example, c can be equal to one if the order of the model is one less than number of observations.

APPENDIX E: CONFIDENCE INTERVAL (CI) ON THE MEAN RESPONSE

In statistics, confidence interval (CI) is an interval based on the variance calculations. CI covers a specific portion of a sample data which can be indicated by the confidence coefficient of the CI. The confidence coefficient of a CI indicates this portion (Montgomery and Runger 2014). The desired level of confidence is optional and depends on how the result of the calculation is going to be applied; for example 50 percent, 95 percent and 99 percent can be chosen. A CI can evaluate the reliability of a sample or collected data. If the interval width is sufficiently large, the data is not reliable. Certain factors may affect the CI size including sample size, confidence coefficient, or level. If the sample size is large, a better estimation can be obtained. For example, 60 percent means that for a calculated interval on sample data, 60 percent of the population of the data lies within this CI. In this example, if the variance of the collected data was constant, 20 percent of the observations would be above the upper boundary of the CI and 20 percent below the lower boundary.

The CI can be obtained by calculating the mean response at a specific value. The CI is often obtained along the mean regression line. The variance of a mean response is:

$$\text{Variance} = \sigma^2\left(\frac{1}{n} + \frac{(x_0 - x_{Mean})^2}{S_{xx}}\right) \qquad \text{(E.1)}$$

where σ^2 is the variance of x, n is number of collected data, x_{mean} is the average of x, and S_{xx} is the sum of the squares of the x data from x_{Mean}. S_{xx} can be calculated using following equation:

$$S_{xx} = \sum_{i=1}^{n}(x_i - x_{Mean})^2 \qquad \text{(E.2)}$$

The equation of a CI with a confidence coefficient of 100 × (1- a) % along the mean response at $x = x_0$ is obtained by equation E.3.

$$|\text{CI} - \text{Mean Response}| \leq t_{\frac{a}{2},\ n-2} \times \sqrt{\sigma^2\left(\frac{1}{n} + \frac{(x_0 - x_{Mean})^2}{S_{xx}}\right)} \qquad \text{(E.3)}$$

The CI value depends on the value of x_0. Therefore, the interval width increases as the $(x_0 - x_{Mean})^2$ increases. As a result, it can be inferred that the CI of a linear regression line is not parallel with the mean regression line.

APPENDIX F: PREDICTION INTERVAL (PI)

In statistics, a prediction interval (PI) is an interval with a certain probability and range to cover the observations based on the data, which have already been collected or observed. PIs are usually used for regression analysis because they can estimate or predict future observations with a specific probability (Montgomery and Runger 2014). The equation of a CI with a confidence coefficient of 100 × (1-a) % on the mean response line at x = x_0 is obtained by following equation:

$$|\mathrm{PI} - \mathrm{Mean\ Response}| \leq t_{\frac{a}{2},\ n-2} \times \sqrt{\sigma^2 \left(1 + \frac{1}{n} + \frac{(x_0 - x_{\mathrm{Mean}})^2}{S_{xx}}\right)} \tag{F.1}$$

The PI value depends on the value of x_0. Therefore, the interval width increases as the $(x_0 - x_{\mathrm{Mean}})^2$ increases. In addition, it can be inferred that the PI of a linear regression line is not parallel with the mean regression line. By comparing equation F.1 and E.3, it can be inferred that the PI is wider than the CI at point x_0 for the same data. The reason is that the PI depends on both the error of the fitting model and the error associated with the future observations.