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IntelliSensorNet: A Positioning Technique Integrating Wireless Sensor Networks and Artificial Neural Networks for Critical Construction Resource Tracking

by

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I dedicate this thesis to

my family and my beloved husband, Sadegh, for their constant support and unconditional love.

I love you all dearly.

Abstract

The increasing needs for safety and productivity improvement in the field of construction engineering and project management have stimulated research interests in developing cost-effective resource tracking and positioning solutions for challenging indoor or partially covered site environments. This thesis has proposed a robust positioning architecture called IntelliSensorNet that relies on an integrated environment of Wireless Sensor Networks and Artificial Neural Networks for construction resource localization. The wireless sensor network (WSN) based component of the architecture determines the location of mobile sensor nodes ("tags") by evaluating radio signal strengths (RSS) received by stationary sensor nodes ("pegs"). Only a limited quantity of reference points with known locations and pre-calibrated RSS in relation to the pegs are used to determine the most likely coordinates of a tag. Moreover, to effectively reduce uncertainty and improve accuracy, an on-line error correction approach based on a Radial Basis Function Neural Network (RBF NN) model is embedded in the proposed architecture. In short, this localization technique produces a cost-effective solution to positioning and tracking critical construction resources such as laborers and equipment for challenging indoor environments or partially covered site environments in construction, thus lending itself well to potential deployment in real-world construction sites.

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CHAPTER 1: INTRODUCTION

1.1 Resource Tracking in Construction

Construction projects, by their nature, have dynamic environments with constant movement of resources including laborers, materials, and equipment. Locating and tracking these resources is critical in construction applications for achieving productivity and safety on site (Goodrum et al., 2011). For instance, in construction sites significant time is spent on searching for required materials within the lay down yard. An example of material handling is the delivery of the steel components from the fabrication shop to a temporary lay down yard during structural steel erection process. In the assembly process of steel components, the components are stored in the lay down area. This provides a temporal buffer to ensure parts availability when needed. However, recent studies have revealed that the current process of material handling on industrial job sites is inefficient (Navon and Sacks, 2006). Moreover, production control procedures in the construction industry are still labor intensive, often manual, and error prone.

It is generally accepted that resource management practices have been gradually improved in recent years. In order to improve resource management, many research studies focus primarily on the improvement of material management in order to increase labor productivity and construction performance. The main purposes of material management in construction sites includes receiving, warehousing, tracking, locating, finding, and distributing the right materials in the right quantity to the right locations at the right time. However, material management on construction projects still entails tedious manual processes and, in reality, remains a challenge.

A large number of construction resources, including equipment, tools and workforces, are involved in the process of design, fabrication, delivery, storage, installation and inspection. The functions of resource management should be efficiently performed in order to prevent material shortage, surplus, cash flow problems and labor delay. For example, if materials are purchased and delivered early, capital may be tied up and interest charges may be incurred on the excessive inventory of materials. Moreover, special care should be taken in order to prevent material deterioration or theft during storage.

The current practice of tracking resources in construction is still largely dependent on manual systems, which often results in errors and delays jeopardizing entire projects. Therefore, inefficiency of the manual operations in reporting, recording and transferring field data in current tracking systems, which in turn adds to field overhead costs, is still an important management function especially on large construction projects. The performance of materials management can be further improved if information about materials can be collected in time, with ease and accuracy. This calls for development of more effective resource positioning and tracking solutions based on emerging automated technologies.

Furthermore, in terms of safety, knowing the locations of workers within a tunnel being built or a hazardous structure (burning or partially collapsed) is very critical. According to the U.S. Bureau of Labor Statistics' (BLS) Census of Fatal Occupational Injuries, construction has historically been the most hazardous industry in the United States in terms of the number of fatalities. Therefore, considerable time and economic resources are lost when workers are injured or even killed by equipment or loads during work tasks (Teizer et al., 2007a; Teizer and Allread, 2010; Hinze and Teizer, 2011).

However, current safety practices are not sufficient to prevent worker injuries and fatalities on a daily basis when they are in too close proximity to heavy equipment or loads of materials. Recent developments in remote sensing and automated data acquisition technology have the potential to improve upon existing productivity and safety management strategies (Song et al., 2006a; Song et al., 2006b; Song et al., 2007; Akini and Anumba, 2008; Grau et al., 2009a; Grau and Caldas, 2009b). For instance, a safety warning system with mobile tracking devices attached to construction workers can trigger a warning when the workers are in hazardous areas or working in an unsafe manner (Kim et al. 2007).

In general, timely information about construction resources can assist in fast and effective real-time decision making. Emerging localization and tracking technologies have spurred research efforts leading to automated resource tracking and data acquisition for control and improvement of construction processes (Jang and Skibniewski, 2009). Due to the need for reliable solutions for real-time asset localization and resource tracking in the dynamic environment of construction sites, many have attempted to develop a reliable framework for enabling the application of these technologies (Goodrum et al., 2006; Song et al., 2006a; Ergen et al., 2007; Teizer et al., 2007; Behzadan et al., 2008; Chin and Yoon, 2008; Khoury and Kamat, 2009; Torrent and Caldas, 2009).

In recent years, the need for indoor localization has also been rapidly increasing on construction sites (Khoury and Kamat, 2009), presenting opportunities for research in this area. Construction tasks, such as inspection and progress monitoring, should have access to project information, especially in indoor or partially covered environments, like tunnels and buildings that are under construction. The Global Positioning System (GPS) is an attractive option for outdoor environments, but is not suitable for indoor applications because its positioning mechanism requires that any location to be fixed should have line-of-sight with at least three satellites. While outdoor localization techniques have been developed and deployed, indoor resource positioning solutions remain a research challenge. In addition, due to the complexity of indoor environments, the development of an indoor localization technique is always impeded by a set of hurdles such as dense multipath effect, lack of line-of-sight, noise interference and building material dependent propagation effects (Zhang et al., 2010).

1.2 Research Objectives and Scope

The objective of this study is to propose a new positioning framework called IntelliSensorNet on the basis of relating the distances between sensor nodes in a wireless sensor networks with the strengths of received radio frequency signals, so as to facilitate the localization of construction resources in both indoor and outdoor environments. This study attempted to create a framework for integrating advances in Wireless Sensor Networks (WSN) and Artificial Neural Networks (ANN) in an attempt to automate tracking and monitoring construction resources.

Advancements in low power microelectronic devices and sensor network technologies provide the capability to automate tracking and monitoring resources in the construction industry. However, there has been a lack of interdisciplinary research activities among different areas of expertise such as Computing science, Electrical engineering and Construction management, resulting in less efficient or effective use of emerging technologies for increasing the cost-effectiveness of resource tracking in construction.

Therefore, in order to bridge the gap between the emerging technologies and their implementations, an RSS-based indoor localization scheme recently developed in the computing science field by Haque et al.(2009a) has been utilized for customizing cost effective wireless sensor network-based solutions for resource positioning and tracking applications in construction sites. The simplicity and accuracy of this positioning approach has made it a good candidate to achieve the desired “meter level” localization error in indoor environments. In addition, consistent performances and low cost of the equipment have made the solution highly viable and very practical. However, this new indoor positioning architecture has not yet been convincingly substantiated by experiments in realistic site environments or under practical application scenarios, which consist of metallic facilities, walls and feature constant changes over the time. Hence, indoor experiments in a car park simulating a reinforced-concrete building construction site were designed and conducted in order to evaluate and confirm the capability and limitation of the proposed RSS-based positioning architecture in construction.

Indoor experiments have revealed that acceptable position estimation of one to two meter accuracy can be obtained with this flexible sensor network architecture. However, construction sites inevitably involve the movement of equipment, materials and laborers. The construction environment changes dynamically, which would mean that localization results might no longer be accurate in the continually modified environment. To address this problem, a systematic approach to perform error calibration by an efficient form of artificial neural networks and re-profiling by re-measuring the received signal of the tags on profiled points is proposed to create more accurate localization results.

To confirm the viability and limitations of the proposed solution and to evaluate the effect of environment variations due to the presence of a metal object the size of a car, the prototyped WSN-based localization system was assessed in an underground parking lot. To simulate the dynamic setting of a construction site, controlled experiments were conducted by parking a car at various locations in the testing environment in order to evaluate the impact of the imposed metallic object on location estimation performance. The results demonstrated that a car-size metallic object can change the environment and generally increase the localization error. After conducting the re-profiling solution, it was observed that re-profiled localization remains within the degree of accuracy attained prior to the introduction of the car. This is a promising finding since re-profiling does not add to the cost of the localization system. Considering the fact that the effort for re-profiling an entire area is quite demanding, we also explored the idea of only determining a possible small subset of locations to be re-profiled so as to improve achievable localization accuracy.

The feasibility of a WSN-based positioning system was also evaluated in an underground tunnel construction site in an attempt to locate the workers inside the tunnel for safety management. The results indicated that the system could lock onto the position of the workers with one to two meters accuracy. The tunnel site provides a “linear” test bed due to the unique design of the tunnel. Thus, to further improve the feasibility of our system in a “non-linear” indoor environment, we designed experiments to test the system in a car park setting, with particular emphasis on evaluation of the localization error calibration approach based on artificial neural networks.

To effectively reduce the uncertainty and the error of the location estimation system in real-time and to improve the location accuracy and data communication efficiency, a real-time error calibration approach was proposed based on a Radial Basis Function Neural Network (RBF NN) model. The difficulty in quantifying the impact of indoor wireless signal propagation on localization accuracy has made RBF NN an appropriate technique for quantifying such impact and reducing localization errors. The proposed framework was then prototyped and tested in indoor scenarios in order to examine its positioning performance, its precision and its robustness in a dynamic construction environment. This study showed that RBF could decrease the localization error from 1.11 m to 0.57 m on average. This localization technique was found to produce consistent positioning accuracies based on lab testing scenarios simulating realistic construction sites, thus paving the way for potential deployment in real-world construction sites.

Finally, by designing experiments we investigated the smallest number of reference points and pegs that are sufficient for an acceptable positioning accuracy. This would help reduce the time and labour requirements for re-profiling the WSN-based positioning system and control the application cost of the localization system particularly in covering a large scale construction site. Figure 1-1 shows the flowchart of the positioning framework.

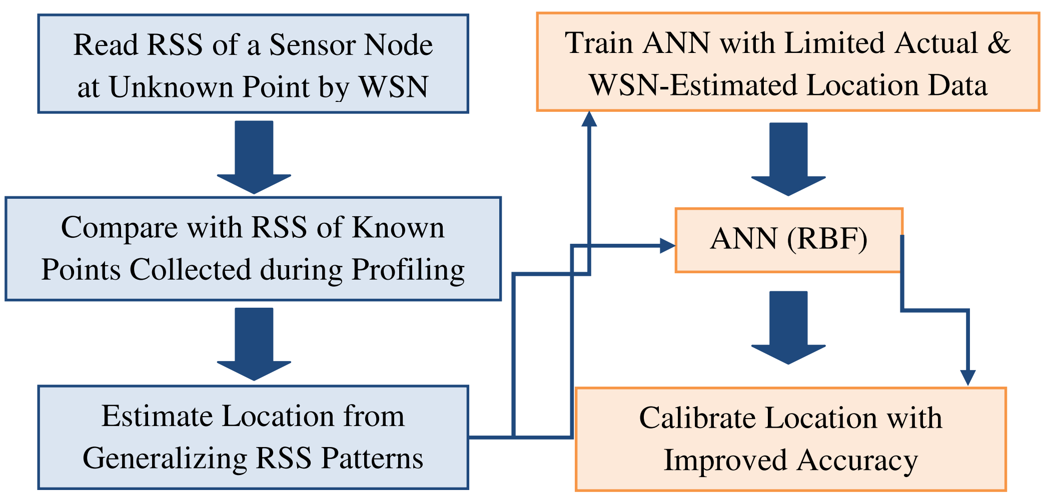


Figure 1-1: Flowchart of the positioning framework

The proposed system architecture and results of the experiments are then presented. This framework is expected to deliver cost effective automation solutions for resources positioning and tracking on construction sites with acceptable accuracy and reliability in a wide range of construction applications. Future work on how to further improve accuracy and robustness is discussed in the conclusion.

1.3 Thesis Organization

The remainder of this thesis is organized as follows:

Chapter 2 first provides a background to localization technologies employed in construction industries and presents a literature review on resource localization. Chapter 3 describes the architecture of the proposed positioning system of IntelliSensorNet. The IntelliSensorNet is prototyped as a tool for resource localization on construction projects. The development of the IntelliSensorNet is also elaborated. Next, in chapter 4, practical applications of the proposed system are illustrated through a lab testing example in an attempt to locate a tracked object in an underground parking lot.. Chapter 5 explains the impact of sensor node placement and profile point selection on indoor localization accuracy. Finally, chapter 6 provides conclusions and summarizes the contributions of this thesis; limitations and ideas for future research are also addressed in this final chapter.

CHAPTER 2: LITERATURE REVIEW ON POSITIONING TECHNOLOGIES AND APPLICATIONS IN CONSTRUCTION

2.1 Introduction

This chapter reviews the literature on the previous related research to provide a background and to justify the need for developing a positioning technique by integrating Wireless Sensor Networks and Artificial Neural Networks for critical construction resource tracking. A brief background in these areas is provided in Section 2.2.

2.2 Resource Tracking Systems in Construction Industry

Over the past decades, construction industries have expressed an increasing interest in location-aware systems and services (Kim et al., 2010; Cho et al., 2010). Field data collection and communication techniques have become more efficient in construction with the help of advanced computer and localization methods. The information enables construction managers to be aware of the current states of construction resources. At present, Radio Frequency Identification (RFID) systems and the Global Positioning System (GPS) are the predominant technologies for automated tracking and monitoring of construction resources and assets (Jaselskis and El-Misalami 2003; Goodrum et al., 2006; Song et al., 2006a; Ergen et al., 2007; Lu et al., 2007; Wang et al. 2008; Behzadan et al., 2008; Chin et al., 2008; Khoury and Kamat 2009), outperforming previous technologies (such as barcode) in resource positioning, tracking and automated data collection in construction. However, limitations of current positioning methods have been identified; these limitations impede their wide application in the construction field. The application of radio frequency technologies, such as Radio Frequency Identification (RFID) and Ultra-Wide Band (UWB), has, to date, been proposed for dynamic indoor resource tracking. However, they have not yet been proven viable as cost-effective tracking frameworks for large-scale dynamic construction projects. RFID does not meet application requirements in harsh construction conditions due to inaccurate positioning (Pradhan et al. 2009) inflexible and limited networking capabilities, and the high cost of RFID readers (Skibniewski and Jang 2009). Moreover, the communication distance between RFID tags and readers decreases significantly with the existence of metals, concrete and moisture in their vicinity, reducing the performance of the technology (Ergen et al., 2007). Current stand-alone GPS can lock positions in open areas with accuracy of around 10 m. Real-Time Kinematic GPS (RTK GPS) can further improve positioning accuracy to centimeters (and even a few millimeters), by applying special algorithms to process the measurements of satellite signal carrier phases from both base and rover receivers. Nonetheless, the performance of a GPS-based localization system can be substantially compromised on the dynamic construction site due to blockage and the multipath effect, which is caused by deflection and distortion of satellite signals in highly dense areas or by temporary structures or facilities such as hoarding, scaffold and formwork (Lu et al. 2007).

Ekahau is another technology that has been developed based on the Wi-Fi technology for tracking and positioning applications. Although Ekahau is reported to result in position accuracy up to 1 m (Shen et al., 2008), it needs an already installed Wi-Fi network infrastructure, which may not be available on many construction sites. In addition, many studies have attributed the low accuracy of Wi-Fi localization to the multipath errors in complex environments (Ekahau Inc., 2010). Similar to Wi-Fi, Bluetooth can also provide positioning accuracy of a few meters and is vulnerable to multipath interferences. For instance, field tests in complicated site conditions found that the communication range of Bluetooth can be reduced from a nominal range of 100 m to an actual range of 20 m (Lu et al., 2007). Besides, the UltraWideBand (UWB) technologies confer the advantages of high immunity to interference and multipath, thus leading to higher accuracy in localizing objects. Khoury and Kamat (2009) performed some indoor experiments as a part of robot performance evaluation using a UWB-based positioning system. The results indicated that the tracking system could obtain an accuracy of 10 to 50 cm. On the other hand, the UWB technology is still expensive and requires a dense and expensive network of fixed receivers. UWB can be difficult to deploy in a crowded construction environment and its performance may suffer from harsh weather conditions such as high humidity (Torrent et al., 2009).

In order to overcome the limitations of traditional monitoring systems, the interest of utilizing Wireless Sensor Networks (WSN) in recent construction research has been growing. A WSN is a self-organizing network composed of a large number of sensor nodes which closely interact with the physical world. It features low-cost sensors and extensible networking capability, thus making it cost effective and straightforward to deploy a large quantity of sensor nodes so as to increase the network coverage, stability, and communication reliability. In addition, low power consumption facilitates operation and maintenance of the system (Shen et al., 2008). And the ad-hoc network architecture supports flexible implementation and adjustment of the network (Shen et al., 2008; Baronti et al., 2007). WSN can also provide context-aware and application-specific sensing data in a ubiquitous computing environment (Sugano et al., 2006; Kim et al., 2010; Shin et al., 2011).

Jang et al (2008) demonstrated the steps as needed to make use of advanced ZigBee based wireless sensor network technology to monitor situations inside and around buildings. Based on this preliminary study, a new tracking architecture was implemented using wireless sensor modules by combining radio frequency signals (RF) and Ultrasound (US), delivering an acceptable measurement accuracy (Jang and Skibniewski 2009; Skibniewski and Jang 2009; Shin and Jang 2009). However, traditional ultrasound positioning has some disadvantages including line-of-sight requirement, multipath, high cost and power consumption; these factors all hinder potential applications in complicated construction environments (Purushothaman, and Abraham 2007; Shen et al., 2009; Wu et al., 2010). According to the technological and economical constraints and management application requirements, various combinations of RFID and Zigbee-based sensor networks have also been applied for materials tracking and supply chain management (Cho et al., 2010; Cho et al., 2011). RFID tags were attached to and used to identify various kinds of construction materials, and the

Zigbee communication technology was used to wirelessly transfer such information. These studies confirmed that WSN can improve wireless communication and network flexibility.

Moreover, to address the limitations of RF (Radio Frequency) technologies, recent construction research has investigated the possibility of developing cost-effective positioning solutions by measuring the received signal strength (Luo et al., 2010). In particular, with the advent of the low-cost WSN technology, RF-based real-time positioning solutions can be easily designed and deployed (Haque et al., 2009a).

In conclusion, based on the literature, there is a recognizable need for WSN-based location sensing in construction industry due to technical and economical drawbacks of aforementioned approaches. The practical goal of this research is to find a cost-effective and fully automated solution that satisfies the practical requirements of a reliable and stable system for tracking and monitoring of construction resources.

CHAPTER 3: ARCHITECTURE AND SYSTEM DESIGN OF "INTELLISENSORNET"

3.1 Introduction

This chapter introduces the positioning framework called IntelliSensorNet as a tool for resource localization in construction projects. IntelliSensorNet consists of a Wireless Sensor Network (WSN) based localization architecture and a Radial Basis Function Neural Network (RBF NN) based error calibration algorithm. In section 3.2 the WSN based localization technique is introduced. The system architecture of the WSN-based positioning technique is discussed in section 3.3. Section 3.4 provides a state of the art review regarding techniques that have been used to date to improve the accuracy of location-aware systems based on Received Signal Strength (RSS). This review justifies the application of RBF NN for reducing localization errors. The error correction algorithm using RBF NN modeling is also provided in this section. The system architecture is further clarified with a sample experiment in Section 3.5.

3.2 Wireless Sensor Network Localization Techniques

The localization research attempts to solve the problem of determining the location of a sensor node within its environment. The approach chosen to solve the localization problem depends on the assumptions about capabilities of particular networks and devices, including configurations of the hardware device, signal propagation models, timing and energy requirements, the network structure, the nature of the environment (indoor vs. outdoor), node or beacon density, time synchronization of devices, communication costs, error requirements, and device mobility. Localization algorithms can generally be divided into three categories: range-based, range-free and RSS profiling.

The range-based algorithms (Khalid and Gulliver 2010) estimate the distance between nodes using measurements such as time of arrival (ToA), time difference of arrival (TDOA), received signal strength (RSS), or angle of arrival (AoA). For GPS, triangulation analysis requires being in range of at least four known satellites in order to find the 3D coordinates of the receiver, entailing the removal of the clock bias of the receiver. GPS systems require energy-consuming electronics to precisely synchronize the receiver's clock with the satellite's clock. AOA, TOA, and TDOA methods (Shen et al., 2008) depend greatly on line-of-sight communication and require expensive infrastructure. They are also negatively affected by the presence of different materials, equipment, and building structures at construction sites. The hardware limitations and the energy constraints along with the need to synchronize clocks presents a cost barrier to implementing the range-based approach necessary for realizing localization through WSN. On the other hand, RSS-based techniques require less complex and low cost RF hardware (Haque et al., 2009b). As such, RSS is considered to be more suitable for localization applications on construction sites. Past studies verified that the majority of positioning systems employed the RSS-based technique because of its broad accessibility in connection with wireless radio signal communication (Lymberopoulos, 2006). RSS-based localization has the advantage of using the same hardware for providing both communication and localization functionalities, resulting in a simple design framework (Elnahrawy et al., 2004). However, it is commonly acknowledged that the correlation of RSS with distance can be poor and unpredictable due to the multi-path effect of radio waves, which is typically much more serious inside a building than in an open area. It is also indicated that practical performances of the Zigbee-based WSN using RSS and geometric trilateration decrease under realistic construction environments (Shen et al., 2011). However, as already mentioned, performances of the other two techniques tend to drastically deteriorate under multiple paths as well. Therefore, considering the complexity and cost of the required hardware, RSS-based schemes outperform the other two schemes in indoor environments.

Finally, the solutions in the range-free localization are being identified as a more cost-effective alternative to the range-based approaches for large scale sensor networks (He et al., 2003). The range-free algorithms depend on proximity sensing or connectivity information to estimate the node locations. The principle of these algorithms is a sensor being in the transmission range of another sensor, which defines a proximity constraint between both sensors. This constraint can be utilized for localization (Mao et al., 2007). With the range-free approach, the localization problem is easy to solve, but the estimated locations tend to be inaccurate. Additionally, utilizing a RSS profiling method will help to compensate for the effect of environment on the reliability of estimated locations, which is obtained from correlating distances with strengths of received RF signals (Haque et al., 2009a).

RSS profiling-based localization techniques first develop a map of the radio signal strength behavior in the coverage area. The map is constructed either offline by pre-collected measurements or online using sniffing devices (Krishnan et al., 2004) placed at known locations. Such techniques have been mainly used for location estimation in Wireless Local Area Network (WLAN), but are also applicable to Wireless Sensor Networks. In addition to a finite quantity of stationary sensor nodes (e.g., access points in WLANs) and mobile sensor nodes, a large quantity of sample points are distributed throughout the monitored area covered by the sensor network. At each sample point, a vector of signal strengths is obtained by reading all stationary nodes. Of course, many entries of the signal strength vectors may be zero or very small, indicating the stationary sensor nodes are fixed at longer distances (relative to the transmission range or sensing radius) from the sample point. The collection of all these vectors provides (by extrapolation in the vicinity of the sample points) a map of the whole region. The collection of RSS vectors at all the profiled points make up the RSS model, which is ad hoc with respect to the node locations and the states of the environment. The RSS model is stored in a database maintained on a central server. By referencing the RSS model, the location of a mobile node can be estimated by comparing the RSS measurements at all the fixed nodes against those on the profiled points of the RSS model.

3.3 Architecture of the Positioning System

The localization architecture of IntelliSensorNet implements an RF-based localization scheme (Haque et al., 2009a) similar to the RSS-profiling methodology, which operates based on sensing the strengths of the received RF signals. This architecture is a combination of a range-free method and RSS profiling. It is simpler and more accurate than other approaches and the uniformity and low cost of devices makes it a highly viable and very practical solution for construction. The infrastructure nodes of the proposed localization architecture are low-cost, low-power wireless devices [EMSPCC11 by Olsonet Communications (2011)]. The node makes use of the CC1100 RF module from Texas Instruments operating within the 916MHz band. The RF module of EMSPCC11 proposes several settings (Haque et al., 2009a) of the packet bit rate, transmitted power level, and the channel number. The bit rate alternatives are 5 kbps, 10 kbps, 38 kpbs, and 200 kbps. The transmission power can differ from -30 dBm to 10 dBm, and there are 256 different channels with 200 kHz spacing. All combinations are possible and, in principle, sensible. From an operational point of view, the node is called a “peg” when it captures signal strength. The pegs’ locations are fixed (static nodes) and their precise location need not be known. A monitored device, which is a node of the same type as a peg, is called a tag. See Figure 3-1.

Figure 3-1: EMSPCC11 wireless nodes by Oslonet Communications Corporation

The task of location estimation in this architecture consists of two phases: profiling and actual localization. Generally, during operation in both phases, a tracked tag periodically emits RF packets. In the profiling stage, tags are located at predetermined known locations called reference points. In this phase, all the pegs that can “hear” the RF packets emitted by the tags will forward a report consisting of its own ID, the Tag ID, the packet number and class to the central server. This system maintains a database of signal strength readings from tags on a central server. Collecting samples of the profiling phase may involve a person moving around the monitored area equipped with a clickable map and a number of tag nodes. The database consists of samples which are stored as Triplets $< C;\Omega;\tau >$ in which C represents the known coordinates of the sampled point, Ω stands for the association set (which comprises peg ID and the RSS value received by that Peg), and τ symbolizes the class of sample, identifying the RF parameters of the transmitter (such as transmission power, bit rate, and channel number).The process of actual localization of the tracked tag is similar to the profiling stage with the only difference being that, in the profiling stage, the association set of tag profiling reports also includes the known coordinates of the sampled point; but in the actual localization stage, the location of the tracked tags needs to be estimated based on the location of profiled points.

In the localization stage, the server compares the perception of the tracked tag's RSS measured by all the pegs in the monitored area and the RSS of each profiled reference point and evaluates the difference between the tag and all the profiling points. If $\Omega = \{w_1,...,w_k)$ and $\Psi = \{\psi_1,...,\psi_k)$ are assumed to be two association's sets, the distance between these sets will be:

$$D(\Omega,\Psi) = \sqrt{\sum_{j=1}^{N}(R_\Omega(j) - R_\Psi(j))^2} \tag{1}$$

where N is the total number of pegs in the network and $R_\Omega(j)$ is defined as r_j , which is the pair $< p_j, r_j >$ occurs in Ω , and 0 otherwise. Therefore, the server evaluates the distance of each pre-selected sample (its association set) from the tag's association set, representing the combined momentary perception of the tag's RSS by all the pegs that can hear it. Then it selects an arbitrary K number of profiled samples with the smallest distance from the tracked tag, which is called a best matched set of profiled points. Subsequently, the coordinates of the selected samples are averaged to produce the estimated coordinates of the tag. The averaging formula biases the samples in such a way that the ones with a smaller distance contribute with a proportionally larger weight. If $D_{\max}$ is the maximum distance among the best k selected samples and $S_d = \sum_{i=1}^{K} D_i$ is the sum of all those distances then the tag coordinates are estimated as:

$$x_{est} = \frac{\sum_{i=1}^{k} x_i \times (D_{\max} - D_i)}{K \times D_{\max} - S_d} \tag{2}$$

$$y_{est} = \frac{\sum_{i=1}^{k} y_i \times (D_{\max} - D_i)}{K \times D_{\max} - S_d} \tag{3}$$

where $(x_i - y_i)$ are the coordinates associated with sample i. Note that in this approach, RSS is only used as a numerical attribute of a profile sample whose value should be close to the perceived value.

It is also noteworthy the current system design is concerned with positioning on a 2-D domain. Positioning in a 3D building space can be converted into a system of 2D domains by defining walls and ceilings. For instance, once pegs have been established and reference points profiled in different areas on different floors, the system should be able to decide on which side of a wall or in which floor (in a multistory building) a tracked tag is currently located. As such, a particular area on a particular floor can be identified with measured signal strengths of relevant pegs.

3.4 Applying Radial Basis Function Neural Networks to Reduce Localization Error

Inside the building, radio signal propagation follows a complex model due to non-line-of-sight multi-path effects caused by the building materials, human body absorption, neighboring devices, metallic materials and the dynamic nature of the environment. Due to these limitations, indoor location estimation becomes a complex problem and is difficult to engineer using classical mathematical methods. Therefore, RSSI alone does not provide sufficient accuracy for location systems due to high fluctuations of the received signal over measuring time (Lymberopoulos et al. 2006).

To improve the accuracy of the location-aware systems based on RSS, several techniques have been employed, including Bayesian classification and filtering, K-Nearest Neighbors, GPS-like triangulation and Kalman Filtering. However, these approaches have not yet been proved for indoor localization applications (Ahmad et al., 2006) since indoor wireless signal propagation is so complex and indefinable that it is still hard to attain a steady accuracy level. Traditionally, many researchers have used Nearest Neighbors based pattern recognition technique and its derivatives. This technique requires a database of sample RSS readings at the estimation time for pattern matching. As the region and number of target locations grow, this size of the database dramatically increases and it becomes impractical to achieve sufficient scalability. On the other hand, GPS like triangulation methods present poor performance because of multi-path propagation effects in covered environments. Probabilistic approaches such as Bayesian networks based solutions achieve better performance but they are computationally exhaustive and difficult to scale. As the area and quantity of target locations and wireless access points increase, the computational complexity of Bayesian structures increases (Ahmad et al., 2006). In general, noises must be detected, modeled, and filtered out to improve the accuracy of the developed system. The signal reception rate can be adjusted to cope with environmental variations. Such environmental changes can incur signal loss and reduction, exerting a negative effect on signal and noise distributions. So, it is necessary to model and remove noises from signals while minimizing signal losses. Kalman filtering is applicable to error correction on the next position in addressing "inertial navigation" problems which generally apply instrumentation for positioning (gyroscope or compass): time-dependent patterns in positioning errors on previous positions can be represented by a steady noise distribution. Shareef et al. (2008) conducted an RSS-based localization method using Kalman filtering and Neural Networks, observing better performances with RBF Neural Networks in terms of accuracy based on experimental results. Compared with Neural Networks, Kalman filter made fewer mistakes but produced larger magnitude of errors especially on the boundaries of the testing area.

Ahmad et al. (2006) compared the results of previous research in indoor positioning techniques and found Neural Networks provides a better solution to the location determination problem. For instance, Note, in contrast with the Kalman filters, Neural Networks perform well only for the area in which they have been trained. In other words, if the tracked object passes beyond the boundaries of the area where the Neural Network model has covered, the Neural Network will not be able to localize the tag with reliability. However, the proposed WSN based positioning method provides an "ad hoc" solution for a particular application purpose. The WSN coupled with RBF NN provides a cost effective infrastructure for real-time re-profiling and re-calibration of the positioning solution on a continuous, real-time basis without the need to model the noise distribution explicitly as required in Kalman filtering. For instance, to cope with the dynamic nature of the working environment, the WSN-RBF can be automatically recalibrated at a preset frequency (once per ten minutes or every half an hour).

The Kalman filtering technique iteratively refines the position estimates of an object in a continuous motion path over time based on the noise parameters that follow a Gaussian distribution. The Kalman filter uses the laws of kinematics to predict the location of the tracked object, requiring several iterations before it begins to reach the accuracy of the Neural Network (Shareef et al., 2008). For Radio Frequencies based positioning (RSS), the position errors may not exhibit continuity over time and space as the collected RSS data are likely to contain many "outliers". This can render the application of the Kalman filtering to be ineffective. The proposed RBF NN method for error correction is more tolerant of potentially substantial fluctuations in the RSS results (which can be classified as noises contained in the data) associated with two consecutive positions of a moving object.

The difficulty in quantifying the impact of indoor wireless signal propagation on localization accuracy has made Neural Network (NN) an excellent technique for quantifying this effect, to reduce the localization error. Radial Basis Function (RBF) NN is preferred over the classic back-propagation (BP) algorithm due to two factors: 1) RBF's training time is short and deterministic; and 2) the RBF algorithm is free from local minimum trap and overtraining (Shareef et al., 2008).

Localization performance in indoor environments can be improved by utilizing a premeasured map of estimated locations base on RSS measurements. In this case, a set of predefined locations is associated with vectors containing estimated locations values determined by the positioning system. These vectors, referred to as location fingerprints, are collected offline and stored in a database followed by the location coordinates. The unknown location can then be estimated online from the current estimated location fingerprint by finding the best match in the database. Matching is based on a distance measure between the current and collected fingerprints.

Radial Basis Function Neural Network is proposed as a solution to the location determination problem. We adopt RBFNNs in a function approximation scheme to map estimated location of the mobile node by the WSN-based positioning fingerprints in the input space to locations in the physical space In the envisioned indoor localization system, data collected offline is used to train the RBFNN. Subsequently, when a mobile device enters a building, its WSN-based location is estimated in a server running a location-based application associated with

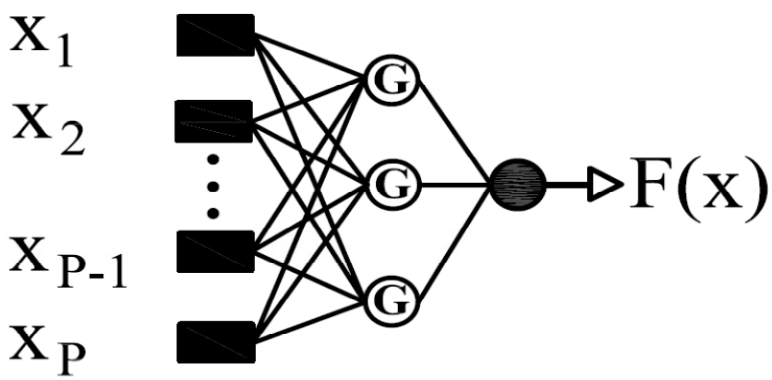
RBFNN, and its actual location will be determined by finding the best match in the trained NN database.

3.4.1 Problem Formulation

The theoretical framework is introduced for localization techniques based on location fingerprints, assuming WSN-based architecture and availability of WSN. Let $\mathbb{D} \subset \mathbb{R}^2$ be a 2-dimensional physical space indicating the area of interest. The predetermined set of locations $\mathcal{R} \subset \mathbb{D}$ can be defined as reference points, where $\mathcal{R} = \{\mathrm{r_i} \in \mathbb{D} | \mathrm{r_i} = (\mathrm{x}_i, \mathrm{y}_i), i = 1, \dots, \mathcal{R}\}$. At each location of $\mathrm{r_i} \in \mathcal{R}$, a mobile tag is used to collect the WSN-based estimated location. Thus, a 2-dimensional input space is formed represented by X. A reference fingerprint $\mathrm{x} \in \mathrm{S}$ is a vector of WSN-based locations collected at locations $\mathrm{r_i}$. The reference points can be placed over a uniform grid to cover the whole area with the preferred resolution. However, the grid is usually non uniform due to building walls, temporary facilities and other objects that limit the area where measurements can be performed. During localization the goal is to obtain an estimate represented as $\hat{\mathrm{r}}$, given a fingerprint x' that is measured at the unknown location.

3.4.2 Error Correction Algorithm Using Radial Basis Function (RBF)

The Radial Basis Function (RBF) Neural Networks consist of neurons which are locally tuned and attractive due to their fast training and simplicity (Fasshauer, 2007). Figure 3-2 shows the basic RBF Neural Networks that consist of three layers: an input layer, hidden layer and output layer. The RBF network with m-dimensional real vector input and real output can be considered as a mapping$F(x): \mathbb{R}^n \rightarrow \mathbb{R}$. We examine a fully connected RBF network to approximate $F(x): X \rightarrow \mathbb{D}$ and use the normalized Gaussian function for neurons in a single hidden layer.



Input X Radial Basis Functions Output F(X)

Figure 3-2: Architecture of a radial basis function network.

The network has two inputs and two outputs.

$$f(x) = \sum_{i=1}^{N} w_i \, \varphi(\| x - c_i \|) \tag{4}$$

where $x \in \mathbb{R}^n$ is the input vector of a sample record, N is the number of hidden neurons, w_i are the weights to the output layer, φ is the basis function and c_i is the center of the i-th basis function. $\| x - c_i \|$ is the Euclidean distance between x and the c_i and w_0 is the bias weight with input $\varphi(\| x - c_0 \|) = 0$. The weights

w_i can be estimated using the matrix methods of linear least squares, because the approximating function is linear in the weights. The Gaussian function and thin-plate-spline function are two popular choices. Usually the Gaussian radial basis function is used, i.e. $\varphi(\| x - c_i \|) = \exp(-\beta \| x - c_i \|^2)$. We can use RBF networks to approximate any continuous function by fitting the values of the function $f(x_i) = b_i,\ i = 1, \ldots, C$ at known points x_i.

In the proposed method, the network has two inputs and two outputs. The initial stage entails the deployment of the wireless sensor network in the actual working environment and the collection of a "calibration" data set containing both the actual position data and the estimated position data resulting from WSN-based positioning algorithm for the known points. Presented with the "calibration" set, RBF NN will be trained to decipher hidden relationships and complex patterns on the positioning errors of the wireless sensor network. Once trained, RBF NN will be used to recall the actual position of a mobile node when presented with a new positioning scenario. In order to achieve high accuracy, the RBF NN will be continuously updated by adding new training cases to the underlying calibration set. A major benefit of a Neural Network model is that prior knowledge of the noise distribution is not required. Noisy location measurements can be used directly to train the network with the actual coordinate locations. The resulting NN model is capable of characterizing the noise and compensating for it to obtain the accurate position. This differs from the Kalman filtering technique, which depends upon the knowledge of noise distribution to enhance localization accuracies (Shareef et al. 2008).

3.5 System Illustration

The system architecture will be further clarified by the following illustrative case. Figure 3-3 shows a node distribution layout for an experiment carried out in an outdoor area at the University of Alberta.

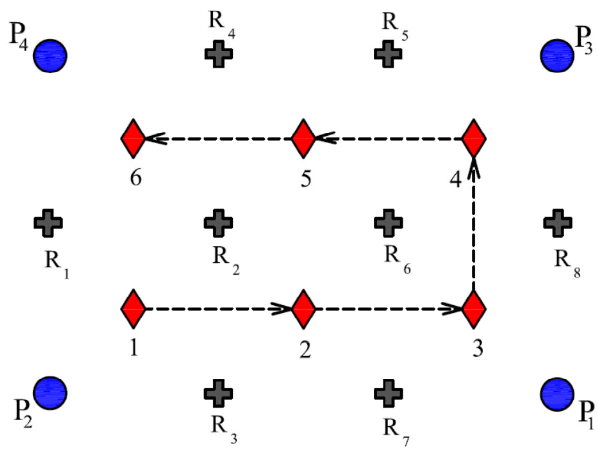


Figure 3-3: Experiment Layout

The grid was 6×4 m in which all marks represent nodes. 4 solid circles (on the corners) were pegs, while 8 crosses provided profile samples. The diamonds acted as tags whose locations were to be determined by the positioning system.

Table 3-1 is a simplified format of profiling data in the positioning database, which shows Received Signal Strengths of tags perceived by the pegs located on the profiling points in the profiling stage. It is noteworthy that the local coordinates of the profiling points were also recorded together with the signal strengths. This information was saved in a database on a central server, which in this case was a laptop.

Table 3-1: Received Signal Strengths perceived by pegs collected from profiling points

Profiling Point ID	Profiling Coordinate		Peg ID			
	X	Y	1	2	3	4
1	0	2	121.82	146.33	114.36	143.05
2	2	2	107.19	135.00	123.93	129.61
3	2	0	121.23	140.87	89.13	120.62
4	2	4	96.51	126.66	118.88	135.09
5	4	4	129.14	110.15	138.60	105.73
6	4	2	121.41	107.20	134.36	116.57
7	4	0	137.63	127.51	122.32	96.15
8	6	2	140.79	118.58	139.90	109.95

After the profiling stage, tags were located at the center of each square, for the sake of localization and error evaluation. In the localization stage, the same data was collected as during the profiling stage, except for the location of the tags that were yet to be determined. Table 3-2 shows the Received Signal Strength of the tracked tags received on the pegs.

Table 3-2: Received Signal Strengths of different tags by pegs

Tag ID	Peg ID			
	1	2	3	4
1	119.26	147.69	95.82	131.04
2	115.97	123.89	119.90	109.28
3	148.68	124.95	132.23	97.23
4	139.65	108.34	157.77	102.72
5	108.38	117.46	124.49	122.60
6	109.13	136.24	117.39	151.21

After the data became available for the tags, the tag locations were calculated for a given number of *k*. First, the Euclidean distance of all tags' RSS were calculated from all profiled points' RSS to find the closest profiling points to the tags. For instance, the Euclidean distance of the Tag #1 with the first profiling point (located at (0, 2)) is calculated as follows:

$$\sqrt{(119.26-121.82)^2+(147.69-146.33)^2+(95.82-114.36)^2+(131.04-143.05)^2} = 22.28$$

In the same way, the Euclidean distances between all of the tags' RSS and the profilings' RSS were calculated (see Table 3-3 for the results).

Table 3-3: Euclidean distances between Profiling Points' RSSI and Tags' RSSI

Profiling Point ID	Tags' Location					
	1	2	3	4	5	6
1	22.28	41.34	59.98	72.61	39.18	18.41
2	33.15	25.10	54.22	60.27	18.93	22.69
3	14.27	37.31	58.41	80.18	44.36	43.61
4	38.83	32.46	65.85	68.96	20.32	22.65
5	63.07	26.92	26.72	22.14	31.12	60.00
6	57.78	23.88	37.91	32.76	20.22	49.82
7	51.61	25.70	15.10	40.88	40.76	62.80
8	60.81	32.32	17.99	21.86	38.07	59.36

Then *k* was selected as 5, meaning five profiled samples with the smallest distance from the tracked tag were selected. Subsequently, the coordinates of the selected samples were averaged according to Eq.2. and Eq.3. to produce the estimated coordinates of the tag. Here, $D_{\max} = 51.61$ is the maximum distance among the best k selected samples and $S_d = 160.14$ is the sum of all those distances. Table 3-4 shows the actual location, the estimated location and the localization error of this experiment. It is noteworthy that the localization error is the Euclidean distance between the estimated and actual locations, which is shown in Figure 3-4.

Table 3-4: Estimated local position of the tags for K=5

Tag ID	Tag Location (m)		
	Actual (x,y)	Estimated (x,y)	Error(m)
1	(1,1)	(1.40,1.50)	0.64
2	(3,1)	(3.48,1.91)	1.03
3	(5,1)	(4.61,1.81)	0.90
4	(5,3)	(4.62,2.30)	0.79
5	(3,3)	(2.80,2.80)	0.28
6	(1,3)	(1.32,2.46)	0.63

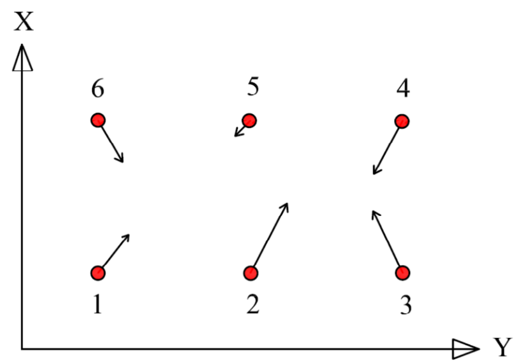


Figure 3-4: Localization error vectors of the tracked tags

In the error calibration phase, if we assume the locations 1, 3, 4, 6 as a set of predefined locations, their associated vectors containing both estimated location values determined by WSN and their actual locations can be used to train the RBF NN. These vectors are collected offline and stored in a database as shown in Table 3-5.

Table 3-5: Training samples of the experiment in RBF NN

Training samples	
Input (Estimated Location)	Output (Actual Location)
(1.40,1.50)	(1,1)
(4.61,1.81)	(5,1)
(4.62,2.30)	(5,3)
(1.32,2.46)	(1,3)

Consequently, when the tags are located on positions 2 and 5, their WSN-based locations will be provided to the RBF NN. Therefore their actual locations will be retrieved by finding the best matches in the trained RBF NN database as illustrated in Table 3-6.

Table 3-6: Expected error calibration of the experiment in RBF NN

Expected Locations	
Input (Estimated Location)	Output (Actual Location)
(3.48,1.91)	(3,1)
(2.80,2.80)	(3,3)

CHAPTER 4: SYSTEM VALIDATION

4.1 Introduction

Construction sites are dynamic environments which inevitably involve the movement of equipments, materials and laborers. To confirm the viability and limitations of the proposed solution and to evaluate the environment variation due to the presence of an obstacle, a prototype WSN-based localization system was assessed in an underground parking lot on the University of Alberta campus, which resembles an indoor area. The indoor experiments and their results are presented in section 4.2. A experimental design to evaluate the sensitivity of localization errors to the changing environmnet is then proposed in section 4.3 to address the problem of continuous changes of the construction environments which affect the accuracy of the location estimation. Additionally, to check the feasibility of a WSN-based positioning system at an actual indoor construction site, the wireless sensors were installed to evaluate the location of the workers inside the tunnel, which is discussed in section 4.4. A dynamic error test using a prototype IntelliSensorNet combining the WSN-based localization scheme and RBF NN based error calibration was performed in an underground parking lot to evaluate the proposed localization system's performance for tracking mobile assets that frequently travel from one location to another, such as construction laborers and material delivery systems. The experiment and the results are then provided in section 4.5.

4.2 Indoor Experiments

The absence of interior finish features in the underground parking lot makes it a reasonably good approximation of a structure being built; the space consists of concrete floor, ceiling and pillars and metal beams to support the loading of the structure. Thus, the car park can mimic the challenges and complex characteristics found on a real construction site with random and continuous movement of vehicles and people. In the data collection phase, the central node was connected via a USB dongle to a laptop, where all the data collected by the network were stored and processed. During the data collection, some of the collected readings were saved in the system profile database, while others were stored and used as tracking data for method verification.

The experiment began by deploying a certain quantity of nodes (10) within the monitored area. Figure 4-1 shows a sample distribution of nodes for the experiment. The grid was 12×8 m (consisting of 24 (2×2 m) squares), in which 10 solid squares (all around the grid) were pegs, while the 25 crosses marked with asterisks provided profiling samples whose pre-defined locations were known. The circles acted as tags whose locations were to be determined. Tags were placed in the centers of the grid squares to compare their exact locations with the estimated ones in order to evaluate the accuracy of the system.

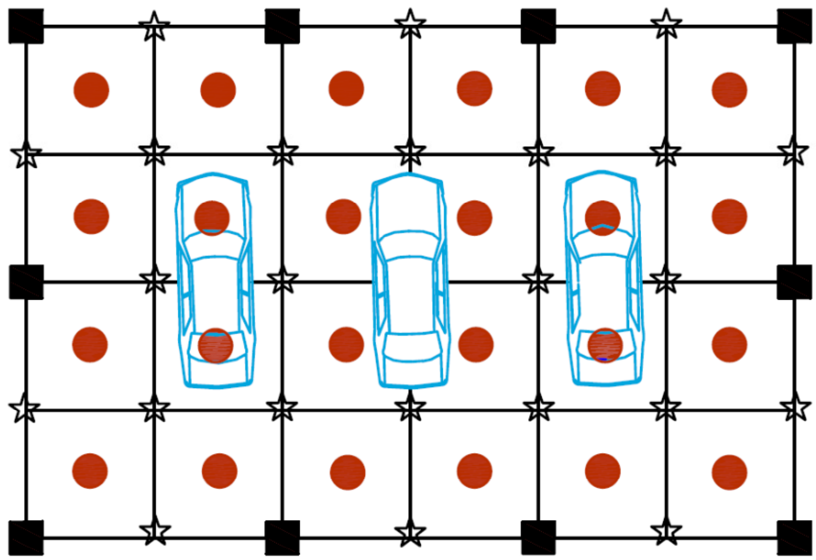


Figure 4-1: Experiment layout

The objective of this test was to check the performance of the WSN-based localization system under a traffic flow-controlled setup including four different cases: without any car, with the car on the right side of the monitored area, with the car in the middle, and with the car on the left. All the profiling points or tag locations, even those obstructed by the car, were considered. In the four "car parking" scenarios, tags were located using the profiling data, which was collected at reference points from the original setup (without any parked car in the grid), in order to identify changes in the environment. The experiments were carried out at power level 2 with 5 kps transmission rate using channel 0 of the prototyped WSN system.

In this experiment, the localization error magnitude is the Euclidean distance between the estimated and actual locations of a point. The average magnitude of error given different k (number of best-matched samples) of the locations of all the points in each case were investigated in order to find the best k (Figure 4-2). A k of 6 was selected as it resulted in the smallest average localization error. Once an appropriate k was decided and applied in all subsequent experiments, we turned our attention to the question of how an obstacle, which was a medium sized automobile in this case, could degrade the localization accuracy. The inclusion of an automobile (or any other movable metallic facilities) is used to mock the situations of imposing metallic objects commonly encountered in construction sites.

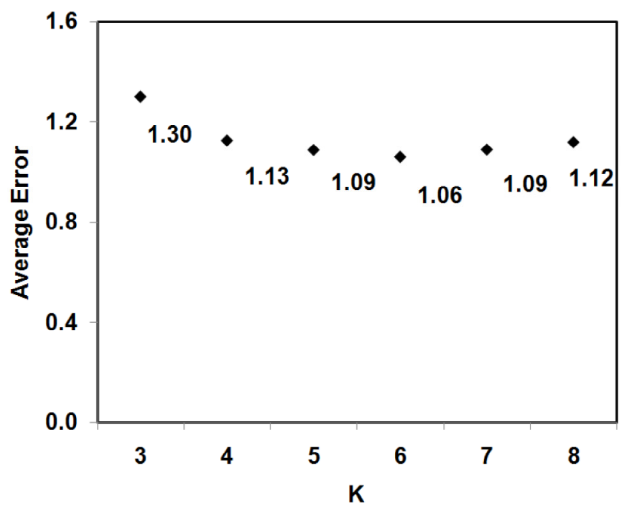


Figure 4-2: Average localization errors for different k (no car)

We try to determine how the localization has changed qualitatively and quantitatively. To this end, we use localization error vectors to express the localization error. We note that such error vectors are plotted in the case when no obstacle is present in order to serve as a baseline case. The goal is to understand if the inclusion of a metallic object the size of a car has a tendency to distort the localization in certain areas (relevant to the car) and in what ways and by much magnitude. The results are plotted in Figure 4-2, confirming our expectation to see more discrepancies close to the car, albeit not exhibiting any systematic patterns. In Figure 4-3, for visual clarity, arrows are scaled to half, and the tags whose location error vectors have been changed considerably either in error magnitude (more than 1m) or in terms of angle (more than 90^{o}) are marked, respectively, by a solid circle and an outer ring (some points may exhibit both features). Noticeable differences in localization error magnitude and angle are shown with different icons.

The results from the experiments (Figure 4-4) indicate that the system is able to precisely locate all the tags with the accuracy between roughly 0.8 meters and 1.9 meters (with the approximate standard deviation of 1 meter for the case of the car in the middle of the grid and 0.5 meter for the other three). It also demonstrates that a metallic object can change the environment and generally increase the localization error. The desired accuracy as needed to locate mobile laborers in construction sites is 1.5 to 4 meters (Khoury and Kamat 2009, Torrent and Caldas 2009). Therefore, for the prototype system, a localization accuracy of less than 2 meters is acceptable and the localization error we observed in the presence of a simple car object was marginally around the original localization error determined in the absence of the obstacle. The “robust” nature of this localization technique thus implies its potential for deployment in real dynamic construction sites which are by nature prone to the introduction of permanent as well as of temporary metallic objects. It is noteworthy that the limits of the positioning accuracy can be further enhanced by applying a finer grid setup in RSSI profiling or applying real-time error correction algorithms. The second alternative is more cost effective and appealing to construction applications and will be addressed in the following chapter.

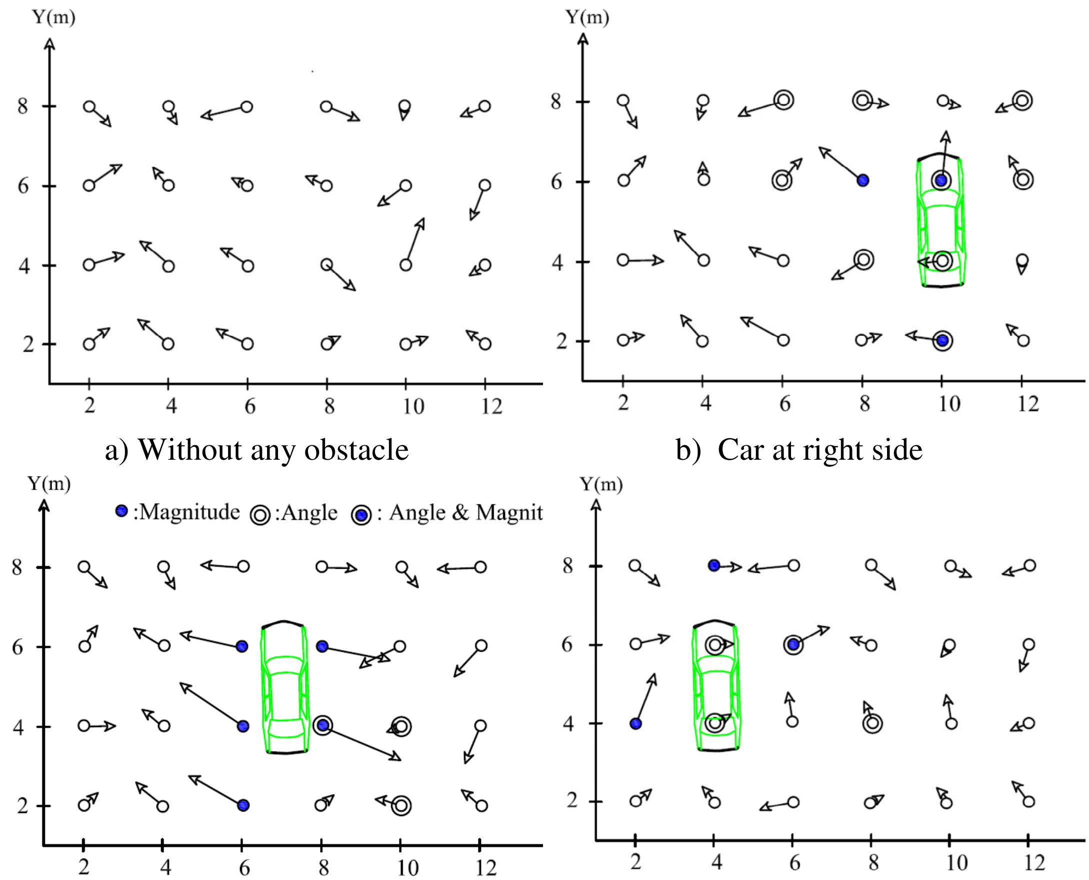


Figure 4-3: Localization error vector for different position of the car in the grid for K=6.

Additionally, RSS values might not be available at some locations all the time. Since the positioning reliability and accuracy is directly affected by the quality of wireless signal sample data collected at target locations, we managed to collect an adequate quantity of RSS samples at each target location. In our experiments, we observed that the cases of inaccessible points were rare. In such cases, the inaccessibility at a given access point could also occur on adjacent profiling points. Thus, the proposed methodology employed a statistical learning approach (RBF NN) in order to tolerate a certain amount of noise (such as unavailable RSS signals) in fixing a tag's position.

4.2.1 Localization Error Enhancement Utilizing Complete and Partially Re-profiling

The construction environment changes dynamically, which would mean that localization results might no longer be accurate in the (continuously) modified environment. To address this problem, two approaches could be tried out: (a) a systematic analytical characterization of the localization distortions created by modifications, and/or, (b) a systematic approach to perform re-profiling, on an as-needed basis, to create more accurate localization results.

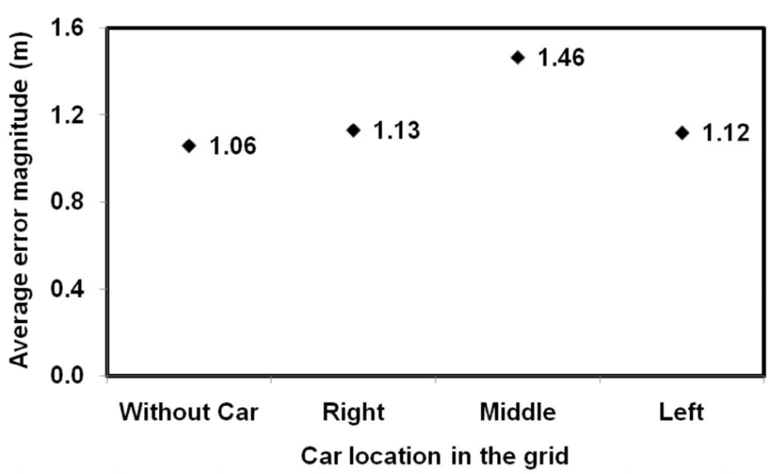


Figure 4-4: Average error magnitude for different car location in the grid for K=6

We note that option (a), apart from being a demanding task that entails some form of wireless propagation characteristic modeling, would still not be sufficient because we would still have to, first, identify that the environment has indeed changed, before applying any analytical/computational localization correction model. If this requires re-measuring signal strengths then it turns effectively into a form of option (b). Hence (b) is an unavoidable step, even if it does not imply the re-measuring/re-sampling of all the points in the space of interest.

Re-profiling has the merit of cancelling the effects of changes in the environment. We conducted the following experiment: in each test bed, each time an automobile was introduced at any of the three locations, new reference point measurements were collected and used to localize the tags. Figure 4-4 shows the localization in the modified environments using the previous profiling data, while Figure 4-5 shows the localization accuracy using the new profiling data. Both result in similar accuracy (Figure 4-4). The standard deviations are 0.47m for car on right, 0.71m for car in the middle and 0.66m for car on the left side of the monitored area.

Note that the effort for re-profiling an entire area is quite demanding. To this end, we would like to "stage" the re-profiling task in two steps: (i) to understand what observations could trigger the re-profiling so only necessary re-profiling is performed and (ii) to determine a possible small subset of locations that, upon being re-profiled, improved localization can be obtained. In other words, we imply a semi-automatic process whereby task (i) is performed automatically and then a set of points to-be-re-profiled is identified (again automatically) and provided to either human operators to conduct the task (ii) or, even, without an operator in the loop, selecting points to re-profile are given and acted upon.

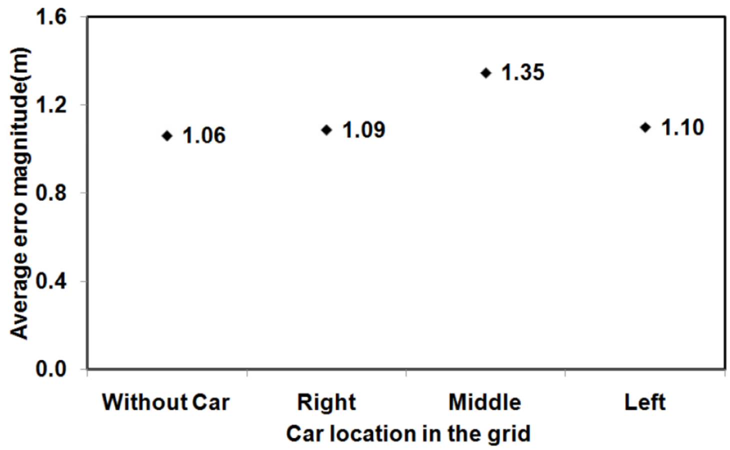


Figure 4-5: Average error magnitude utilizing new profiling data for different car location in the grid for K=6

If the localization pegs are part of a fixed (or rarely changing) infrastructure, then preference could be given to using them as profile points as well (we will explore this idea in the following experiment), with the advantage being that the re-profiling for those particular points can be performed without on-site human intervention (such as surveying and re-profiling points by walking in a construction area).

To address point (i), as previously seen, a significant increase of magnitude and angle change in localization errors is an indication of a new object being introduced to the environment. In this case, if it goes beyond a certain threshold (in our experiments the thresholds were set 1 meter and 90º), re-profiling can be indicated as necessary. To perform task (ii) in an automatic way, we treat the pegs as profiled points (with their exact locations known, so they can inform on precise localization error figures). Note the research prototype system of WSN does not have the ability to interchange the roles of a peg and a tag on the fly. It is feasible we place a tag very close to the peg and measure the signal strengths that the other pegs receive from this tag so as to correlate those strengths with the location of the peg. In our experiments We identified the one peg (representative profiled point) which showed the most significant localization error (according to criterion (i)) when a car object was introduced. This operation is captured in Figure 4-6. Note the location of the so called "most distorted" localization is based on *k* measurements which could fall on any positions throughout the area of interest. At that point, we dispatched a human operator to re-profile the *k* points that had contributed to this most distorted localized peg. We also compared the results of this partial re-profiling to the results of a complete re-profiling.

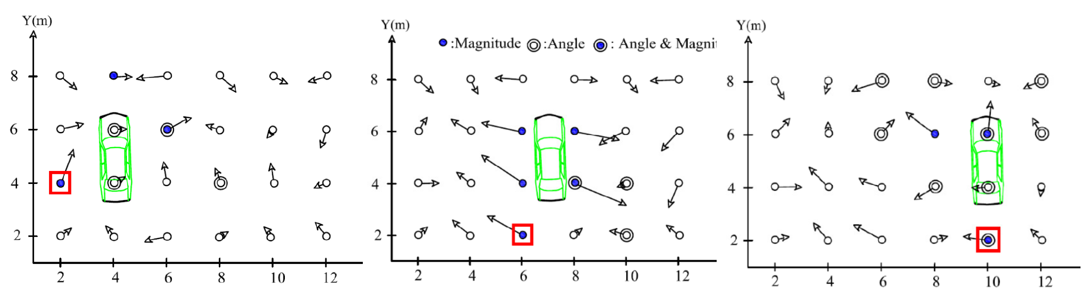


Figure 4-6: Selected tags whose profiling points need to be re-profiled

Table 4-1 shows that localization average error magnitude utilizing a limited quantity of partially re-profiled reference points (6), which resulted in nearly the same improvement on localization errors as a complete re-profiling undertaking.

These empirical results suggest that the proposed approach can be used to monitor construction resources on a typical dynamic job site with changing locations of metallic objects. With less effort in performing partially re-profiling, the effect of imposing temporary metallic objects on the job sites can be controlled and the accuracy can be maintained to a certain degree.

Table 4-1: Localization average error magnitude using a) original profiling samples in absence of obstacle b) partially and complete re-profiled reference points

Car position	Using Original reference points	Using re-profiled reference points	
		Partial(6)	Complete(25)
Car at Right	1.13	1.08	1.09
Car at Left	1.12	1.09	1.1
Car at Middle	1.46	1.4	1.35
Average	1.24	1.19	1.18

4.3. Validation of the WSN-based Localization System for Labour Tracking in the Tunnel

The inherent nature of underground tunnels and the working environment for the workers present challenges in addressing the safety issue in the tunnel construction. Tunnel construction generally faces high risks and a wide range of safety hazards to workers, including toxic gas emission, fire, mud slides, and active faults in geological structure, water breakage, roof collapses.. All of these safety hazards could lead to catastrophic incidents such as the loss of human lives as trapped workers. Lack of real time positional and environmental information inside the tunnel hinders the rescuers' ability to react promptly and accurately in the event of a disaster. Companies know only who is in the tunnel at a given time, but have little knowledge of each individual's location.

Current monitoring systems in underground tunnels employ wires to connect sensors to the processing server and require a great amount of wire deployment, which is complex and difficult due to poor working conditions and high maintenance costs. Moreover, the wired communication method reduces the scalability of the system; as the tunnel extends, more sensors and wires need to be deployed. In addition, wire-based systems are expensive because of the initial cost associated with laying out the wire and the maintenance costs associated with the system. The utilization of the Wireless Sensor Network (WSN) system being proposed to monitor the locations of labourers in the underground environment benefits from the characteristics of WSN in terms of wireless communication and flexible deployment. Moreover, the scalability of system construction can be realized by the multi-hop wireless data communication scheme of WSN. A multi-hop network is dynamically self-organized and self configured, with the nodes in the network automatically establishing and maintaining mesh connectivity among themselves. In other words, a wireless multi-hop network is a collection of wireless nodes that dynamically form a temporary network without an infrastructure. This feature brings many advantages to multi-hop networks such as low upfront cost, easy network maintenance, robustness, and reliable service coverage.

4.3.1. Field Experiment in the Tunnel Project

Tunnels being constructed in the underground space are long, narrow and closed environments that are generally 2 to 6 meters wide and several hundred meters to several kilometers long. Experiments were conducted at a shield tunnel site being constructed by the City of Edmonton in Edmonton, Canada (Figure 4-7). The tunneling project, in which the proposed system was deployed, was a 2 meter in diameter underground sewer tunnel project using a Tunnel Boring Machine (TBM) excavation method.

Figure 4-7: Positioning system deployment on tunnel construction site

The objective of the study was to check the feasibility of the proposed WSN-based positioning system at an actual “indoor” construction site. In this case, the wireless sensors were used to evaluate the location of the workers inside the tunnel. A tag was attached to a worker’s safety helmet so as to reduce the body's interference with the Radio Signal Strength, as shown in Figure 4-7. Nineteen pegs were installed every 8 meters along the tunnel ceiling with the same antenna directions, using fabric hook-and-loop fasteners. 120 meters of the tunnel was surveyed by profiling every two meters. Tracked tags were assumed to be located every 2 meters interpolated between the reference points. A laptop computer was used as the server. The computer received, processed and stored the signal information from the tag through the wireless network.

The environmental conditions of the tunnel construction site were generally harsh in comparison with laboratory conditions: for instance, lower temperature, dampness and many obstacles to signal processing. Tunneling construction also involved disposal of dirt and material handling processes which included the transportation of spoil, materials and workers from the tunnel face to the shaft and vice versa using trains. This may interfere with WSN sensor operations and the system performance.

The results showed that the WSN based indoor positioning system could locate the worker with a average location error of 1.88 meters and standard deviation of 1.40 meters for k=3 as shown in Figure 4-8, thus proving the utility of the system for tracking the approximate locations of laborers on practical tunnel construction sites. It is found that the system delivers consistently a localization accuracy of 1-2 meters. The software automatically dispatches worker positioning information to the managers and ensures that immediate action can be taken if a worker is identified to be near any hazardous locations in the tunnel.

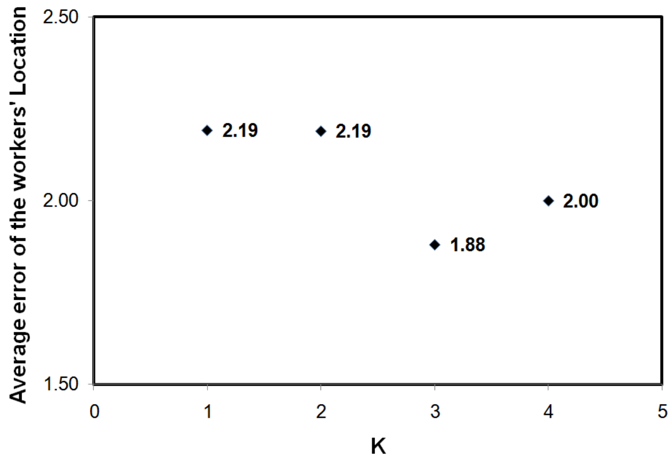


Figure 4-8: Average errors of the worker locations

An integrated labour position monitoring system with graphic user interface can be installed at a construction manager's office or other sites where the monitoring of labour locations is crucial to the company's overall operation. The system is a potential replacement for conventional labour safety monitoring and job costing systems. In addition, the system could also be used for monitoring of the locations of other construction resources such as vehicles and materials. This system is capable to operate in the event of an emergency, after power is shut off inside the tunnel. In the event of a disaster, the last known location of the miners will be mapped, even if hardware of the wireless sensor network has partially collapsed inside the tunnel.

To guarantee a safer environment for tunneling crews, dust, oxygen, water level and temperature of the tunnel can also be monitored through relatively simple physical/chemical sensors. For instance, the underground tunnel has a problem of air circulation. So it is necessary to inspect the amount of poisonous gas to prevent accidents. The flexibility to attach gas sensors to the wireless sensor network allows for detecting toxic gasses at certain locations such as Carbon monoxide, Carbon dioxide, Methane ,and Sulphur dioxide and subsequently transmitting that information in real time to a monitoring station on the surface. This would create the critical visibility of the underground tunnel environment for safety management.

4.4 Implementation of WSN-Based System Integrated with RBF NN

The tunnel site provided a “linear” test bed due to the unique design of the tunnel. To further examine the feasibility and limitations of our system and to evaluate the performance of our system in a “non-linear” indoor environment, a dynamic error test using a prototype IntelliSensorNet system was performed in an underground parking lot at the University of Alberta. Construction sites are dynamic environments, which are exposed to movement of equipment, materials and laborers. Therefore, we intended to evaluate the proposed localization system’s performance for tracking mobile resources that frequently travel from one location to another, such as human and material delivery systems; e.g., a moving laborer or an indoor crane. The objective of the dynamic error test was to evaluate the difference between the true traveling path and the estimated path to find the level of accuracy of the system. An underground parking lot was selected for this purpose because it can simulate the challenges and complex characteristics posed by the construction environment. The building is built with concrete and has steel access doors, metallic cages, concrete columns and power cables located near the test area that may cause interference with the WSN communication system. In addition, heavy pedestrian and vehicle traffic in this area can cause signal communication errors because human bodies can absorb the signal, while metallic obstacles tend to reflect the signal.

The proposed WSN based positioning method provides an "ad hoc" solution for a particular application purpose and application setting. The experiments were designed to mimic the movement of a laborer on a building construction site who performs repetitive wall form working activities. Note the laborer's movement generally follows certain patterns instead of being totally random). Such patterns make it possible to carefully design and deploy a layout of pegs, which ensures the radio signals are available at the majority of peg sensor locations.

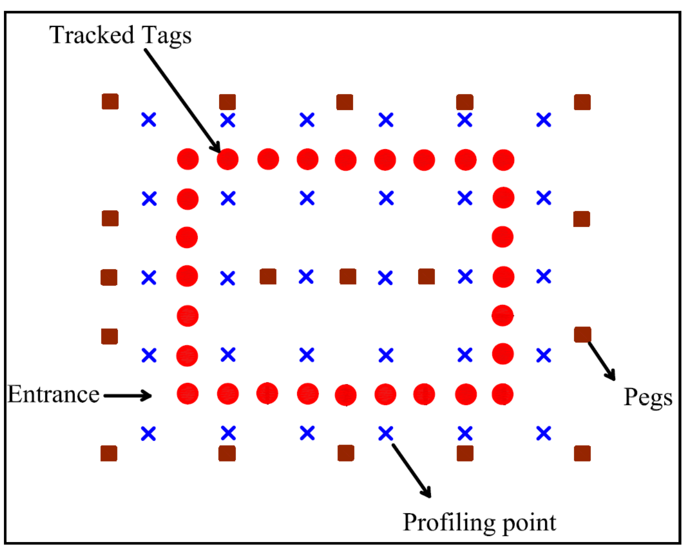


Figure 4-9: Tag placement in the parking lot

The experiment was conducted by deploying a number of nodes within the monitored area. Figure 4-9 shows a sample distribution of nodes for the experiment and describes the test area layout with 18 receivers at fixed locations (marked as solid squares) and a remote node (marked as solid circle) which is set to move along a square-shaped path of 8×6 meters. Profile samples are marked as × every 2 meters whose pre-defined local locations are known. A path was determined and a tag was carried by a person who walked along the path at a speed that is lower than normal walking. During the data collection process, some of the collected readings were saved in a profile database of the IntelliSensorNet, while others were stored as tracking data. The experiments were carried out at power level 2 with a 5 kps transmission rate using channel 0.

The position of the tag was measured every 1 meter. The localization error vector is assumed to be the Euclidean vector connecting the actual and estimated location in the Euclidean space (Figure 4-8). As such, the localization error magnitude is the Euclidean distance between the two points. The average errors' magnitudes for different k (the quantity of best-matched samples) were investigated in order to find the best k (Figure 4-10). k=7 was selected as it results in the smallest average localization error. The standard deviation of the errors was determined to be from 0.42 to 0.76 meters, demonstrating that the greater the number of k, the smaller the standard deviation.

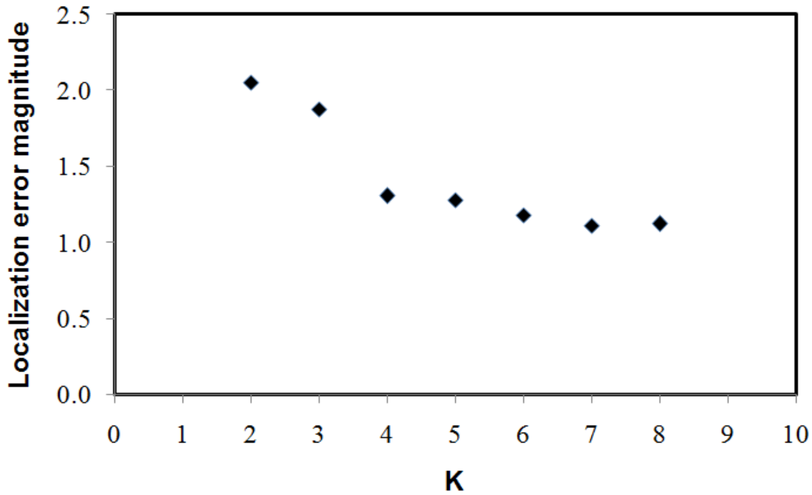


Figure 4-10: Average localization errors for different *k*

The results from the experiment (Figure 4-10) indicate that the system is able to locate the tracked tag with an accuracy of 1.11 meters only by using WSN-based positioning architecture. Considering the application requirements, a localization of less than 2 meters is acceptable to locate mobile resources in construction sites. Therefore, these findings may attract application interests and provide motivation for possible deployment in construction, because an average error of 1 meter could provide a sufficient level of accuracy for many large-scale construction sites.

Figure 4-11 shows the true path and the estimated path resulting from the WSN positioning system. The observed path agrees closely with the true path with an acceptable level of accuracy. However, the introduction of significantly bigger (or many) obstacles is bound to downgrade the localization performance. In an extreme situation, the wireless signals used can be drastically attenuated.

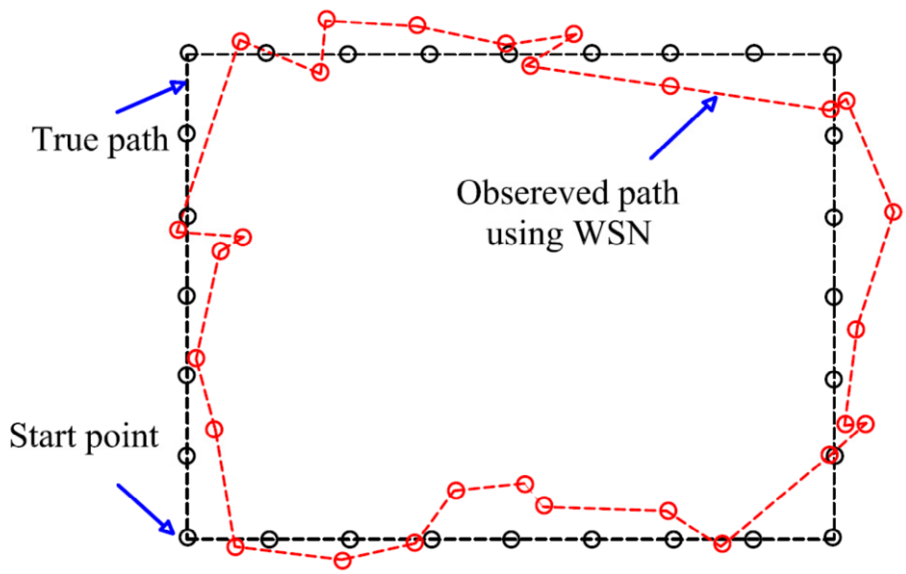


Figure 4-11 Observed points versus true points on traveling path before applying RBF NN

Therefore, for many applications in the construction site, there is a need for a robust positioning system with higher localization accuracy. In the following section, an error enhancement approach utilizing RBF NN is described and the results are discussed.

In the calibration phase, we collected samples of estimated locations by WSN every 2 meters on the desired path. The locations are measured in two dimensional coordinates and are stored in a database called "Location Map". Later, this Location Map was used to provide training samples for the RBF NN model. The training phase was used to train different Neural Networks and analyze their comparative performance. The Radio Map generated in the calibration phase was used to train RBF NN. After the training phase, additional data collected from the environment were used to test the performances of the trained RBF NN model.

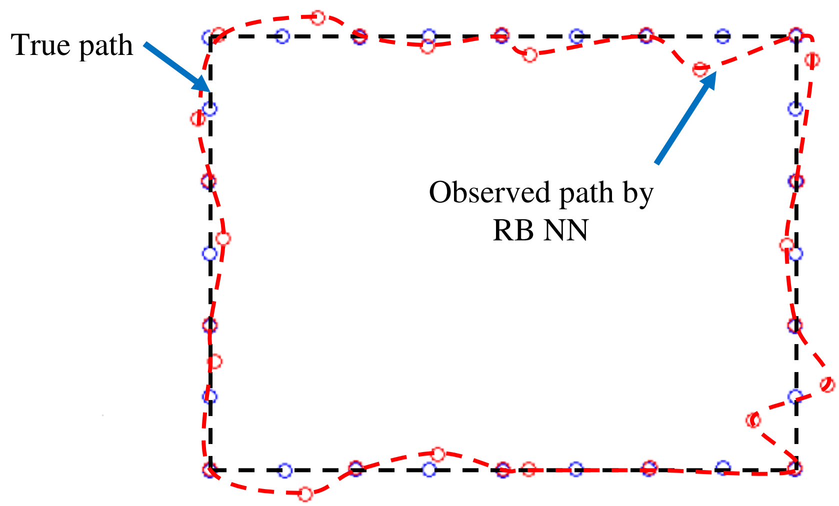


Figure 4-12 Observed points versus true points on traveling path after applying RBF NN

In the estimation phase, the WSN-based estimated location captured on the mobile device was presented to the input layer of RBF NN model. Thus, RBF NN was used to recall the actual position of the mobile node when presented with estimated positions of the rest of the points on the path. Results are presented as estimation errors in terms of meters. We employed Euclidean distances between estimated and actual locations to represent errors. The results demonstrated that the average localization error and the standard deviation on the testing data is reduced from 1.10 meters and 0.92 meters to 0.57 meters and 0.55 meters, respectively, for 14 positions (See Figure 4-12). The accuracy enhancement resulting from RBF NN modeling for the proposed localization technique in a dynamic environment thus implies its potential for deployment in real dynamic construction sites.

CHAPTER 5: IMPACT OF NODE PLACEMENT AND PROFILE POINT SELECTION ON INDOOR LOCALIZATION

The proposed WSN-based positioning system can easily be applied to in-building localization using inexpensive devices and can provide an average localization error well below 2 meters. We previously noted that the received signal strength (RSS) is the simplest form of information that can be reasonably extracted from real time measurements of WSN. This is because RSS measurements do not require specialized additional hardware, as they are normally available from most RF transceivers. However, the disadvantage of RSS lies in its poor and irregular correlation with distance resulting from the multi-path effect, which is typically quite serious inside a building. In the proposed WSN-based localization method, location fingerprinting was utilized. In this method, the received signals of the tags are compared against a pre-collected set of samples from known reference points - a process called profiling. Profiling can help to decrease the impact of the environment on the transformation of the RF signals into distances. For this purpose, it seems that we would need to measure a large number of profiled points to offset the imprecise nature of the RF measurements. Therefore, it is important to determine the smallest number of reference points that are sufficient for an acceptable positioning accuracy in order to reduce the time consuming and labour intensive task of profiling. In addition, whenever the environment changes significantly, e.g., when a big obstacle is introduced to the environment, re-profiling (re-measurement of the received signal of the tags from profiled points) would be necessary. Therefore, the smaller the number of required profiling points, the less effort in reprofiling and model updating.

5.1 Effect of Reference Points

In this section, we explore the effect of the number of reference points and their arrangement on localization errors. For this purpose, we removed reference points from the parking lot database in a way such that the density of reference points remained roughly the same across the grid. Figure 5-1(a) shows the layout of reference points after removing 10 points. The resulting setup consists of measurements from 20 reference points. By further removing points in the same fashion, i.e., one at a time, we achieve the new layouts with 12 profiled points (see Figure 5-1(b) and 5-1(c)).

The average error for the WSN-based positioning system with all the initial 30 reference points was 1.11 meters, but we could remove points in a regular fashion and end up with 12 points while the error distance was still less than 2 meters. The localization errors of the system are as follows respectively: 1.16m with 20 profiling points in 5-1(a), 1.36 m with 19 profiling points in 5-1(b) and 1.40 m with 12 profiling points in 5-1(c). This indicates that it is possible to have a less complex deployment of reference points without degrading the performance significantly. Overall, we have observed that the more the reference points the better the localization (Figure 5-2). Yet, the number of reference points alone is not sufficient, as their placement matters as well (see for example the case of 5-1(c) vs. 5-1(d). In both layouts, 12 profiling points contributed to the location estimation problem. However, the case of 5-1(c) resulted in 1.40 m of localization accuracy, hence, the localization error for the case layout in 5-1(d) is 3.09 m).

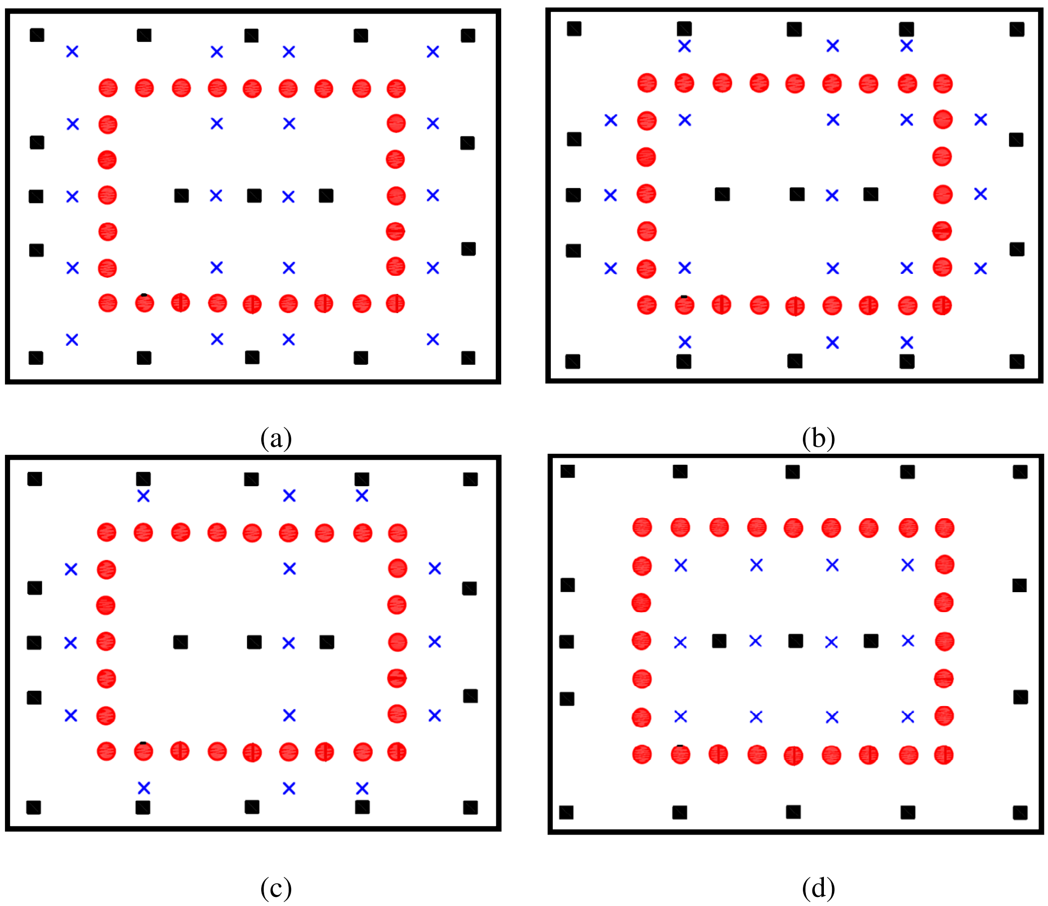


Figure 5-1: Layouts of profiled placements: (a) 20 profiled points, (b) 19 profiled points, (c) 12 profiled points and (d) 12 profiled points

The localization error for Figure 5-1(d) demonstrates that limiting the localization to a subset of reference points to track the mobile nodes could result in losing information essential to localization, i.e., the adjacent reference points are also important. This is because the final accuracy of estimation substantially depends on the information collected from distant reference points.

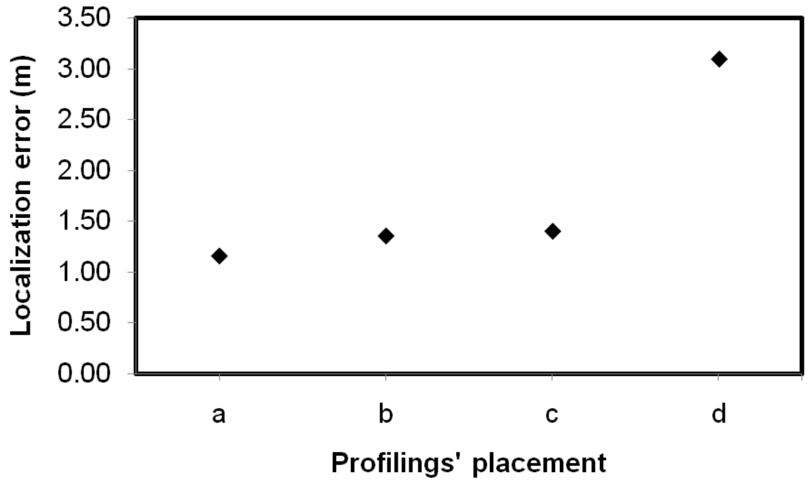
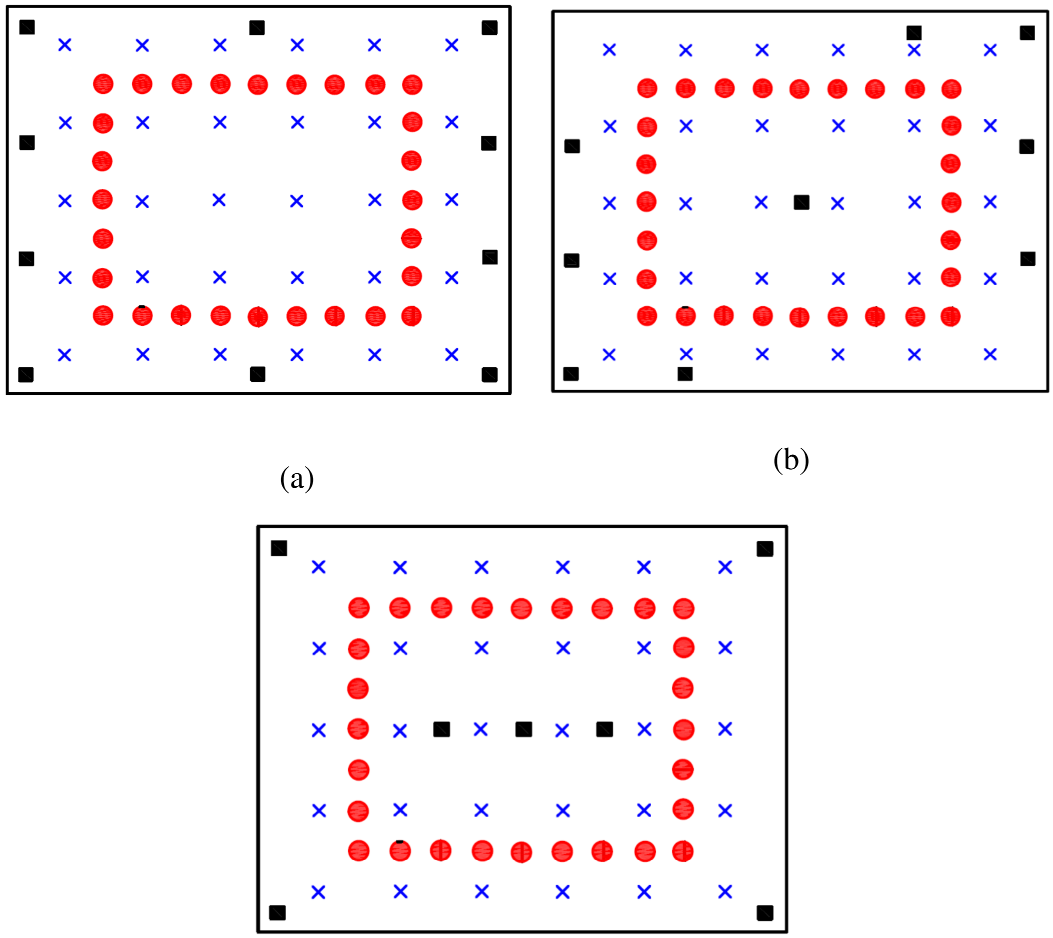


Figure 5-2: Localization error for different layout of reference points

5.2 Effect of Peg Placement

In this part of the study, we examine the impact of the number and placement of the fixed nodes called pegs on localization. In essence, this study is motivated by cost considerations. In the proposed WSN-based system, the decision about the number of pegs is flexible and they can be used as needed without any restrictions on numbers. However, the placement of the pegs might affect the location estimation. For instance, we may not need 18 pegs (see Figure 4-9) for a 10×8 grid to keep the error distance below 2 meters. Thus we conducted another experiment to obtain an arrangement with fewer pegs that could still provide a localization error less than 2 meters. Figure 5-3 shows two such layouts with 10 and 9 pegs with the corresponding average localization error 1.64 meters and 1.89 meters respectively. As we can see, in Figure 5-3(a) and 5-3(b), it is possible to eliminate a large number of pegs (here almost half of the pegs) and still maintain error distance well below 2meters.



(a) (b)

(c)

Figure 5-3: Layouts of peg placements: (a) 10 pegs , (b) 9 pegs and (c) 7 pegs

However, it is found that removing a large number of the pegs from the surrounding area may not be a good idea and would result in higher localization error, for instance, 2.23 meters for only 7 pegs in Figure 5-3(c)). Generally, it is noteworthy that the WSN-based positioning system is relatively much less sensitive to the peg layout, compared to the impact that the layout and the quantity of reference points could have.

Therefore, peg placement is not as critical of an issue as the density of reference points in the area. This is a promising finding, as the placement of pegs is likely to be constrained or even dictated by external factors, e.g., placement of walls and obstacles etc. Therefore, it can be concluded that a smaller set of reference points or a smaller set of fixed pegs can provide good localization, in particular if their layout has been carefully designed. Based on lab experiments, this holds principally valid in terms of the layout and quantity of reference points. In fact, for a choice between having more reference points or more pegs, the answer appears to be in favor of more reference points. This optimization solution may guide real-life deployments of pegs and the ways of collecting reference points (profiling points) so as to minimize the system's complexity or cost while attaining the required accuracy of localization.

CHAPTER 6: CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusion

The construction industry is currently willing to introduce new technologies in order to reduce project time and cost, and improve safety, productivity and performance (Aziz et al., 2004). Automated tracking of project related resource entities in construction sites (e.g. personnel, equipment, and materials) is necessary for main construction management functions such as productivity monitoring, progress measurements, locating resources, and safety management. Effective management of construction resources is critical to project success. Completion of project tasks on schedule, safely, and within the planned budget needs a coordinated planning effort that allocates adequate availability of project resources (Teizer, 2008). Thus, successful deliveries of construction projects are often determined by the level of awareness of resource status and tracking and control of project performances.

Research studies show that supervisors spend 30% to 50% of their time manually collecting data to manage resources (Jang, 2007). In terms of cost savings, inefficient manual handling operations associated with field data collection in current tracking systems present urgent issues to address as the size and the complexity of construction projects increase. However, advanced methodologies that would increase the efficiency of material tracking in construction have not been developed since there has been a lack of interdisciplinary research activities among different areas of expertise resulting in inefficient use of emerging technologies. In addition, current safety practices are also not sufficient in preventing worker fatalities or injuries on a daily basis when they are in too close proximity to heavy equipment or material loads. Based on this motivation, the proposed research examines a hypothesis that the integrated and practical resource management systems will have the potential to improve the productivity and safety of project performance. The research approach is intended to bridge the gap between manual and automated construction resource management.

To this aim, the presented study introduces a new framework called IntelliSensorNet for automating the identification and localization of construction resources in industrial projects. In this approach, a methodology associated with Wireless Sensor Networks (WSN) was used to facilitate an indoor data collection process. The localization approach utilizes a database of signal strength readings from tags located at known positions within the monitored area which were obtained during a profiling phase. Subsequently, a best matched set of profile points was selected to determine the location of the closest reference points to a tracked tag emitting an RF signal from an unknown place. The average coordinates of those points will be an approximate location of the tracked sender. A error calibration approach based on a Radial Basis Function Neural Network was then proposedto reduce the localization errors, and the experimental results indicated potentially significant performance improvement in localization with only limited training data. An indoor experiment was designed and conducted in order to assess the feasibility of this automated methodology in a realistic construction scenario. The localization approach resulted in good estimated locations that could facilitate the efficient localization of the tagged components. Employing a WSN based positioning system as the infrastructure coupled with RBF NN as an error filter construction resource positioning and tracking is a prudent choice due to its low cost and pervasive coverage. In comparison with the other technologies used for resource tracking in indoor or partially covered construction environments, site resources and assets can be cost-effectively located on large industrial or building projects utilizing the proposed system.

6.2 Future Direction

One of our goals for the future is to investigate the placement of the pegs in the monitored area in order to identify a peg layout design that features a smaller set of fixed points (pegs) while still resulting in good localization performance in a particular experimental setting. Moreover, the method being proposed will be refined into a self-adaptive, self-calibrating, real-time positioning solution based on frequent, dynamic RSS re-profiling. We observed from the testing patterns that the changes in the RSS map are insignificant with the introduced one "car" obstruction; however, the proposed methodology will remain feasible and computationally efficient for re-profiling and recalibrating the positioning solution on a preset time frequency. As such, the added profiling points in the testing area can be removed; instead, each peg node fixed on a known location can be taken as a profiling reference point. The RSS between one peg node and other pegs in the system will be collected and mapped onto the location coordinates of the peg from time to time. This helps address the dynamic working environment changes on a practical construction site.

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APPENDIX A. WSN_BASED POSITIONING ALGORITHM IN C++

```
#include <cstdlib>
#include <iostream>
#include <stdio.h>
#include <conio.h>
#include <string.h>
#include <math.h>

using namespace std;

`
struct signal{
        int id;
        double strength;
        int count;
};

struct position{
        double x,y;
        int signalcount;
        signal s[sensorarray];
        double D[cornerarray];
        int sortedD[cornerarray];
        int Dcount;
};

position corner[cornerarray];
int cornercount = 0;

position tag[tagarray];
int tagcount = 0;



void calcXY(){
     for(int l = 0; l < tagcount; l++){
         double SSumX = 0;
         double SSumY = 0;
         double Sd = 0;
         double Dmax = tag[l].D[tag[l].sortedD[0]];
         for(int i = 0; i < K; i++){
               Sd += tag[l].D[tag[l].sortedD[i]];
               Dmax = max(Dmax, tag[l].D[tag[l].sortedD[i]]);
         }
         for(int i = 0; i < K; i++){
               SSumX  +=  corner[tag[l].sortedD[i]].x  *  (Dmax  -
tag[l].D[tag[l].sortedD[i]]);
               SSumY  +=  corner[tag[l].sortedD[i]].y  *  (Dmax  -
tag[l].D[tag[l].sortedD[i]]);
         }
```

```
        tag[l].x = SSumX / ((K * Dmax) - Sd);
        tag[l].y = SSumY / ((K * Dmax) - Sd);
    }
}

void sort(){
    for(int l = 0; l < tagcount; l++){
        for(int i = 0; i < tag[l].Dcount -1; i++){
            for(int j = tag[l].Dcount -1; j > i; j--){
                if(tag[l].D[tag[l].sortedD[j]]                    <
tag[l].D[tag[l].sortedD[j-1]]]){
                    int tmp = tag[l].sortedD[j-1];
                    tag[l].sortedD[j-1] = tag[l].sortedD[j];
                    tag[l].sortedD[j] = tmp;
                }
            }
        }
    }
}

int findbyxy(double x, double y, position *p, int pcount){
    for(int i = 0; i < pcount; i++){
            if(p[i].x == x && p[i].y == y){
                    return i;
            }
    }
    return -1;
}

int findbyid(int id, signal *s, int scount){
    for(int i = 0; i < scount; i++){
            if(s[i].id == id){
                    return i;
            }
    }
    return -1;
}

void calcD(){
    for(int l = 0; l < tagcount; l++){
        tag[l].Dcount = cornercount;
        for(int i=0;i< tag[l].Dcount; i++)
                tag[l].sortedD[i] = i;
        for(int i = 0; i < tag[l].Dcount; i++){
                tag[l].D[i] = 0;
                for(int j = 0; j < corner[i].signalcount; j++){
                        int            signalindex            =
findbyid(corner[i].s[j].id, tag[l].s, tag[l].signalcount);
                        if(signalindex > -1){
                                tag[l].D[i]            +=
pow(corner[i].s[j].strength - tag[l].s[signalindex].strength, 2);
                        }
                }
                tag[l].D[i] = pow(tag[l].D[i], 0.5);
        }
    }
```

```
}

void loadcornerdata(){
    FILE *fp;
    char line[1024];
    int index = 0;
    fp=fopen(CornerFile, "r");
    while(fgets (line, sizeof line, fp) != NULL){
        int len;
        char *p = line;
        sscanf(p,          "%le%le%*d%n",          &corner[index].x,
&corner[index].y, &len);
        p += len;

        int sindex = 0;
        while(sscanf(p,   "%d%le%n",   &corner[index].s[sindex].id,
&corner[index].s[sindex].strength, &len) == 2){
                        corner[index].s[sindex].count = 1;
                        sindex++;
                        p += len;
        }
        corner[index].signalcount = sindex;
        int      cornerindex      =      findbyxy(corner[index].x,
corner[index].y, corner, index);
        if(cornerindex > -1){
                       for(int      i      =      0;      i      <
corner[index].signalcount; i++){
                       int                signalindex                =
findbyid(corner[index].s[i].id,            corner[cornerindex].s,
corner[cornerindex].signalcount);
                       if(signalindex > -1){

corner[cornerindex].s[signalindex].strength                     +=
corner[index].s[i].strength;

corner[cornerindex].s[signalindex].count++;
                       }

               }
        }else{
               index++;
        }
    }
    cornercount = index;
    for(int i = 0; i < cornercount; i++){
            for(int j = 0; j < corner[i].signalcount; j++){
                    if(corner[i].s[j].count > 0){
                                          corner[i].s[j].strength
/= corner[i].s[j].count;
                                          corner[i].s[j].count    =
1;
                    }
            }
    }
    fclose(fp);
}
```

```
void loadtagdata(){
    FILE *fp;
    char line[1024];
    fp=fopen(TagFile, "r");
    int index = 0;
    while(fgets (line, sizeof line, fp) != NULL){
        int len;
        char *p = line;

        sscanf(p,   "%d%d%*d%n",   &tag[index].x,   &tag[index].y,
&len);
        p += len;

        int sindex = 0;
        while(sscanf(p,    "%d%le%n",    &tag[index].s[sindex].id,
&tag[index].s[sindex].strength, &len) == 2){
                        tag[index].s[sindex].count = 1;
                        sindex++;
                        p += len;
        }
        tag[index].signalcount = sindex;
        int  tagindex  =  findbyxy(tag[index].x,  tag[index].y,  tag,
index);
        if(tagindex > -1){
                        for(int  i  =  0;  i  <  tag[index].signalcount;
i++){
                        int              signalindex               =
findbyid(tag[index].s[i].id,                     tag[tagindex].s,
tag[tagindex].signalcount);
                        if(signalindex > -1){

tag[tagindex].s[signalindex].strength                           +=
tag[index].s[i].strength;

tag[tagindex].s[signalindex].count++;
                        }
                }
        }else{
                index++;
        }
    }
    tagcount = index;
    for(int i = 0; i < tagcount; i++){
            for(int j = 0; j < tag[i].signalcount; j++){
                    if(tag[i].s[j].count > 0){
                                        tag[i].s[j].strength   /=
tag[i].s[j].count;
                                        tag[i].s[j].count = 1;
                    }
            }
    }
    fclose(fp);
}

int main(int argc, char *argv[])
```

```
{
    loadcornerdata();
    loadtagdata();
    calcD();
    sort();
    calcXY();
    for(int i = 0; i < tagcount; i++){
            printf("Tag: %d -> Xest=%g Yest=%g\n", i+1, tag[i].x,
tag[i].y);
    }
    system("PAUSE");
    return EXIT_SUCCESS;
}
```

APPENDIX B. RBF NN ALGORITHM IN MATLAB

```
%%

clc,clear

x = 1:9;

y = 1:7;

X=[x,ones(1,length(y)-2)*x(end),x,ones(1,length(y)-2)*x(1)];

Y=[ones(1,length(x)),y(2:end-1),ones(1,length(x))*y(end),y(2:end-
1)];

%%

load data

N=length(X);

z{1}=zeros(1,N);

z{2}=z{1};

for i=1:N

    for j=1:N

        if X(i)==data(j,1)&&Y(i)==data(j,2)

            z{1}(i)=data(j,3);

            z{2}(i)=data(j,4);

            break;

        end

    end

end

figure;quiver(X,Y,z{1}-X,z{2}-Y)

%%

ind=1:2:N;
```

```
indTest=2:2:N;



% T=[X(ind);Y(ind)];

T=[X(ind)-z{1}(ind);Y(ind)-z{2}(ind)];

P = [z{1}(ind);z{2}(ind)];

net1 = newrb(P, T,2,2);

a= sim(net1,[z{1}(:) z{2}(:)]');

% a=a+[z{1};z{2}];

%%

figure



hold on;plot(a(1,:),a(2,:),'ro');plot(X,Y,'o')

%%

disp(sqrt(mean((X-z{1}).^2+(Y-z{2}).^2)))

disp(sqrt(mean((X(indTest)-a(1,indTest)).^2+(Y(indTest)-
a(2,indTest)).^2)))

figure;quiver(X,Y,-a(1,:),-a(2,:))
```