Evaluation of Passive RFID System in a Dynamic Work Environment

by

SHRINIWAS AYYER

A thesis submitted to the

Graduate School – New Brunswick

Rutgers, The State University of New Jersey

in partial fulfillment of the requirements

for the degree of

Master of Science

Graduate Program in Electrical and Computer Engineering

written under the direction of

Professor Ivan Marsic

and approved by

____

____

____

____

New Brunswick, New Jersey

October 2012

ABSTRACT OF THE THESIS

EVALUATION OF PASSIVE RFID SYSTEM IN A DYNAMIC WORK ENVIRONMENT

By SHRINIWAS AYYER

Thesis Director:

Professor Ivan Marsic

RFID has been one of the most widely used sensing technologies. Due to its ease of integration, low cost and minimal system intervention required, a lot of domains are deploying RFID for their applications. A major market of RFID technology applications has been the inventory and tracking application. The data obtained from RFID, however, also contains high level of information in it, which can be used and exploited for sensing applications like localization, motion detection, activity recognition, etc. Despite, the widespread use of RFID, there are some technical shortcomings and lack of a system design approach which hinders the performance of RFID systems in dynamic and critical settings. Our goal is to introduce the Passive RFID technology in a dynamic work environment like the Trauma Resuscitation Bay as part of a context-aware system to support activity recognition. Mobility of an object is closely related to its usage and hence the activity being performed.

Detecting mobility of an object using passive RFID technology is the first step towards activity recognition.

The deployment of the RFID system and the placement of the antennas play a crucial role in the performance of their sensing application. In this work, we have devised a method to determine the effectiveness of an RFID equipment setup. We have analyzed different RFID setups and we discuss the metrics used to determine their effectiveness. We conducted experiments with different scenarios to collect the data and evaluated the performance of a setup in each scenario. The results obtained helped us to correlate the RFID setup with its detection performance. We also ran a classification algorithm on the data collected and evaluated the object motion detection accuracy for all the set ups. Our work provides a ground rule for the RFID set up requirements to be considered for detection applications and also provides insights into the features that can be used for state classification of objects using the RFID data.

Dedication

To My Parents

Acknowledgment

I would like to thank Professor Ivan Marsic for allowing me to work on this highly engaging project. I would like to thank him for all the guidance and constant feedback and also for inspiring me throughout. I would like to thank Siddika Parlak for helping me in this project and her guidance. I would also like to thank my friends who have helped me in conducting the experiments. Without their help, we could not have collected reliable RFID data. Finally, I would like to thank my parents without whose support and motivation all this would not have been possible.

Contents

List of Tables

List of Illustrations

Chapter 1: Introduction

1.1 Motivation

A lot of technological advancements have been made in the fields of voice recognition, gesture recognition, emotion detection opening up a lot of prospective areas of research for improving the safety and quality of patient care. Among these, radio-frequency based identification is most promising given its unobtrusiveness and easy integration into the healthcare systems. Other advantages of RFID over other sensing technologies include low cost, no line of sight requirements, minimal human intervention. Initial attempts to deploy information systems to aid trauma teams have been promising, but have shown limited usability.

RFID technology is widely used in inventory tracking, access control systems, vehicle identification, ticketing, etc. All these application domains focus on item level tracking where the main aim is to detect the object. In a healthcare domain, item level detection will not be of any significant use if the state of the object or the location of an object is not known. Developing a context aware system in a trauma room requires state identifications like mobility detection of objects, usage detection and also the information regarding the location of the object. All these things will contribute to determine the current activity being conducted in the trauma room. Unlike item level tracking where a signal from a particular tag is enough to identify the presence of the object, all these identifications require high level information from the RFID data being extracted at the reader, rather than just identifying the tag as present or not present.

Introduction of these identification techniques with Passive RFID technology in a dynamic and time critical environment like the trauma resuscitation room is very challenging due to several reasons. Firstly, trauma rooms are crowded with many people moving around causing a lot of interference. Secondly, there are many medical objects in use at the same time reducing the detecting capabilities of the readers. Thirdly, the position of the tag on the object matters since if the tag gets covered during usage, then the reader will not be able to detect it. Fourth, medical tools are made of different materials and some object contains liquids affecting the radio signals. Fifth, certain objects come with a plastic packing and hence the tags can only be placed on the plastic cover. Once the cover is removed, the object can no longer be tracked. Lastly, due to the shape of certain medical objects e.g. stethoscope, it becomes difficult to place the tag properly on the object so that it emits sufficient radio signal back and is getting detected.

Thus, with a lot of potential for the RFID technology in the field of healthcare, there is not enough work done to develop a set of rules, guidelines to follow to deploy an RFID system in the healthcare domain and get satisfactory results. Our aim is to introduce the passive RFID technology in a trauma resuscitation bay as a part of a future context-aware system to track the activities of a trauma room [6].

1.2 Contribution of the thesis

RFID technology can be used for inferring high level information, such as motion, location or activity. However passive RFID technology is affected by external interferences as well as a lot of other factors like multipath propagation, inter tag collision, human interference, etc. The Received Signal Strength Indicator (RSSI) can be very noisy even when both the tags and readers are stationary. Hence, for reliability, generally multiple readers or multiple antennas with a single reader are used. Currently, number and placement of antennas, as well as tags, is determined based on heuristics, which aims to maximize the read rate or the accuracy. A lot of work has been done previously [1, 2, 3] on the read rates obtained from an RFID set up and is focused on improving the coverage area/read range for a given system. No work is done so far on optimizing the RFID setup considering the motion detection or activity detection application using an RFID system. Read rates are not that intuitive and for motion detection or activity recognition, we need to extract high level features from the received signal.

It is important to note that RFID is a unique sensing technique which uses the wireless link to communicate the information. Hence it differs from other sensors in being sensitive to tag orientation, antenna orientation, antenna placement and other setup parameters. In our thesis, we develop a setup evaluation method based on distribution distance, and apply our method to human activity recognition in a dynamic medical setting, an example of which is trauma resuscitation. Our thesis explains the techniques to follow and the metrics to consider for RFID set up evaluation in an application domain where state recognition is used.

Our long term goal of the project being activity recognition in a trauma resuscitation room, we simulated a trauma bay in our research lab and conducted motion detection and location change experiments. We developed an algorithm for classification and evaluated the accuracy for different set ups, and by changing different parameters. In our work, we also explore the problem of long-range object motion detection using passive RFID. Our work focuses on dynamic settings suffering interference caused by humans and multiple tags. We observed that, the change in signal due to actual tag motion and the variations in signal due to external interferences are separated and distinguishable using statistical methods.

We extract descriptive features from the received signal at the reader and classify them using machine learning techniques. In our thesis, we have reported the experimental results obtained with several statistical features and classifiers.

Thus, the contribution of our thesis is twofold - First, we perform experimental verification and evaluation of RFID setups to determine the most optimum set up for the domain of object state classification. Second, we perform classification of the object state for the different RFID setups and analyze the results.

Chapter 2: RFID Technology

2.1 Introduction

Radio Frequency Identification (RFID) is the use of an object (typically referred to as an RFID tag) applied to or incorporated into a product, animal, or person for the purpose of identification and tracking using radio waves. RFID simply extracts the data present in the memory chip and makes it available for further processing.

A basic RFID system consists of three components:

a) An antenna or coil

b) A transceiver (with decoder)

c) A transponder (RF tag) electronically programmed with unique information more often a serial number unique for that tag.

There are many different types of RFID systems available in the market. These are categorized according to their frequency ranges. Some of the most commonly used RFID kits are as follows:

1) Low-frequency (30 KHz to 500 KHz)

2) Mid-Frequency (900 KHz to 1500MHz)

3) High Frequency (2.4GHz to 2.5GHz)

These frequency ranges mostly tell the RF ranges of the tags from low frequency tags ranging from 3m to 5m, mid-frequency ranging from 5m to 17m and high frequency ranging up to 200m.

With RFID, the electromagnetic or electrostatic coupling in the RF (radio frequency) portion of the electromagnetic spectrum is used to transmit signals. An RFID system consists of an antenna and a transceiver, which reads the radio frequency and transfers the information to a processing device (reader) and a transponder or RF tag, which contains the RF circuitry and information to be transmitted. The antenna provides the means for the integrated circuit to transmit its information to the reader that converts the radio waves reflected back from the RFID tag into digital information that can be passed on to computers that can analyze data.

There are three types of RFID technology:

1) Active RFID Technology - Active RFID tags are typically larger and more expensive to produce, since they require a power source. Active RFID tags broadcast their signal to the reader, and are typically more reliable and accurate than passive RFID tags. Since active RFID tags have a stronger signal, they are more adept for environments that make it hard to transmit other types of tags, such as under water, or from farther away.
2) Passive RFID Technology - Passive RFID tags, on the other hand, do not have internal power supplies and rely on the RFID reader to transmit data. A small electrical current is received through radio waves by the RFID antenna, and power the CMOS just enough to transmit a response. Passive RFID tags are more suited for warehousing environments where there is not a lot of interference, and relatively short distances (typically ranging anywhere from a few inches to a few yards). Since there is no internal power supply, passive RFID tags are much smaller and cheaper to produce.

3) Semi-Passive RFID Technology - Semi-passive RFID tags are similar to active RFID tags in that semi-passive RFID tags have an internal power supply, but they do not broadcast a signal until the RFID reader transmits one first.

2.2 RFID Technology: Advantages and Challenges

RFID is one of the most widely used sensing technologies. In our work, we are using the passive RFID technology in the trauma room for detecting usage because of some of its advantages.

- Compared to the widely used barcode system, RFID does not require line of sight link with the reader.
- Passive RFID tags are cheaper and can be easily deployed on any object.
- Unlike, computer vision, RFID tags are easily re-programmable and hence no permanent data is maintained.
- RFID technology enables faster and easier detection of multiple tags simultaneously.
- It does not require focused passing of sensors over the scanners, thus minimizing human interference.

Due to its passive nature, it also has certain disadvantages compared to other sensors:

- It is sensitive to the environment in which it is deployed. External factors such as metallic cabinets, human intervention cause a lot of interference in the signal.
- It is also affected by the material of the object on which it is tagged; we need special tags for metals and liquid containers.

- It has a limited read range due to its backscatter mechanism. Due to the absence of an external power source, it cannot be detected over long distances.

2.3 RFID Equipment and Environmental Setting

We are performing our experiments in a lab room which is partially filled with furniture like metal cabinets, wooden desks ad separators, which caused multipath fading and distortion of RF signal. We have tried to simulate a setting similar to the trauma bay [Figure 2.1] in the lab room, with a patient bed in the center, side furniture and free space. A tagged object was interacted near the patient bed and this area was our focus of attention throughout the experiments. We performed two distinct set of experiments: Set one - with respect to the RFID setup evaluation. Set two - with respect to the motion detection classification analysis.

We have used off the shelf RFID equipment from Alien [4]: an RFID reader (ALR-9900), circularly polarized antennas (ALR – 9611 – CR) and passive tags (Squiggle ALN-9540). The number of antennas and the antenna setup varied according to the experimenting sets. Regardless of the number of tags used in any experiment, the reader scanned for multiple tags in the environment, rather than a fast search for the single tag. The readers were operated in a dense reader mode (DRM), which prevents interference among readers, to obtain results scalable to larger deployments with multiple readers. Also, DRM yields the best performance when tag-to-reader distance is greater than 1.5 meters. Radio signal was emitted in a round robin fashion through one antenna at a time (for 0.5 seconds). The reader emitted 1 watt of RF power. The number of readers used in an experiment depended upon the number of antennas used in the experimental set up. Only three antennas were connected to a reader. So for experiments dealing with more than three antennas, two readers were used.

The experiments were conducted in a closed lab (Figure 2.1) which had multiple sources of interferences like desks, glass cabinets, metal cabinets etc. A wooden cart was used as a patient bed on which the RFID tagged object was placed during the experiments.

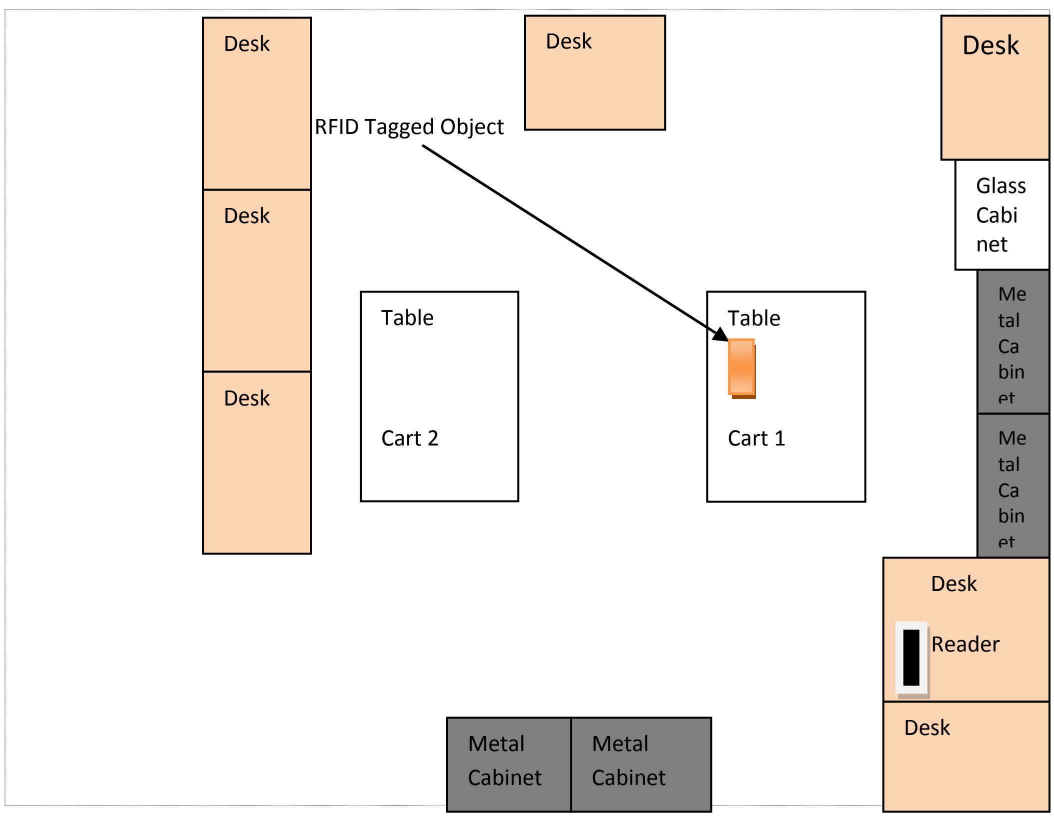

Figure 2.1: Experimental Lab Setup – Top View

Table 2.1: RFID Reader Specifications

Name	Alien Multi-Port General purpose RFID Reader
Model Number	ALR 9900
Architecture	Point-to-multipoint reader network, mono-static antenna
Operating Frequency	902.75 MHZ – 927.25 MHZ
Hopping Channels	50
Channel Spacing	500 KHZ
Channel Dwell Time	< 0.4s
RF Transmitter	< 30 dBm at the end of 6 m LMR-195 cable
Modulation method	Phase Reversal – Amplitude Shift Keying (ASK)
20 dB Modulation Bandwidth	< 100 KHZ
RF Receiver	2 channels
Power Consumption	30 watts
Communications Interface	RS-232 (DB-9 F), TCP/IP (RJ-45)
Inputs/Outputs	4 coax antenna, 4 inputs/8 outputs (optically isolated), RS-232 com port, LAN, power
Dimensions	8* x 7* x 1.6*
Weight	Approximately 1 kg
Operating Temperature	-20^{o}C to + 50^{o}C
LED indicators	Power, Link, Active, Ant0-3, CPU, Read, Sniff, Fault(Red)
Software Support	APIs, sample code, executable demo app(Alien Gateway)
Protocol Support	Comply with EPC Class 1 Gen 2 and 18000 -6C
Compliance Certifications	FCC Part 15;FCCID;P65ALR9900IOC:4370A-ALR9900

Figure 2.2: Alien ALR 9900 RFID Reader

Table 2.2: RFID Reader External Circular Polarized Antenna Specifications

Model	ALR-9611-CR and ALR-9611-CL
3 dB Beamwidth	E plane: 65^{o} , H plane: 65^{o}
Frequency	902-928 MHZ
Gain (dB)	6.0 dBiL (maximum)
Polarization	Circular
RF connector	6 m LMR-195 with reverse polarity
VSWR	1.5:1
Dimensions	8.5 x 10.5 x 1.65 (inches)
Weight	.57 kg

Figure 2.3: Alien ALR 9611 CR Antenna

Table 2.3: Passive RFID Tag Specifications

IOC/IEC 18000-6C	
EPCglobal Class 1 Gen 2	
Integrated Circuit	Alien Higgs-3
EPCglobal Certificate	950110126000001084
Operating Frequency	840-960 MHz
EPC Size	96-480 Bits
User Memory	512 Bits
TID	32 Bits
Unique TID	64 Bits
Access Password	32 Bits
Kill Password	32 Bits

Figure 2.4: The squiggle passive RFID Tag

Chapter 3: Evaluation of RFID Equipment Set Up

3.1 Introduction

The RSSI data obtained from the reader contains a lot of high level information which can be used for inferring the state of the object. The RSSI or read rate can be very noisy even when both the reader and antenna are static. For reliability, multiple antennas and tags must be used. Currently, there is no specific protocol or guideline that could be used for the RFID system design from a state recognition point of view. The RFID system usually gets deployed in a manner that maximizes the coverage area and guarantees a respectable read rate [2, 3]. Read rates are not always indicative for inference of high-level information. Accuracy, on the other hand, depends on the methods used for data processing such as features and classifiers selected. Current practice is placing antennas in a regular grid based on intuitions without performing controlled experiments, optionally performing preliminary experiments to find the best placement. Or using different styles and discussing their usefulness after performing all experiments.

Although optimum placement problem arises for other sensors as well, passive RFID has two properties that make the problem different: 1) Sensing components 2) Sensitivity. Most sensors (e.g., accelerometers, temperature sensors and humidity sensors) have a single component for sensing. Wireless communication is used only for transmitting to or receiving data from other devices, such as a data processing unit. In case of RFID (as well as Wi-Fi), both sensing and data transmission is performed via the wireless communication signal. Therefore the sensing system consists of two components: sensors on objects (tags) and readers (base stations). The deployment strategy must consider both components, possibly in conjunction.

Second, RFID is very sensitive to orientation and interference due to human occlusion and movement. The received signal strength changes with the change in orientation of the tag placed on the object. This might result in false positives or missed reads. RSSI (Received Signal Strength Indicator) is also affected by the presence of human in the environment. Both these factors are quite common to occur in a trauma resuscitation room.

In this chapter, we will explain about the setup evaluation method we developed based on distribution distance, and apply our method to human activity recognition in a dynamic medical setting, an example of which is trauma resuscitation. First, we list the requirements for antenna and tag deployments in a trauma resuscitation setting. Next we define our criteria for evaluating the goodness of placement, along with the other two criteria: read rate and accuracy. Then, we discuss the results obtained from our experimentation and the defined metrics used.

There are two main components in an RFID set up which determine the performance of the set up – Antenna Placement and Tag Placement. Antenna placement refers to the positioning of the antenna in the system so as to transmit and receive the signals. Improper positioning of antennas might lead to reduced coverage area, overlapping of antenna regions, missed readings. Tag placement refers to the positioning of tag on the object. Since the positioning of the tag on the object depends upon the object itself, we experimented with several different medical objects with different tag positions on them.

Thus to evaluate an RFID equipment setup, we performed two types of experiments – antenna experiments and tag experiments.

3.2 Criteria for evaluating the goodness of a setup

In this section, we describe our criteria for evaluating the goodness of deployment and discuss their relation. Since, we performed two kinds of experiments in analyzing the optimum RFID setup; we need to use the appropriate criterion for evaluating each experiment type.

3.2.1 Read Rate

Read rate has been defined in different ways in the literature depending on the use case. Our goal of object-use detection requires a substantial amount of data from each tag to obtain reliable results. Accordingly, we define read rate as the number of responses obtained from a tag per unit of time. Read rate is simple to calculate and provides the basic high-level information about the goodness of deployment. Most of the prior work [1, 2, 3] has evaluated their RFID system performance in terms of read rate.

3.2.2 Distribution Distance

The RFID system deployment strategy usually focuses on the read rates of the tags. High read rates are desirable and good, but they are not good indicators of usage. An object standing still near to the reader will give good read rates compared to an object in use but at a distance away from the reader. Hence we need to study the RSSI pattern obtained from the signals to infer their usage. Distribution distance is one such feature which helps to determine the usage by detecting the change in the pattern. Distribution distance is nothing but the difference between the distributions of two signals. When an object is in use, the RSSI pattern received at the reader is more fluctuating and varies a lot. Hence, the standard deviation of the signal is higher when the object is in use. Thus the RFID setup should be such that it complements the standard deviation when the object is in use. For example – Suppose there are two available set ups A and B. We conduct an experiment in both the set ups where a tagged object is not in use for the first 10 seconds and then used for the next 10 seconds. Now, we calculate the standard deviation of the data collected in the entire 20 seconds for both the set ups - stdA and stdB. We need to select the set up which is more sensitive to the tag activity i.e. with higher standard deviation. If stdA > stdB, then set up A will be the set up of our choice. Thus usage is very closely related to the standard deviation of the signals which in turn is related to the distribution distances of the signals. Higher the distribution distance, farther apart the signal patterns are, greater is the standard deviation. In other words, distribution distance helps us to determine the sensitivity of an RFID set up to location changes, motion, and usage of the tagged objects.

We calculate the distance between two RSSI patterns as follows: Let X_p is the RSSI sequence generated when the tag is in one state (e.g., standing still), and X_q is the RSSI sequence generated when the tag is in another state (e.g., in motion). We assume X_p and X_q are generated by normal probability distributions *P* and *Q*, respectively, which are modeling object's state of motion. Mahalanobis distance is one such tool which is most commonly used for calculating the difference between two distributions.

Mahalanobis Distance: Mahalanobis distance is a measure of similarity between a vector and a set of vectors characterizing a distribution. Unlike the Euclidean distance, it takes the correlations between variables into account and it is scale invariant (does not change when variables are multiplied with a common factor). Formally, Mahalanobis distance of a multivariate vector p to a multivariate distribution Q with mean μ and covariance S is calculated as:

$$d_M(p,Q) = \sqrt{(p-\mu)^T S^{-1}(p-\mu)} \qquad (1)$$

To find the distance between distributions *P* and *Q*, we define the following distance metric, which favors high inter-distribution distance and low intra-distribution distance:

$$M(P,Q) = 1/2\,(m(P,Q) + m(Q,P)) - 1/2\,(m(P,P) + m(Q,Q)) \qquad (2)$$

Where $m(P,Q)$ is defined as the average distance of samples in *P* to samples in *Q*:

$$m(P,Q) = \frac{1}{n}\sum_{i=1}^{n} d_m(p_i,Q) \qquad (3)$$

The Mahalanobis distance metric is closely related to separability of classes in a classification problem: as the average inter-class distance increases and the average intra-class distance decreases, i.e. classes are more separable, classification performance is expected to improve. We used mahalanobis distance as a distribution distance metric because of its advantages:

- It automatically accounts for the scaling of the coordinate axes
- It corrects for correlation between the different features
- It can provide curved as well as linear decision boundaries

Compared to read rate, distribution distance better characterizes the distinguish ability of object states for different RFID equipment setups. However it is a more complex measure that requires selecting a distance metric and making assumptions on the data (e.g., normal distribution), both of which may bias the judgment on the goodness of an RFID setup.

3.2.3 Use Detection Accuracy

Use detection accuracy represents the similarity between the hypothesis about object use and the ground truth; therefore it is the direct measure to evaluate the goodness of a setup. Several metrics can be used to measure the similarity between the hypothesis and the ground truth, such as precision, F-score or classification accuracy [5]. In this work, we focus on two cues indicating object use: coarse-level location and motion status. We formulate both coarse-level localization and motion detection problems as classification problems and calculate the classification accuracy as follows:

$$\text{Accuracy} = \frac{(\text{true positive+true negative})}{(\text{total no.of test samples})} \qquad (4)$$

Calculating the accuracy requires building a recognition system, which includes feature extraction, model training and classification steps. It measures the setup goodness in the context of the end application; however, unlike read rate, which can be measured directly, measuring accuracy requires building the entire end application system. Also, the overall results may be biased by the selection of recognition system components.

3.3 Experimentation Methodology

Experiment – It basically means the collection of data performing multiple runs of the RFID reading for a given environmental set up and tag set up. Each run of an experiment lasted 20 seconds and 5 runs were performed for each experiment. So we had 100 seconds of data for each experiment. This might look small amount but our main aim was to determine the best RFID set-up that could be used for efficient mobility detection assuming the mobility detection algorithm has already been equipped.

Since the target audience of our mobility detection project was healthcare domain, we wanted to simulate the environment of a typical surgery room in our lab. We used two wooden carts to act as the patient beds and also surgical equipments were our object of use. Our methodology can be broadly classified into two types:

1) Antenna Experiments
2) Tag Experiments

Both the types of experiments had several settings under them which will be explained in detail later. The above classification of the experiments is based on the RFID equipment itself which includes the antennae and the tags. We also performed experiments from the usability point of view. Location estimation and mobility being the two most important applications of RFID, we performed each experiment for both location change of the object as well as the mobility.

- Location change – These experiments basically meant changing the location of the object after a specified time in an experimental run (figure 3.1). Since each run we performed lasted 20 seconds, we changed the location of the object after 10 seconds. We performed this by using two wooden carts separated by a distance of 2m. The object was kept on one cart for 10 seconds and moved to the other cart after 10 seconds. This perspective was used to simulate the scenario where the objects are being moved from one place to the other during its use.

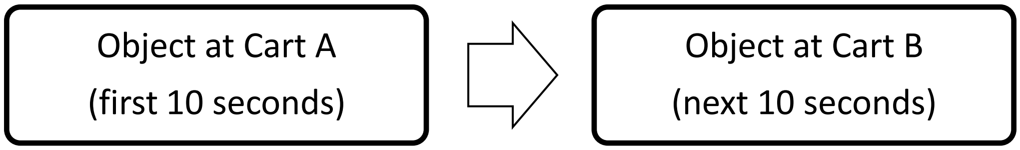

Figure 3.1: Location Change Experiment

- Mobility – Mobility experiments were performed by using the objects and moving them around after they have been stationary for a while (figure 3.2). The objects were stationary for the first 10 seconds of the run and after that they moved around (in close vicinity of the cart on which it was initially kept). This simulated the practice when a person uses particular equipment which was kept on storage or on the table for a while.

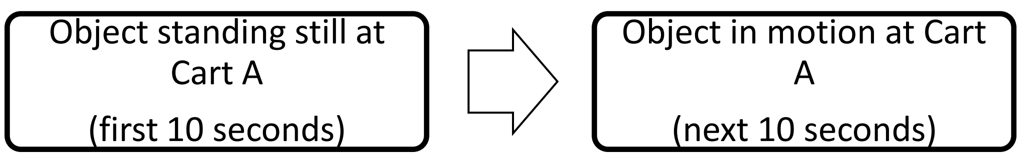

Figure 3.2: Motion Experiments

The object that was used for these experiments is a rectangular cardboard box that is closed from all the sides. The dimensions of the box would be ~ 7 in * 3 in* 3 in. The lab is a closed lab and has many interfering sources like the walls, separators and metallic cabinet.

3.4 Antenna Placement

The trauma bay consists of specific zones in which the objects are concentrated and used (figure 3.3). It is very important to have proper coverage in these zones. In this section, we list the requirements to be met for antenna placement. Next we show the different antenna setups we experimented. Finally we discuss the results obtained for these setups using the distribution distances and also talk about the optimum setup that is preferred for our application.

3.4.1 Antenna Placement Requirements

We analyzed the trauma resuscitation setting focusing on the spatial distribution of objects and identified five main zones where objects are usually located: patient-bed zone, right and left zones, and foot and head zones (Figure 3.3). Objects are often stored, or left idle, in left, right, head and foot zones. Objects cross inter-zone areas when they are relocated for use in the patient-bed zone. Based on our analysis of a typical trauma setup [6], we have come up with the following requirements for the antenna placement:

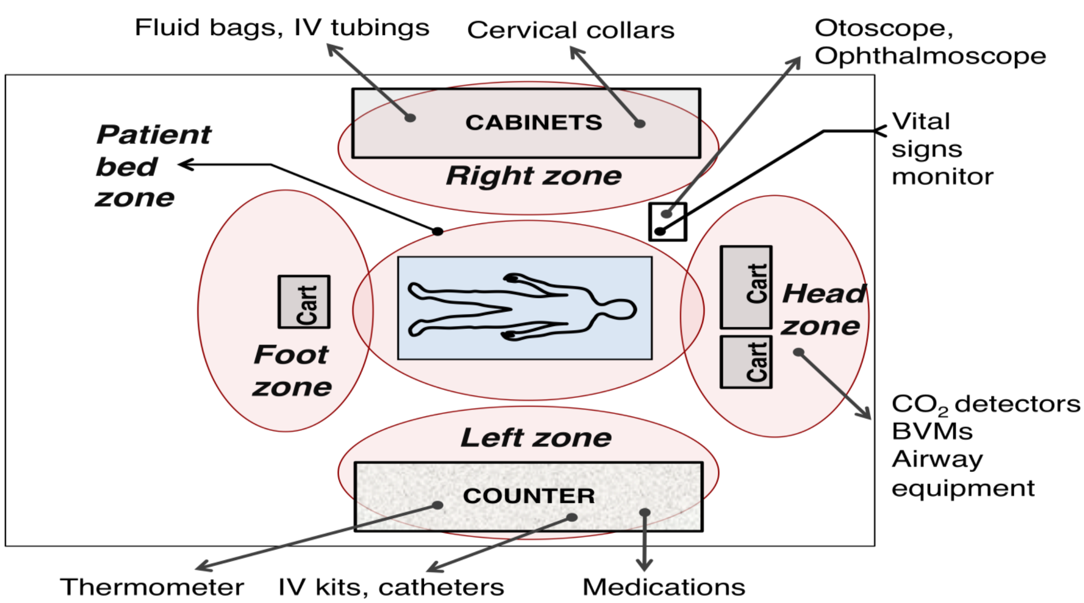

Figure 3.3: Trauma Bay Zones

- For an optimal antenna placement, each zone must be under coverage of at least one antenna. Remaining areas outside the zones need not be covered because non-uniform object concentration of the trauma bay allows for non-uniform antenna coverage.
- Antennas must be placed such that their reception is minimally affected by the object's orientation.
- The interference due to human presence and movement should be minimal.
- The antennas should not hinder providers' movements and task performance.
- The number of deployed antennas should be minimized to reduce the cost of the equipment and the interference between antennas, and to meet the esthetical requirements.

Based on these requirements, we have come up with 5 different antenna setups which are discussed in the following section.

3.4.2 Antenna Setup Experiments

1) Experimental Setup

During trauma resuscitation, medical objects appear either on patient-bed or in one of the storage places (left, right, head and foot zones). We created a prototype environmental setting in our laboratory including only two zones: the patient-bed zone (usage area, Z1 in Figure 3.4) and the left zone (storage area, Z2 in Figure 3.4). Each zone contained a 0.9 m tall cart. The carts were separated between 0.8-2.3 m away from each other, depending on the experimental scenario. A cardboard rectangular box was tagged with an RFID tag and handled by the experimenter as the target object.

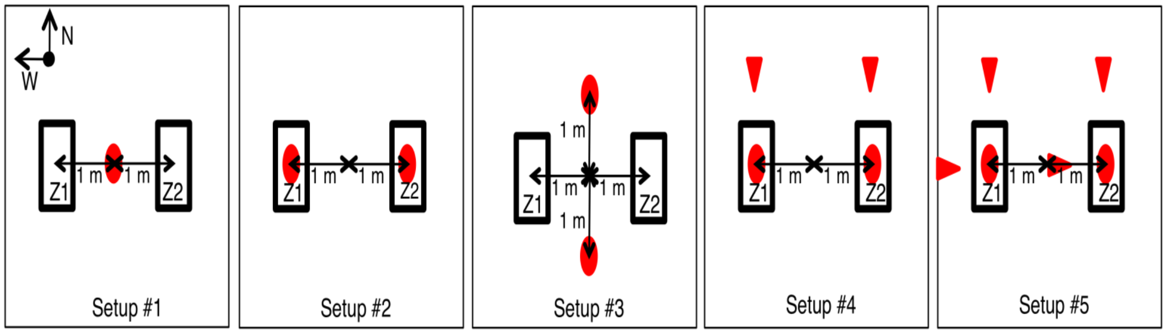

Figure 3.4: Top view of five different antenna setups – Z2 represents the patient-bed zone and Z1 represents the left storage zone. Ceiling-mounted antennas are shown with circles; angled antennas are shown with triangles.

Set Up 1: One ceiling mounted antenna placed between the two carts

As seen in the figure 3.4, this particular setting employs one ceiling mounted antenna placed at the center of the two carts at a height of 2.7m above the cart. The antenna field around each cart is identical not accounting for the interference due to other sources nearby the carts. The area covered by this antenna was determined based on the antenna radiation pattern provided by the vendor. We made a conic beam approximation (a cone with its vertex on the transmitting antenna and its axis along the transmission direction) for the directional radiation pattern of the antenna. The 3 dB beam width (65 degrees), also specified by the vendor (Table 2.2), was used as the aperture angle of the cone. The resulting coverage area for an antenna was a circle with a radius of 1.5 m at the height of carts (distance of 1.8 m from the antenna). The coverage area of the antenna in this setup included both storage and usage zones, meeting the coverage requirement (Req. #1).

Set Up 2: Two Ceiling mounted antennas placed one directly above each cart

This setting uses two ceiling mounted antennae one above each cart. The distance between the two antennas is approximately the same as the distance between the two carts (figure 3.4).

Set Up 3: Two ceiling antennas perpendicular to the carts

There are two ceiling mounted antennae placed perpendicular to the line joining the centers of the two carts. The distance between the two antennae is approximately equal to the distance between the two carts which is around 2m (figure 3.4).

To increase the diversity of signals received from a tag, as well as to account for the variability in object and tag orientation (Req. #2), we mounted the new antennas to sidewalls such that they transmit through a different (ideally perpendicular) direction with respect to the existing antennas (ceiling-mounted). Assuming an average human height of 1.7 m, we positioned the new antennas at a height of 2 m to reduce interference due to human presence (Req. #3), and to minimize the obstruction of equipment on providers' activities (Req. #4). To cover the experimental area, we also slanted the antennas to make 60˚ to the floor.

Set Up 4: Two antennae per zone

There is one ceiling mounted antenna and one side antenna for each cart. Placing of multiple antennas for each zone basically helps in addressing different tag orientations. The antennae in a zone should transmit in different directions. Set up 4 is a modification of set up 2 with two additional side antennae (figure 3.4).

Set Up 5: Three antennae per zone

There is one ceiling antenna right above the cart and additional two side antennae. The two side antennae are placed in such a way that they are radiating in perpendicular directions. Thus this set up involves a total of 6 antennae and accounts more for different tag orientations. However, interference between the antennae will also be high in this case due to the close proximity of the antennae (figure 3.4).

2) Experimental Scenarios

In a dynamic environment like the trauma bay, there are a lot of scenarios which can affect the performance of a given antenna setup [6]. On the basis of the antenna placement requirements and our study of the trauma bay [6], we tested each setup with a list of possible scenarios.

The scenarios simulated the environmental characteristics of trauma resuscitation that may affect propagation of RFID radio signals.

Scenario #1: Stationary environment: This is the baseline scenario without any environmental factors introduced.

Scenario #2: Deviations in zone locations: Although coarse-level zone locations in the trauma bay are fixed (e.g., cabinets and counter along the walls, patient bed in the center of the room), the patient bed and carts may slightly move during the resuscitation. Also, the height of the patient bed is adjustable. To simulate these deviations in zone locations, we moved the zones (i.e. carts) in the following directions:

2-a) Z1 and Z2 moved 0.6 m to north (distance between the zones remained constant).

2-b) Z1 moved 0.6 m to north; Z2 moved 0.6 m to south (distance between zones increased to about 2.3 m).

2-c) Z1 moved 0.6 m to east; Z2 moved 0.6 m to west (distance between zones decreased to 0.8 m).

Scenario #3: Changes in object orientation: Object's tag in the default object orientation was facing the ceiling. However, objects, and hence tags, are not always oriented in the same way because users orient the objects randomly during use. To simulate random orientations, we placed the object in two additional orientations:

3-a) Tag faced north

3-b) Tag faced west

Scenario #4: Changes in providers' mobility: Providers' movement in the environment was simulated as follows:

4-a) Two people walked around zones

4-b) Five people walked around zones.

3) Evaluation Metrics

To evaluate the efficiency of an antenna setup in a particular scenario, we used the metrics of read rate, distribution distance and accuracy. Because each experiment was repeated for five times, we report the average values.

Our first metric, read rate (per second), was calculated by dividing the total number of readouts by 20, which is the duration (in seconds) of a recording. As the second metric, we calculated the distribution distance between the first 10s and the next 10s of an RSSI recording session, using Mahalanobis distances (Equation 1). For setups including multiple antennas, a vector of RSSI values was formed, where each dimension represented RSSI value of an antenna. When an antenna totally lost reception, we generated Gaussian distributed values with low mean to fill the missing values.

For location change experiments, we also performed binary classification to predict whether the object is located in Z1 or Z2 and calculated the accuracy, our third metric (Equation 5). We followed a sliding-window based strategy to map the RSSI data to a set of features. Our feature set consisted of the mean RSSI received from each antenna. At each time instant, the data in the current time interval is processed to obtain the corresponding feature vector. Next, each feature is assigned one of the labels (Z1 or Z2) using a classifier. We experimented with different window sizes and classifiers such as Decision Trees, Random Forests and Support Vector Machines. The results reported in this section are obtained using the classifier Decision Tree with a window length of 5s and a slide length of 1s.

We performed binary classification also for motion state change experiments to predict whether the object is standing still or in motion. We followed the same sliding-window based methodology as in the location change experiments except the feature set. Standard deviation was used as the feature in motion state change experiments.

As seen from the above discussion, we have used two different features for location change classification and motion detection – mean RSSI and standard deviation respectively. This is because, the location change event happens quite quickly and the object remains stationary before and after the location change event. Hence, there are not a lot of variations in the RSSI pattern. Hence standard deviation will not be a good metric. Mean RSSI however depends upon the location of the object with respect to the antennae. When the location of the object changes, the mean RSSI also changes with it. Hence mean RSSI is used as a feature for location change experiments. Motion on the other hand results in a lot of variations in the RSSI patterns of the tag. If an object is in motion, its standard deviation increases and is a good indicator of the motion event. Hence standard deviation is used as a metric for motion detection experiments.

3.5 Antenna Placement Results

In this section, we discuss the results obtained from our experimentation and also analyze it. The results are displaced under two sub-sections – Location Change Experiment Results and Motion Detection Experiment Results. Both the subsections consists of three parts each – Read Rates, Distribution Distance (Mahalanobis) and Classification Accuracy.

3.5.1 Location Change Experiment Results

Table 3.1: Location Change Experiment Read Rate Values

Scenarios		Set Up #				
		1	2	3	4	5
1	Ideal	621	528	534	591	545
2-a	Zone deviation: Z1 and Z2 moved 0.6 m to north	554	588	412	425	584
2-b	Zone deviation: Z1 0.6 m north, Z2 0.6 m south	610	591	384	338	537
2-c	Zone deviation: Z1 0.6 m east, Z2 0.6 m west	623	614	598	542	576
3-a	Different orientation: tag faces north	536	473	431	506	524
3-b	Different orientation: tag faces west	564	587	545	601	575
4-a	Human movement : two people	609	552	535	606	582
4-b	Human movement: five people	611	512	467	392	562
Average		591	555.625	488.25	500.125	560.625

We observed slight changes in read rates obtained under different setups (figure 3.5). Highest read rates were obtained in Setup #1, with an average of 30 readings per second. In Setups #2 and #3, both antennas were connected to the same RFID reader and scanned the experimental area in a round robin fashion. The reader also spent time when switching between the antennas, which caused reduction in interrogation time and hence the read rate (Setup #2: 23 readings/sec, Setup #3: 24 readings/sec). Including two readers and antennas with different vantage points increased the read rate only slightly (Setups #4 and #5: 25 readings/sec). However read rate in Setup #5 was more consistent in different scenarios, which indicates its robustness to environmental changes.

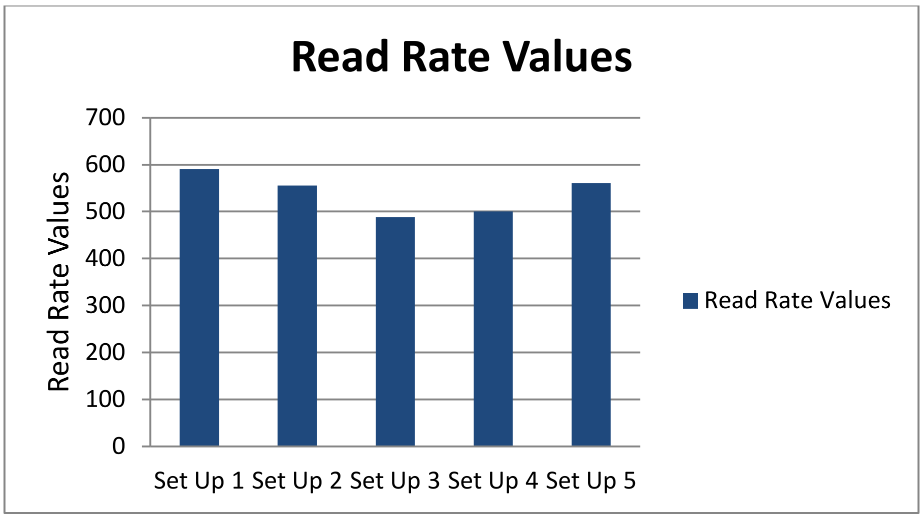

Figure 3.5: Read Rate Values for Location Change Experiments

When multiple tags are present in the experimental area, read rates sharply decrease (e.g., 6 readings/sec in Setup #2). Setup #5 was also advantageous in this scenario allowing read rates up to 13 readings/second.

Table 3.2: Location Change Experiments Mahalanobis Distance

Scenarios		Set Up #				
		1	2	3	4	5
1	Ideal	8.6	140.1	13.2	187	182.1
2-a	Zone deviation: Z1 and Z2 moved 0.6 m to north	8.9	18.1	21.4	37.5	94.4
2-b	Zone deviation: Z1 0.6 m north, Z2 0.6 m south	2.7	22.8	48.8	80.8	80.1
2-c	Zone deviation: Z1 0.6 m east, Z2 0.6 m west	4.9	18.5	8.1	23.7	88.7
3-a	Different orientation: tag faces north	0.2	107.9	1.3	181	411.1
3-b	Different orientation: tag faces west	22.2	41.1	2.3	57.3	76.1
4-a	Human movement : two people	0.5	71.2	0.8	53.7	165.5
4-b	Human movement: five people	1.4	52.1	3	87	175.8
Average		6.175	55.8	12.3625	88.5	200.8455

The Mahalanobis distance showed an increasing pattern with the increasing number of antennas (table 3.2 and figure 3.6). Comparing Setups #2 and #3, both of which included two antennas, Setup #2 provided higher distance, and in turn better separability for statistical classification algorithms. Setup #5 provided the highest distribution distance values, followed by Setups #4 and #2.

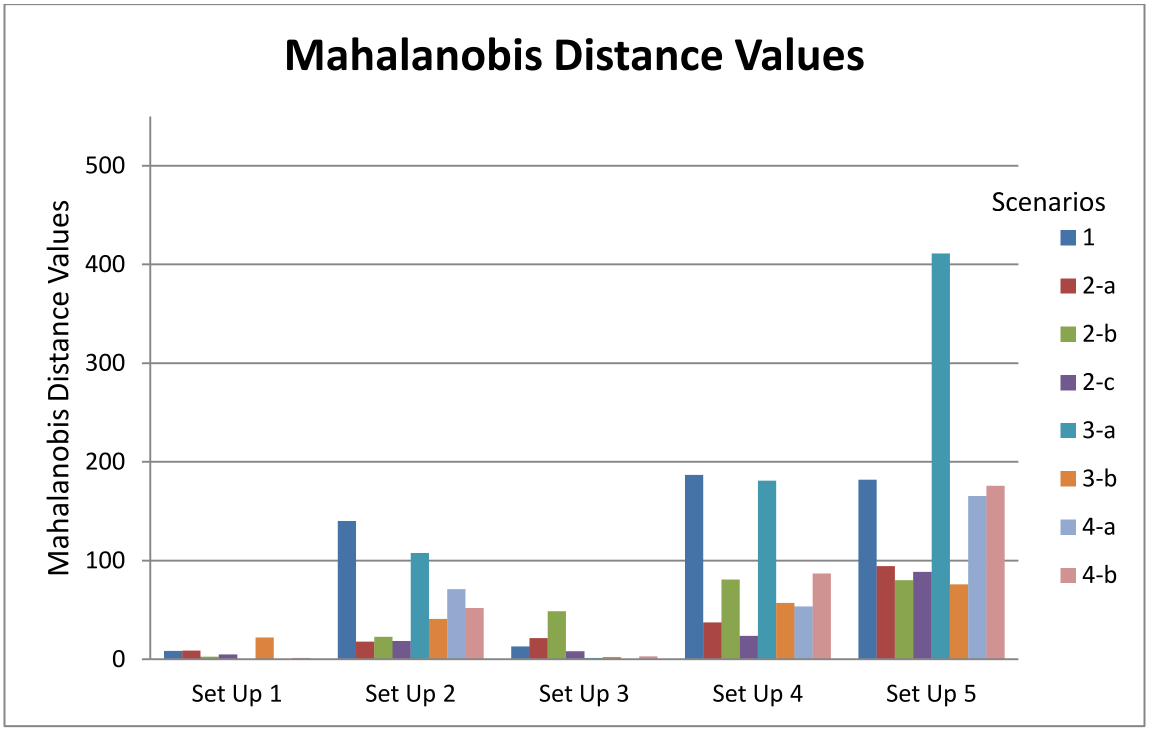

Figure 3.6: Mahalanobis Distance Values for Location Change Experiments

Based on this result, we believe it is required to place at least one ceiling-mounted, floor-facing antenna per zone. Adding more antennas increased the sensitivity of radio signals to different object states however it is also contrary to the cost and esthetic requirements.

Table 3.3: Classification Accuracy for Location Change Experiments

Scenarios		Set Up #				
		1	2	3	4	5
1	Ideal	48	100	85	88	97.5
2-a	Zone deviation: Z1 and Z2 moved 0.6 m to north	95	90	57.5	93	90
2-b	Zone deviation: Z1 0.6 m north, Z2 0.6	88	95	72.5	90	85

	m south					
2-c	Zone deviation: Z1 0.6 m east, Z2 0.6 m west	85	95	67.5	83	72.5
3-a	Different orientation: tag faces north	50	85	50	95	82.5
3-b	Different orientation: tag faces west	100	100	53	98	92.5
4-a	Human movement : two people	60	97.5	68	97.5	90
4-b	Human movement: five people	42.5	92.5	80	90	97.5

Setups #2, #4 and #5 provided the best zone-based localization accuracy for all scenarios (table 3.3). Unlike the distribution distance results, where Setups #4 and #5 significantly outperformed Setup #2, all three setups yielded very close zone-based localization scores.

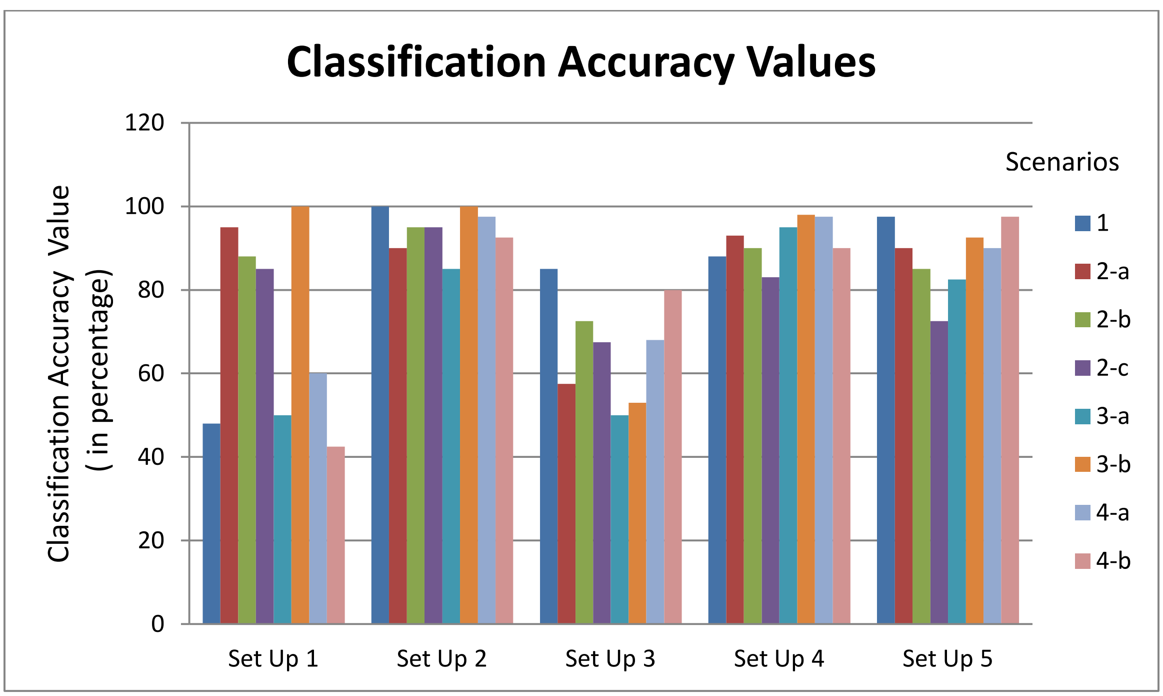

Figure 3.7: Classification Accuracy Values for Location Change Experiments

By plotting the distribution distances and the corresponding classification accuracies, we identified a logarithmic relationship. These results justify the importance of the ceiling-mounted antenna, placed as in Setup #2. The additional antennas may provide gain in challenging conditions.

3.5.2 Motion Change Experiment Results

Results of motion state experiments in terms of read rate, Mahalanobis distance and motion detection accuracy are depicted in the following tables.

Table 3.4: Motion Detection Experiments Read Rate Values

Scenarios		Set Up #				
		1	2	3	4	5
1	Ideal	275	459.6	538.6	589	523
2-a	Zone deviation: Z1 and Z2 moved 0.6 m to north	249.8	376	406.4	593	546.6
2-b	Zone deviation: Z1 0.6 m north, Z2 0.6 m south	314.2	508.8	555	537.4	473.4
3-a	Different orientation: tag faces north	216	483.4	321.6	531.6	486.4
3-b	Different orientation: tag faces west	277.4	539.2	491	427.6	480
4-a	Human movement : two people	278.8	524	526	588.8	508.2
Average		268.53	481.83	473.1	544.56	502.93

The read rate values for the motion detection experiments are quite close for all the set ups except set up 1 (figure 3.8). Set up 1 has only 1 antenna, due to the orientation changes in the object during the motion, it is not being read correctly by a single antenna.

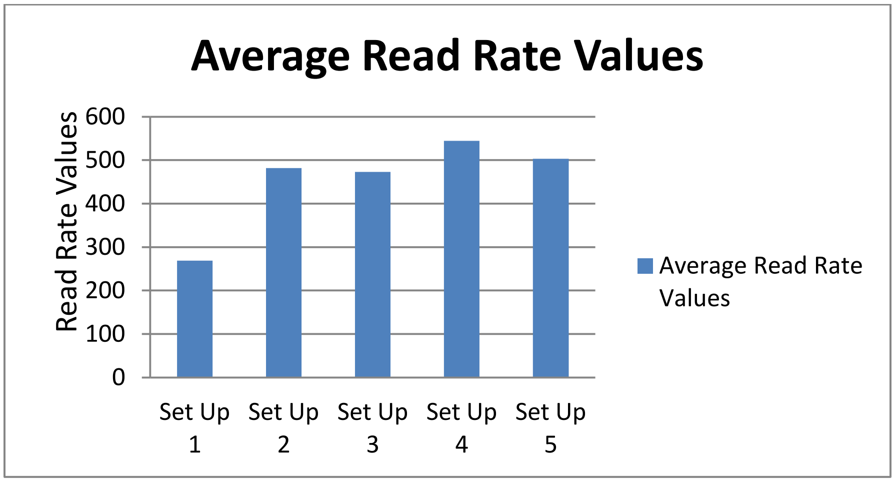

Figure 3.8: Average Read Rates for Motion Detection Experiments

Setups #4 and #5 performed best in terms of distribution distance.

Table 3.5: Motion Detection Experiments Mahalanobis Distances

Scenarios		Set Up #				
		1	2	3	4	5
1	Ideal	19.4	25.9	22.3	32.4	21.2
2-a	Zone deviation: Z1 and Z2 moved 0.6 m to north	5.2	9.2	7.3	12.1	25.9
2-b	Zone deviation: Z1 0.6 m north, Z2 0.6 m south	5.3	31.7	4.1	7.8	12.1
3-a	Different orientation: tag faces north	2.8	5	5.2	16.1	12.9

3-b	Different orientation: tag faces west	9.6	21.7	12.4	26.1	39.5
4-a	Human movement : two people	5.3	27.6	8.7	28.6	54.6
Average		7.9	20.1	10	20.6	27.7

As seen in the table above, set up 2 and 4 have a close value for the average mahalanobis distance while set up 5 has outperformed all other set ups.

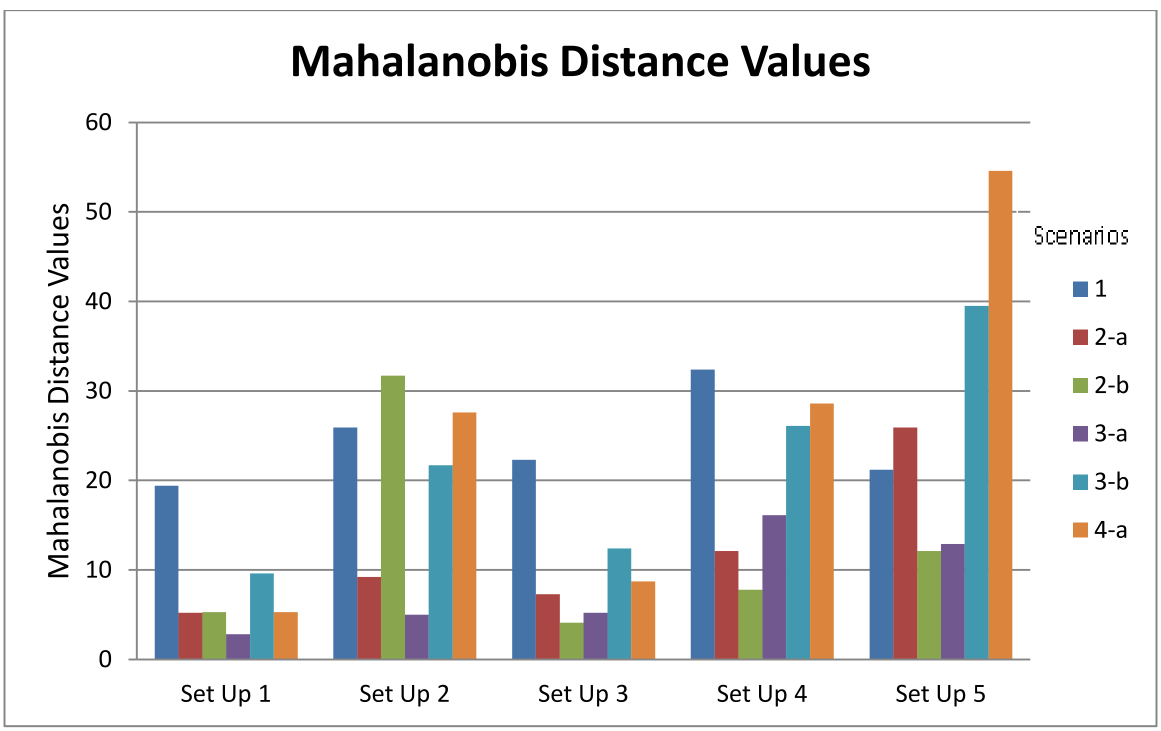

Figure 3.9: Mahalanobis Distance values for motion detection experiments

The classification accuracies for the motion detection experiments are as shown below (table 3.6 and figure 3.10). Unlike, the location change experiments where the object changes its location during the experiments, the motion detection experiments have been performed at the same cart by randomly using the object. Hence lesser variations are expected in the RSSI patterns obtained from the tagged object. This is evident from the low mahalanobis distance values. Since standard deviation was the feature used for the motion detection experiments, we expected the classification accuracies to be less than that obtained for the location change experiments, which is justified in the results obtained.

Table 3.6: Classification Accuracies for Motion Detection Experiments

Scenarios		Set Up #				
		1	2	3	4	5
1	Ideal	92.5	87.5	90	70	82.5
2-a	Zone deviation: Z1 and Z2 moved 0.6 m to north	42.5	90	65	75	65
2-b	Zone deviation: Z1 0.6 m north, Z2 0.6 m south	75	60	80	90	77.5
3-a	Different orientation: tag faces north	65	75	87.5	100	85
3-b	Different orientation: tag faces west	92.5	92.5	87.5	87.5	92.5
4-a	Human movement : two people	67.5	82.5	87.5	85	72.5
Average		72.5	81.25	82.9	84.58	80

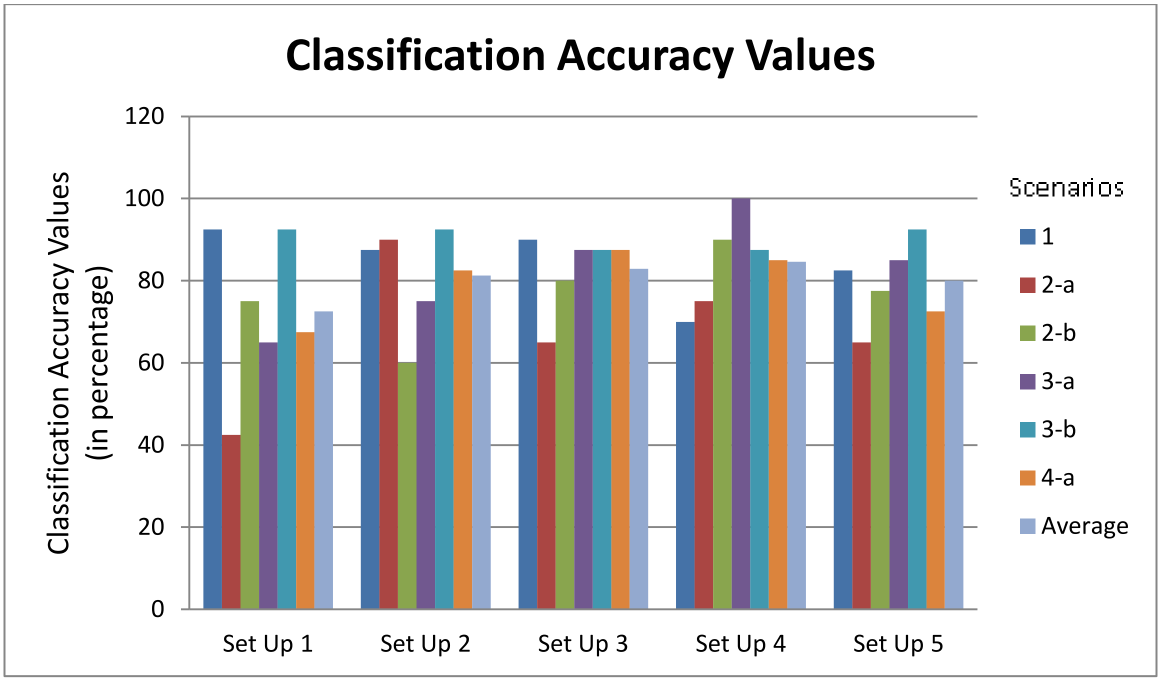

Figure 3.10: Classification Accuracies for Motion Detection Experiments

However we observed lower distance values for motion state, which also caused the motion detection scores (table 3.6 and figure 3.10) to be lower than zone-based localization scores (table 3.3 and figure 3.7). We conclude that location changes cause larger deviations in the RSSI, which makes them easier to detect compared movements at the same location.

From the results, it quite clear that, the distribution distances as well the classification accuracies favor set ups 2 and 5. Set up 2 serves as a more optimum choice since it uses only two antennas but with set up 5 the coverage would be more dense and enabling an enhanced feature set (feature formation and classification algorithm is explained in the next chapter). We chose set up 2 and 5 as the two most optimum set ups and did some further experimentation with them. We added new scenarios which simulate a trauma room more closely and evaluated the performance of set ups 2 and 5. These new scenarios made the testing environment more challenging with regards to interference and multipath propagation. The additional scenarios added are as follows:

- **Scenario 2-d):** Carts Z1 and Z2 were lowered by 0.3 m each (distances between a cart and the antennas increased).
- **Scenario #5: Multiple tags in the environment:** To simulate the presence of multiple objects in the environment, in addition to the target tagged object we placed four tags on Cart Z1 (representing two objects in storage) and six tags on cart Z2 (representing three objects on patient-bed). Tags were scattered uniformly on the carts, with an average separation of 8 cm.
- **Scenario #6: Multiple tags and people movement:** Scenarios #4b and #5 were combined to observe the joint effect of multiple tags and providers' movement in the environment.

The results of the additional experiments for set up 2 and 5 are shown in table 9 and 10 below:

Table 3.7: Location Change Experiment Results - Additional Scenarios

Scenario		Set Up 2			Set Up 5		
		Read Rate	Mahalanobis Distance	Classification Accuracy	Read Rate	Mahalanobis Distance	Classification Accuracy
2-d	Zone deviation: Z1 and Z2 lowered by 0.3 m	562	2.8	92.5	462	114.9	92.5
5	Multiple tags (6tags on Z1, 4 tags on Z2.	128	90.4	95.3	258	523.6	80
6	Human motion (5 people)+ multiple tags.	122	48.8	87.5	255	297	82.5

The scenario 2-d was included to see the effect of the cart movement in vertical direction on the performance of the system. As seen from the results, it does not affect the classification accuracy since the vertical displacement of the carts does not result in any interference with the signal. Scenarios 5 and 6 more closely resemble the trauma bay which consists of multiple tagged objects at a time and multiple people moving around in the room. As seen from the results, set up 5 gives better read rates and mahalanobis distance whereas set up 2 gives better classification accuracy. It is important to note that when there are multiple antennas in the room, the coverage area might be highly affected with lesser number of antennae. Hence the read rates as well as the mahalanobis distance are less for set up 2. Thus set up 5 is a more preferred set up in case of such an environment.

Table 3.8: Motion Detection Experiment Results - Additional Scenarios

Scenario		Set Up 2			Set Up 5		
		Read Rate	Mahalanobis Distance	Classification Accuracy	Read Rate	Mahalanobis Distance	Classification Accuracy
2-c	Zone deviation: Z1 and Z2 lowered by 0.3 m	690.8	7.3	82.5	554.8	25	80
5	Multiple tags (6tags on Z1, 4 tags on Z2.	139.8	18.9	87.5	247.2	37	87.5
6	Human motion (5 people)+ multiple tags.	127.8	12.8	85	263.6	12.1	65

As seen from the table above, the overall performance of set up 5 is better than set up 2 considering the read rates, mahalanobis distance and the classification accuracy. Even though we see that the classification accuracy of set up 2 is slightly better than that of set up 5, set up 5 provides better coverage and separability of classes.

3.6 Tag Placement

In this section we address the tag placement problem. The tag placement problem arises due to the different size, shapes and material of the object on which the tag is placed. This study was done more to understand the effects of the object's characteristics on the tag rather than evaluating the performance of the set up itself. The orientation and the placement of the tag on an object affect the read rates. If the read rate remains constant no matter how we place the tag on the object, then the antenna experiments would be enough to evaluate the system. This section provides an insight into the do's and don'ts to be taken care of while placing a tag on an object. Previously, work has been done to evaluate the characteristics of a passive UHF RFID tag on a general basis [7, 8]. We are studying the tag placement requirements with respect to a dynamic medical set up. In a trauma bay, a lot of medical objects are in use and these objects have different shapes, sizes and are made up of different material. Hence it is important to understand the tag placement requirements and challenges faced.

3.6.1 Tag Placement Requirements

To maximize the object detection rates in a dynamic medical setting, a tag deployment strategy should meet the following requirements.

1) Each object (or a bundle of objects, such as kits) should have at least one tag.

2) Tags must be placed such that they are visible to the antennas regardless of the orientation of the object.

3) When tagging metallic objects and liquid containers, either special tag must be used, or the contact between the object and the tag must be minimized.

4) Tag shape should be preserved as much as possible when attaching it so that its antenna can function optimally.

5) Tags should be placed on object surfaces that are not in contact with providers' hands or body. This is however an interesting requirement, since activity recognition can also be inferred when there is some contact made with the tag.

6) Tag should be placed such that the objects are still comfortable for use.

7) Number of deployed tags must be minimized to reduce costs and potential message collisions during tag-reader communication, as well as meeting the esthetical requirements.

Figure 3.11: Objects used for tag placement experiments - (a) a fluid bag, tag attached along length (b) a stethoscope, tags attached along width with complete folding (c) a foley catheter kit, three tags attached (d) a cervical collar, tags attached in tandem.

3.6.2 Experimental Evaluation

1) Experimental Setup

To evaluate our strategies for tag placement, we performed experiments in our two-zone setting, consisting of a storage zone and the patient bed zone. Each experiment was repeated under antenna setups #2 and #5, which demonstrated the best performances in antenna placement experiments. We also created a combination of setups #2 and #5 by scanning the storage zone (Z1) with a ceiling-mounted antenna and the patient-bed zone (Z2) with one ceiling-mounted antenna and two slanted antennas. We experimented with different medical objects, which represented the different material, size and shape of the objects in the trauma bay (figure 3.11).

2) Experimental Scenarios

We group our experiments based on the different dimensions of tag selection:

Scenario #1: Tag type selection and placement based on material: A major limitation of passive RFID technology is its poor performance on metallic objects and liquid containers. Although off-the-shelf special tags are available for metals, they are not appropriate for disposable objects due to high costs. When tagging the metallic items and liquid containers with regular tags, the overlap between the tag and the object should be minimized for better performance. For example, tags can be attached to the edge of the object, provided that it does not interfere with provider's activities. We evaluated this approach by tagging a liquid container in the following ways: (1) The tag was attached along its length (2) The tag was attached along its width.

Scenario #2: Determining the number of tags: Although a single tag may be sufficient to detect and identify an object, multiple tags can be used for more reliable detection. Multiple tagging is especially useful when one of the tags is subject to low detection rates due to irregularity of object shape, orientation changes or occlusion (by hand, body or another object). We experimented with two objects to analyze the read rates when multiple tags are attached: (1) a Foley catheter kit, which has a regular box-like shape and (2) a stethoscope, which has a thin, cylindrical surface.

The Foley Catheter kit and the stethoscope are shown in figure 3.11. This scenario was studied basically to see the effects of multiple tagging on the read rates.

Scenario #3: Tag placement based on object shape: Most objects in the trauma bay have irregular shapes, requiring different strategies for placing RFID tags. For example, objects with cylindrical surface may require folding the RFID tag, which may impair the radio signal reception. In this experiment, we assess the effect of tag folding on read rates. We performed our experiments with a stethoscope, which has a thin cylindrical surface and requires significant bending of the tag when completely wrapped. We experimented with four folding levels and styles: (1) tag attached along its width without folding (2) tag attached along its width with minor folding (3) tag attached along its width with complete folding and (4) tag attached along its length with complete folding.

Scenario #4: Tandem Tagging: Objects are being contacted when in-use. To exploit this contact cue for object use detection, we propose attaching two tags to an object in tandem: one at a location where the tag will be covered by hand or body when in-use, and one at a location where it will always be exposed to RF signal. When the object is not in-use, we expect strong radio signal from both tags; when the object is in-use, the tag being contacted by a care provider or the patient will emit weaker signal, or no signal at all. Applicability of tandem tagging is limited to objects with a sufficient duration of contact. Due to the dynamic nature of trauma resuscitation, signals from tags may be lost briefly during accidental contacts or occlusions. Distinguishing these accidental contacts from purposeful but brief contacts is almost impossible. Therefore we apply tandem tagging and evaluate its effectiveness only on the objects characterized with relatively longer contacts.

We evaluated the efficiency of this approach using two different objects: a collar and a stethoscope. Each object was first tagged randomly, then using the proposed strategy. The object stood still during first 10 seconds of a recording session and used during the second 10 seconds of a recording session (collar placed on human neck, stethoscope used for listening to breath sounds).

3) Evaluation Metrics

We used the read rate (number of readings collected from an object per second) as the evaluation metric in Scenarios #1, #2 and #3. Because Scenario #4 is directly related to object-use, we used the metrics of distribution distance as well.

3.7 Tag Placement Results

3.7.1 Tagging Liquid Containers (Scenario #1)

Table 3.9: Tag Placement Results - Material of the Object

Scenario		Set Up – Read Rate Values		
		2	5	Hybrid
1-a	Material – Tag attached along long edge	290	206	294
1-b	Material – Tag attached long short edge	413.2	553.2	415.4

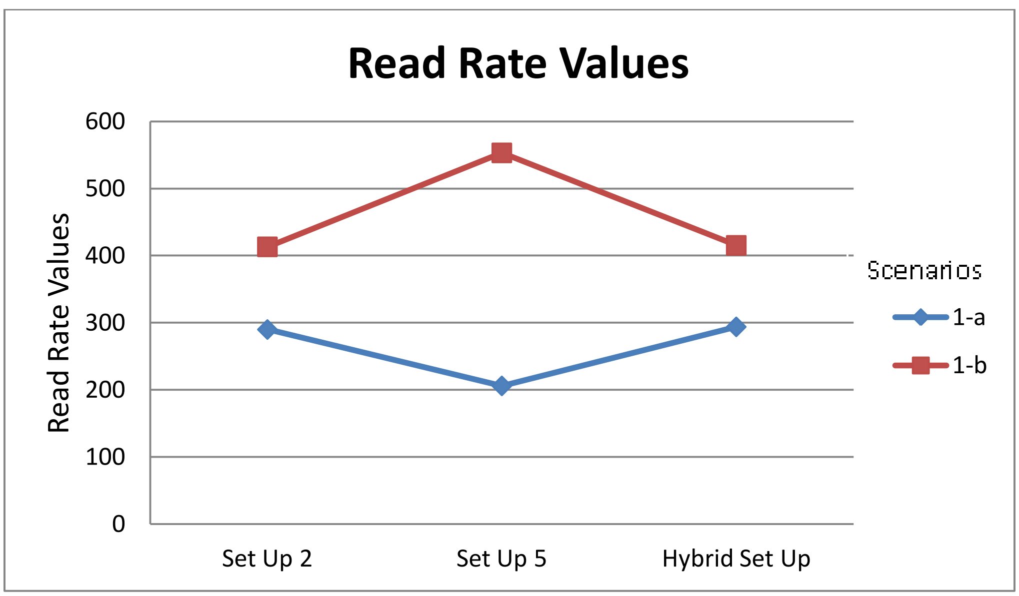

Figure 3.12: Read Rate curve for tags attached on a liquid container.

Our experiments with a liquid container showed that, attaching the tag along its shorter edge further minimized the object-tag overlap, and yielded higher read rates (table 3.9 and figure 3.12).

3.7.2 Determining the Number of Tags (Scenario #2)

Table 3.10: Tag Placement Read Rate values for scenario 2

Scenario		Set Up Read Rate Values		
		2	5	Hybrid
2-a	FC – 1 tag	456.4	734.8	387.6
2-b	FC – 2 tags – 6 inch separation	492.4	961.8	562.8
2-c	FC – 3 tags – 3 inch separation	486	1111.2	682.8
2-d	FC – 2 tags – 2 inch separation	713.6	913.2	610.6
2-e	Stethoscope – 1 tag	88.8	306	253
2-f	Stethoscope – 2 tags	313	509.8	353

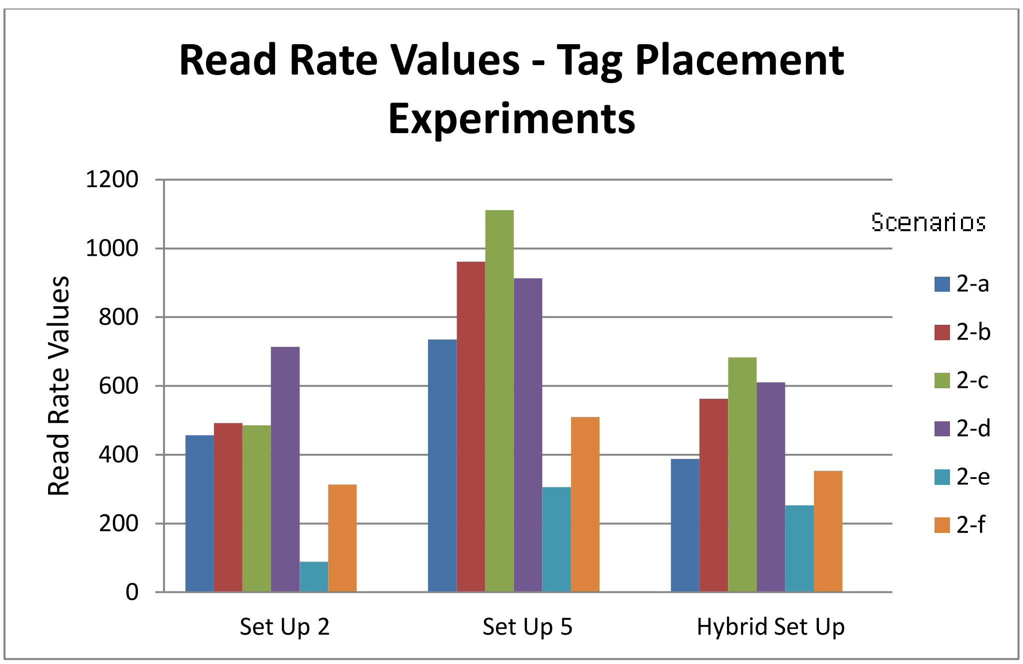

Figure 3.13: Read Rate Graphs for Tag Placement Experiment - Multiple Tagging

Using multiple tags on an object improved read rates from both the Foley catheter and the stethoscope (table 3.10 and figure 3.13). We also observed that, as the distance between tags was increased, or the tags were placed at different orientations, read rates were improved.

3.7.3 Effect of Tag Folding (Scenario #3)

The tag folding (tag bending) experiments were conducted using the stethoscope. We evaluated two cases with tag folding – 1) when the stethoscope was in the storage area 2) when the stethoscope was around the person's neck. Since the doctors and nurses usually hang the stethoscope around the neck, we had to consider both the cases.

Table 3.11: Tag Placement Read Rate values for Scenario 3

Scenario			Set Up		
Number	Object Location	Description	2	5	Hybrid
3-a	Cart	No bending	502	437.6	357
3-b	Cart	Little bending –short edge	466	616.8	343.8
3-c	Cart	Complete bending – short edge	491	573.8	399.8
3-d	Cart	Complete bending –long edge	456	516.2	263
3-e	Neck	No bending	177	244.2	330.8
3-f	Neck	Little bending –short edge	171	285	217.6
3-g	Neck	Complete bending – short edge	192	306	253.4
3-h	Neck	Complete bending –long edge	163	235.2	205.4

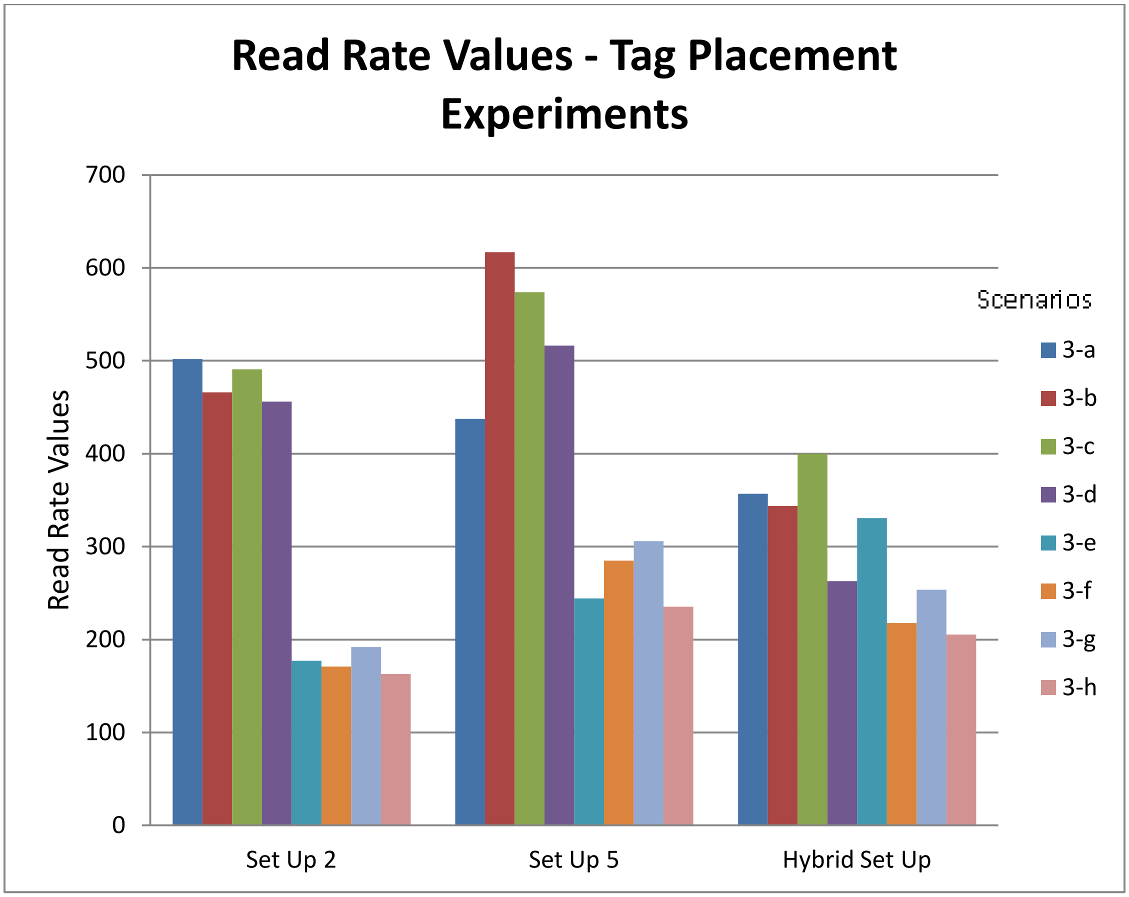

Figure 3.14: Read Rate Graphs for Tag Placement Experiments – Tag Folding

Tag bending caused a degradation pattern in read rates, except the complete bending experiment. Although complete bending reduced read rates obtained from ceiling-mounted antennas, reception from the slanted antennas was increased. Read rates were lower, and impairment of bending was more severe when the stethoscope was around neck (table 3.11 and figure 3.14).

3.7.4 Effect of Tandem Tagging (Scenario #4)

Table 3.12: Tag Placement Scenario 4 – Read Rate and Mahalanobis Distance Values

Scenario			Read Rate Values for Set Ups			Mahalanobis Distance Values for Set Ups		
Number	Object	Type	2	5	Hybrid	2	5	Hybrid
4-a	Collar	Two tags – Both exposed	302.6	752	579.6	12.1	111.2	133.7
4-b	Collar	Two tags – One covered	373.2	542.6	512.2	16.5	90.8	223.3
4-c	Stethoscope	Two tags – Both exposed	278.6	418.4	442.8	7.4	27.4	35
4-d	Stethoscope	Two tags – One covered	313	509.8	353.4	8.9	40	11.2

Because our aim is to infer the usage of objects, we used the distribution distance metric for evaluation. For both collar and stethoscope, proposed tagging strategy yielded higher distribution distance for setup 2 (table 3.12). As seen in the table above, setup 2 provided consistent results with both the stethoscope and the collar. Both the distribution distance as well as the read rates increased when one of the tags was covered.

3.8 Summary

We studied the antenna placement strategy and the tag placement rules in this chapter. The antenna set up results gave us a lot of insights into choosing an optimum antenna setup. We were able to study the effects of environmental conditions on the system performance and also the setups that perform well in challenging conditions. Our antenna setup study provides a guideline to be considered for evaluating an RFID system with respect to its setup. It also provides the tools that could be used to deploy an RFID system efficiently in a dynamic work environment.

The tag placement experiments were conducted to study the effects of the object on the performance of the tag. We discussed the read rates obtained from the tag by considering different aspects of the object. The tag placement results helped us to determine the tag placement strategy on the object considering the material, shape and size of the object. This study acts as a set of rules to be followed while tagging medical equipments.

Chapter 4: Object State Detection

In a trauma room, there are two types of events which change the state of an object – location change and motion. Although the location change event involves the motion of the object as well, we will treat both these events separately on the basis of their event duration and the resulting changes in the signal.

Mobility of a user, or an object, provides valuable information to build context aware applications. In a trauma bay, object motion detection can help in monitoring the medical equipment utilization. In this chapter, we explain the methodology used for long range motion detection of an object using passive RFID technology. We define object motion as any movement experienced by the object due to human interaction such as holding and releasing, using the object. Identification of the location change of an object can also be useful to infer the activities to be performed in a trauma room. For example, a location change of a collar from the storage area to the patient bed may indicate that the collar will be put around the neck of the patient in sometime.

Both the object motion and object location change events result in fluctuations in the received signal strength as well as the read rates. These changes have different statistical characteristics compared to the fluctuations caused due to environmental factors such as human movement near the tag, nearby tag movement, etc. Our methodology for detecting the motion depends on processing the RSSI sequence to detect the fluctuations due to the tag motion.

We extract descriptive features from the received signal strength and classifying those using machine-learning techniques. In the previous chapter, we explained how set up 2 and set up 5 are the optimum set ups for motion detection. In this chapter, we work with those set ups for studying the classification performance with different parameters.

4.1 Data Collection

We have used the same data collected for the set up experiments for studying the classification performance. The dataset comprises of two sets – 1) Location Change Data and 2) Motion Detection Data. Our total dataset for location change comprises of 200 recordings, each recording being 20s long. Our total dataset for motion change comprises of 150 recordings, each recording again being 20s long. The classification algorithm was run for the entire dataset of location change and motion, individually and the results were obtained.

We ran the classification algorithm for the data collected with all the set ups using different classifiers and classification parameters. This gave us insights into the behavior of different classifiers and the effect of the parameters on the classification performance. In this work, we are focusing more on two state classification for both the location change and the motion experiments. The two states in case of the location change dataset are the two different locations itself. For motion detection dataset, the two states correspond to moving and not-moving states.

4.2 Classification Methodology

Our classification approach was to first analyze the RSSI data obtained to study the distribution pattern under different settings. This helps to determine the best features that could be used for classification. The classification is a machine learning problem [9, 10] and we used the WEKA (Waikato Environment for Knowledge Analysis) Classification tool [11] as a reference for this purpose. We created a feature set and classified the dataset into two classes with different window lengths and slide lengths. The feature set for location change experiments consisted of Delta Mean of read rates and Standard Deviation for motion experiments.

4.2.1 Classification Algorithm

Let X denote the RSSI signal received from a tag:

$$X = \{ x_{Tk}^{Ak} \}_{k=1,2,\ldots n}^{Ak=1,2,3} \qquad (5)$$

where x_{Tk}^{Ak} denotes a reading received at the k'th timestamp T_k by antenna A_k.

The mobility status u_t at time t ($0 < t < t_n$), with a classification rule h is given by:

$$u_t = h(X) \text{ such that } u_t = v_t \qquad (6)$$

where v_t is the actual mobility status of the object at time t. RSSI readings from a distant time provide little or no information about the mobility at time t. So the input can be truncated to within a window around t without affecting the performance:

$$u_t = h(X) = h\left(\{ x_{Tk}^{Ak} \}_{\left(t-\frac{w}{2}\right) < Tk < \left(t+\frac{w}{2}\right)}^{Ak=1,2,3} \right) \qquad (7)$$

where w represents the window size. Thus the length of the input signal data to the function depends upon the window size. The window size in turn also determines the latency involved in the state classification. For example, a window of 3 seconds includes about 80 RSSI readings.

Once we have the window of data, we extract the sufficient features from that data such as the standard deviation, delta mean of read rates, etc to form the feature set:

$f_k^t = d\ (\ \{\ x_{Tk}^{Ak}\ \}_{\left(t-\frac{w}{2}\right)<Tk<\left(t+\frac{w}{2}\right)}^{Ak=1,2,3}\ )$ (8)

where f_k^t is the k_{th} feature coefficient at time t. Collectively all these coefficients form the feature vector. Thus the length of the feature vector is equal to the number of windows created which in turn depends upon the window size.

In machine learning applications, the classifier has to be first trained using the training set with pre-assigned labels [9, 10]. The training set used by us is the same data set that is used for testing. We created a labels vector for the each file and trained the classifier. A label indicates the state of the object during that interval. The labels file was created with a 1 second interval. For example, consider an experiment Y being conducted which is 20 seconds long and data is collected. Now during Y, the object was still for the first 10 seconds and was moving for the next 10 seconds. We will label the event stationary as 1 and the event moving as 2. So the labels file generated for the experiment Y will have 20 values, one for each second. The first 10 values in the labels file will be 1 and the last 10 values will be 2. Thus using the pre-defined labels file and the train data set, the classifier trains itself for the features used.

The problem of estimating the mobility status can now be thought as learning a function g that maps the feature vector to the mobility status:

$u_t = g\ (\ f_t\ )$ such that $u_t = v_t$. (9)

In machine learning the function g is known as the classifier, u_t a predicted label and v_t a true label.

4.2.2 Classification Parameters

- Window Length

Several issues must be considered when choosing the window size. A larger w is useful under noisy observations as it yields smoother estimates. However, short movements might be missed with a large w. The latency of the classifier is also proportional to w. The size of the window and the slide length determines the number of windows generated for that file which in turn determines the length of the feature set. The average duration of object use is 20 seconds, implying shorter interactions. For detecting such interactions and generalization, we restricted the window size to 10 seconds.

- Slide Length

The slide length is nothing but the amount by which the window slides after each run.

- Classifier

We experimented with the following non-temporal classifiers:

1. Support Vector Machines (SVM)
2. Decision Trees (DT)
3. Random Forests (RNF)

The non temporal classifiers were built with the WEKA machine learning toolkit [11].

We also used temporal classification with the Hidden Markov Model (HMM). An HMM is a generative probabilistic model, which takes the temporal information into consideration. We built an HMM, where the actual motion states constitute the hidden state set (still or moving) and the estimated states constitute the observation symbols set. Transition probabilities of the HMM were estimated from the training data. Observations were modeled as Gaussian mixtures with parameters estimated from the training data based on the Maximum Likelihood principle.

- Features

When an object is standing still, its RSSI pattern may exhibit only slight deviations due to multipath fading. Changing environmental conditions such as human movement or nearby tag movement may trigger stronger deviations. However, the most fluctuations observed in the tag data were during the tag motion itself. For state classification, our aim is to detect these fluctuations. We have used standard deviation and delta mean as the features to capture this change. Standard deviation was used for the motion detection experiments and is a measure of the variation in the signal in the specified window size. Delta mean was used as a feature for the location change experiments and it represents the amount of change in average RSSI between two successive windows. Delta mean is supposed to be high when a location change happens.

4.3 Classification Results

The classification method requires the train and test sets. The train and the test sets were determined based on the sessions because the readings in a session are correlated. Our evaluation metric is the classification accuracy. Performance score is determined using the average classification accuracy over all the sessions in a test set. We performed the experiments repeatedly with varying window lengths, slide lengths and classifiers to note the effect of each on the classification accuracy. We have calculated the classification accuracy for all the antenna setups with varying window lengths and slide lengths as well as different classifiers. The results help us to see the effect of the parameters on the accuracy and are in correlation with the results from the previous chapter.

We have used three non temporal classifiers namely Decision Tree, Support Vector Machines, and Random Forest for calculating the accuracies. Non-temporal classifiers are better in capturing the change in RSSI signal and distinguishing these from environmental effects.

4.3.1 Location Change Experiments Results

- Decision Tree Classification

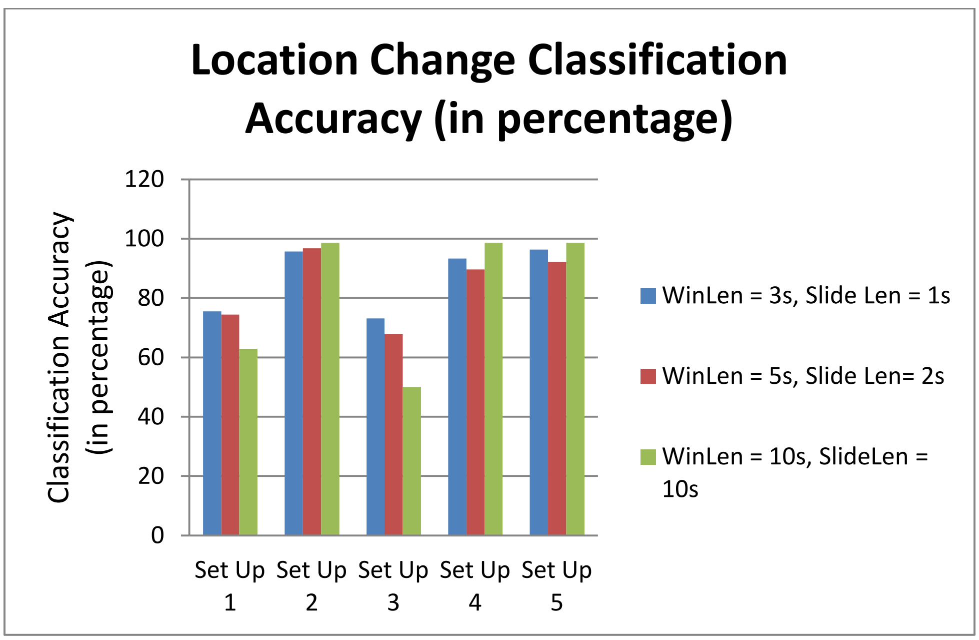

Figure 4.1: Location Change Classification Accuracy (in percentage): Decision Tree Classifier and varying window lengths and slide lengths.

- Support Vector Machine Classification

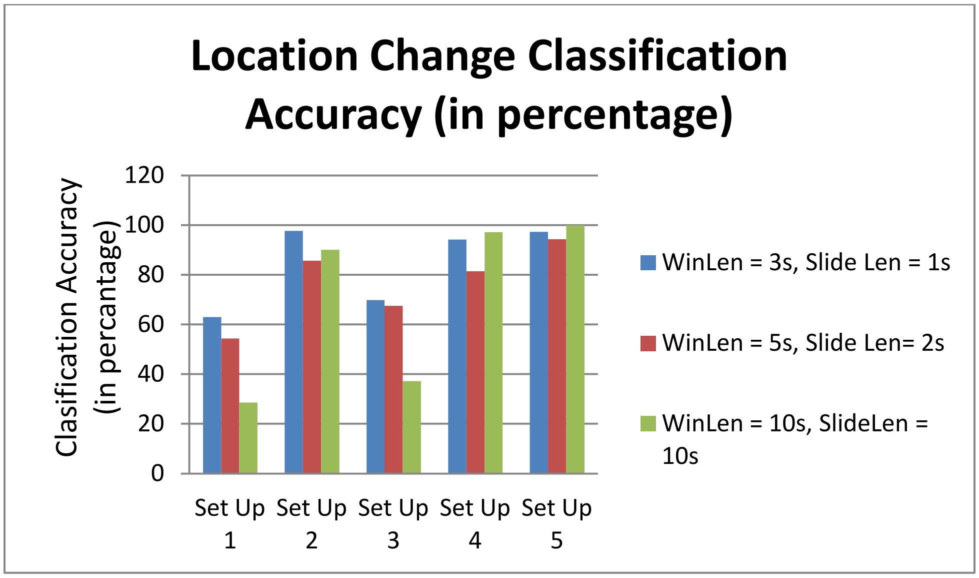

Figure 4.2: Location Change Classification Accuracy (in percentage): Support Vector Machine Classifier and varying window lengths and slide lengths.

- Random Forest Classification

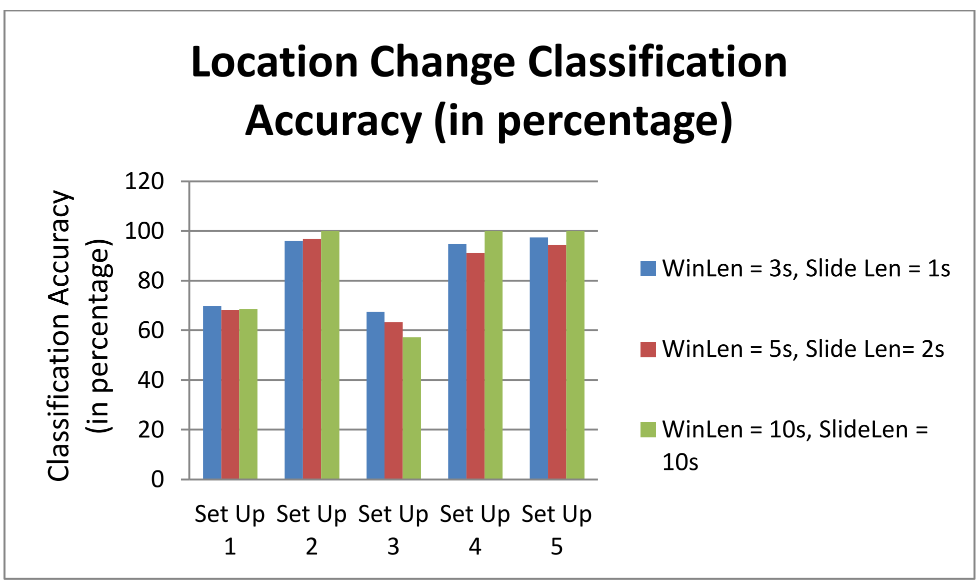

Figure 4.3: Location Change Classification Accuracy (in percentage): Random Forest Classifier and varying window lengths and slide lengths.

4.3.2 Motion Detection Experiments Classification Results

- Decision Tree Classifier Results

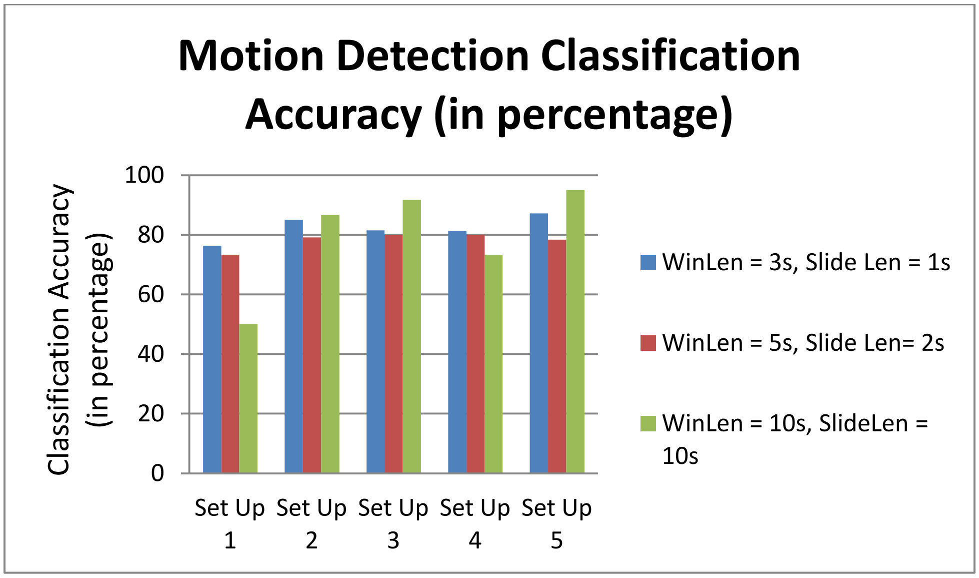

Figure 4.4: Motion Detection Classification Accuracy (in percentage): Decision Tree Classifier and varying window lengths and slide lengths.

- Support Vector Machine Classifier Results

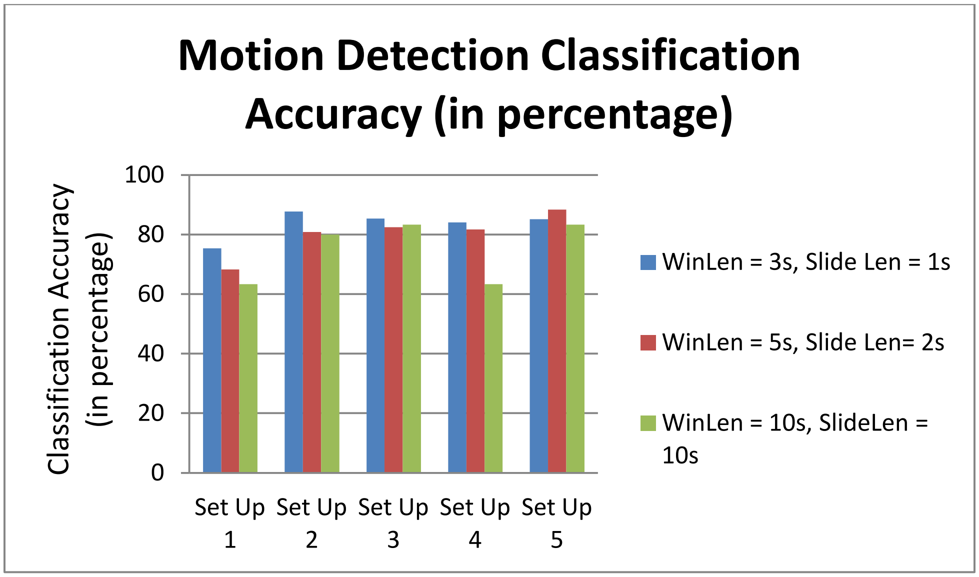

Figure 4.5: Motion Detection Classification Accuracy (in percentage): Support Vector Machine Classifier and varying window lengths and slide lengths.

- Random Forest Classifier Results

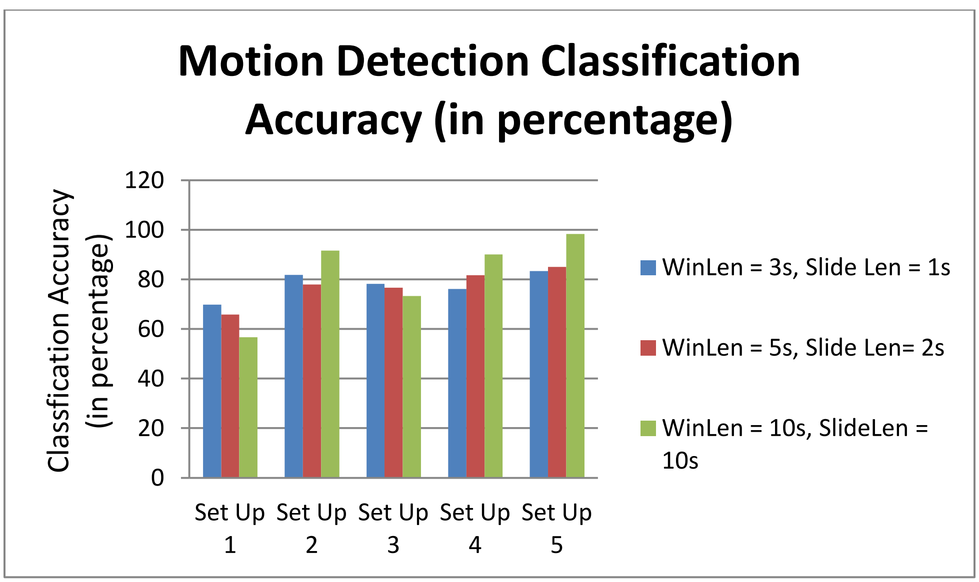

Figure 4.6: Motion Detection Classification Accuracy (in percentage): Random Forest Classifier and varying window lengths and slide lengths.

As seen from the results above for both location change and motion experiments, set ups 2, 4 and 5 give the best classification accuracies. For location change experiments, the third set of parameters (window length = 10s and slide length = 10s) yielded the best results. This is because the experiments were 20s long and the location change happened at the 10th second. So the two sub-intervals of the first 10s and the next 10s belong to two different locations and therefore have different RFID signal patters. Thus the results support the argument that better the separation of the classes, better is the classification accuracy. For motion experiments, however, smaller window lengths and slide lengths show good results. A short window yields fewer amounts of data, causing unreliable estimation of features. In this case, a simple DT can be used.

4.4 Summary

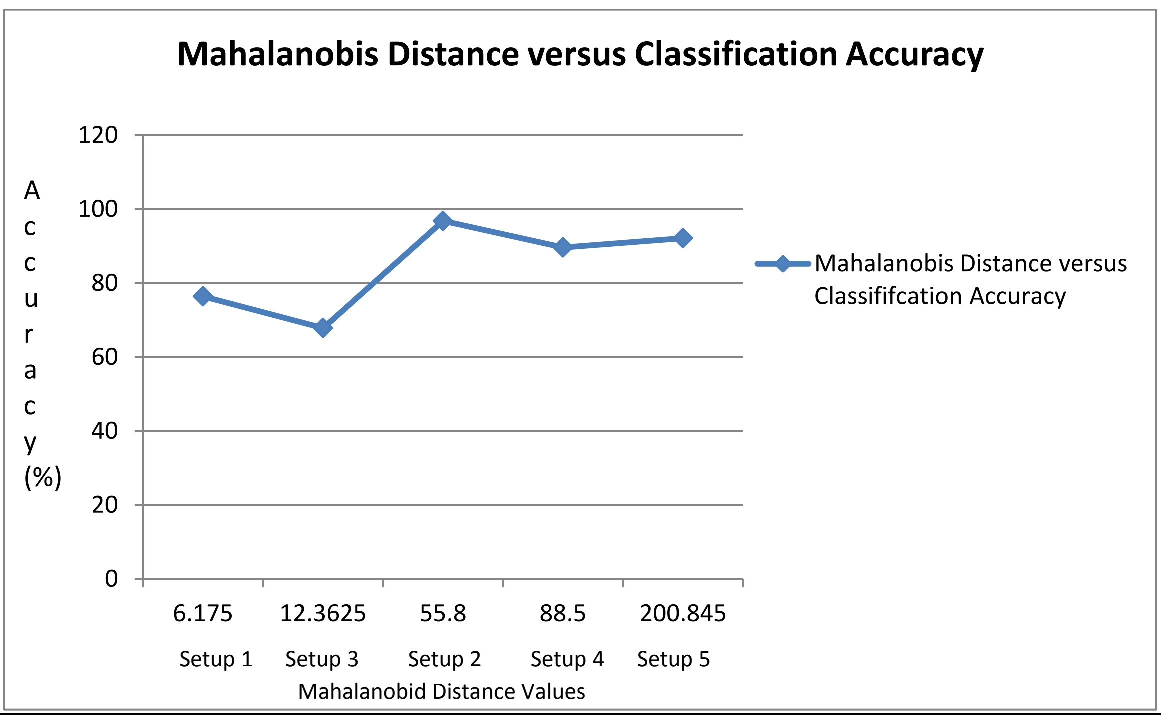

Figure 4.7: Mahalanobis Distance (average) versus Classification Accuracy - All five RFID set ups

The figure above shows the Mahalanobis distances versus the classification accuracy for all the setups for location change experiment. Our results show that the distribution distance values have a correlation with the performance of the RFID set up (as shown in the figure 4.7). More the difference between the distributions of classes, better is the separation between the classes, more is the classification accuracy. The relationship between the distribution distance and the classification accuracy is logarithmic rather than being linear. Setup 2 performs better in terms of classification accuracy because of the presence of two overhead antennae directly above the zones. The feature set thus formed for setup 2 is much smaller and classification problem is simplistic. One more important point to note is that setup 3 has low classification accuracies compared to other setups in spite of having two overhead antennae. As seen in figure 3.4, setup 3 is a symmetric setup with respect to the location of the two carts. Hence the RSSI pattern obtained from both the locations is going to be similar. Hence setup 3 performs badly compared to other setups. Thus, it is important to create an asymmetric RFID setup as much as possible so that the RSSI patterns at different locations are not similar.

Chapter 5: Conclusion and Future Work

5.1 Conclusion

We have proposed a methodology to evaluate the performance of the RFID systems in a dynamic work environment. We have closely studied the trauma bay activities and have proposed five RFID set ups that can be deployed in a trauma bay. We have used the distribution distance to measure the separation of classes in the RSSI obtained from the readers.

The results can be used as groundwork for future work on evaluating the RFID systems from a context aware application point of view. We also conducted experiments for the placement of tags on objects and studied different scenarios. The tag experiment results can act as a guideline to be followed for tagging the objects.

We also ran our classification algorithm for all the proposed set ups using different classifiers and parameters. We have obtained satisfactory results for the classification accuracy. The results gave us insights into the use of classifiers and parameters to optimize the performance.

5.2 Future Work

The results obtained in our work are from the data collected in the research lab. We have also deployed the RFID set up at the Children's National Medical Center, Washington, and collected real data. The trauma bay was set up with the RFID system and the trauma team performed a number of activities. The real data can be explored for evaluating the performance of the RFID set up deployed. The data can be filtered and utilized to evaluate the RFID setup at the trauma bay in a similar manner as done in chapter 3. Also, the classification algorithm can be run on this data. The results will give interesting insights into the performance of RFID systems in real world. We have used Mahalanobis distance as a metric in our work for distribution distance calculation. There are several other distance metrics like Euclidean distance, Earth Mover's Distance that can be used and the results can be compared. The feature set used for location change estimation was delta mean whereas for mobility experiments were standard deviation. Results can be obtained and compared using other features like combination of both delta mean and standard deviation, mean RSSI, etc. The application of RFID technology in the trauma bay looks promising and there is a lot of potential for research in this area.

References

1) Steve Hodges, Alan Thorne, Hugo Mallinson, Christian Floerkemeier, "Assesing and Optimizing the Range of UHF RFID to Enable Real World Pervasive Computing Applications" in Pervasive Computing,vol. 4480. Anthony LaMarca,Marc Langheinrich,Khai Truong, Springer Berlin / Heidelberg, 2007, pp 280-297.

2) Lin Wang, Bryan A. Norman, and Jayant Rajgopal, "Placement of Multiple RFID Reader Antennas to Maximize Portal Read Accuracy", International Journal of Radio Frequency Identification Technology and Applications, vol.1,no.3,pp. 260-277,January 2011

3) Matteo Bertocco, Andrea Dalla Chiara, and Alessandro Sona,"Performance Evaluation and Optimization of UHF RFID Systems",Instrumentation and Measurement Technology Conference (I2MTC), 2010, pp. 1175-1180

4) Alien Technology – Products: http:www.alientechnology.com/products/index.php

5) K. Kleisouris, B. Firner, R. Howard, Y. Zhang, and R.P. Martin, "Detecting intra-room mobility with signal strength descriptors," In *Proceedings of the eleventh ACM international symposium on Mobile ad hoc networking and computing*, 2010, pp. 71–80

6) Parlak, A. Sarcevic, I. Marsic and R. S. Burd, "Introducing RFID technology in dynamic and time-critical settings: Requirements and challenges" *Journal of Biomedical Informatics,* 2012.

7) K. M. Ramakrishnan and D. D. Deavours, "Performance benchmarks for passive UHF RFID tags" In *Proceedings of the 13th GI/ITG Conference on Measurement, Modeling and Evaluation of Computer and Communication Systems*, 2006, pp. 137-154.

8) J. D. Griffin, G. D. Gurgin, A. Haldi and B.Kippelen, "RF tag antenna performance on various materials using radio link budgets," *IEEE Antennas Wireless Propogation Letters*, vol. 5, no. 1, pp. 247-250, 2006.

9) E. Alpaydin, "Introduction to Machine Learning", The MIT Press, 2010.

10) C. Bishop, "Pattern Recognition and Machine Learning", Springer, 2006.

11) Hall, M., Frank, E., Geoffrey, H., Pfahringer, B., Reuteman, P., Witten, I.H.: The weka data mining software: An update. SIGKDD Explorations **11**(1) (2009)

12) Nikitin, P.V. Intermec Technol. Corp., Everett, MA Rao, K.V.S., "Performance Limitations of Passive UHF RFID Systems", Antennas and Propagation Society International Symposium, IEEE, 2006,pp. 1011-1014

13) M. Buettner and D. Wetherall, "An empirical study of UHF RFID performance," In *Proceedings of the 14th ACM international conference on Mobile computing and networking*, 2008, pp. 223–234

14) D. M. Dobkin, "The RF in RFID: passive UHF RFID in practice,". Elsevier, 2008.

15) A. Rahmati, L. Zhong, M. Hiltunen and R. Jana, "Reliability techniques for RFID-based object tracking applications," In *Proceedings of IEEE/IFIP International Conference on Dependable systems and Networks*, 2007, pp. 113-118.

16) Parlak S, Marsic I, Burd RD. Activity recognition for emergency care using RFID. Proc Int ICST Conf Body Area, Networks;2011

17) Parlak S, Marsic I, Bajwa W, Burd RS. Passive RFID for recognizing activities in trauma care. TRU-IT Technical Report, Rutgers University;November 2011. Available from : http://www.tru-it.rutgers.edu/.

18) Want R. An Introduction to RFID technology. IEEE Pervasive Comput 2006;5(1):25-33

19) Sangwan RS, Qiu RG, Jessen D. Using RFID tags for tracking patients, charts and medical equipment within an integrated health delivery network. Proc IEEE Networking, Sensitivity and Control;2005.p.1070-4

20) Turaga P, Chellapa R, Subrahmanian V, Udrea O. Machine recognition of human activities: a survey. IEEE Trans Circ Syst Video Technol 2008;18(11):1473-88.