Automated Hand Hygiene Monitoring System Using Imagery and Bluetooth Low Energy Sensors

By

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Abstract

This thesis designs and implements a hand hygiene monitoring system using Bluetooth low energy and imagery sensors. As the cost of treating healthcare-associated infections increases, the need for monitoring and improving hand hygiene compliance percentages for healthcare providers increases. Several techniques for hand hygiene compliance monitoring exist, but it was found that electronic automated systems are the most reliable solution because they provide more accurate continuous compliance measurements for lower cost. Other similar systems based on a variety of technologies exist, however, they are either uniquely evidence based, so that they capture hygiene moments and apply a statistical model for hygiene opportunities, and they, therefore, do not provide real-time information; or they require human interference to determine compliance rendering them not fully automated. In this thesis, available monitoring techniques, focusing on automated electronic systems, are first introduced. Then, a novel automated hand hygiene monitoring system, capable of capturing hygiene moments with more than 90% precision, is proposed. The proposed system was first tested in a lab environment with private rooms setup, the system was also tested in semi-private rooms setup and then implemented in the Hematology and Oncology Department at the Health Sciences Center of Eastern Health for a pilot study. The study showed a high correlation between the compliance rates calculated by the proposed system compared to the compliance rates found by direct observers.

To my family for all the support throughout the years…

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Chapter 1

Introduction and Overview

1.1 Overview of Hand Hygiene Compliance

"An ounce of prevention is worth a pound of cure", a statement frequently heard in many situations, but when it comes to healthcare-associated infections (HAIs) the significance of such a statement is tremendous and could never be denied. According to the Canadian Patient Safety Institute (CPSI), 220,000 Canadian patients contract an infection from the healthcare environment each year and 8000 patients die due to HAIs costing 100 million dollars per year (Hand Hygiene, 2017).

Hand hygiene has an enormously complicated impact on the spread of HAIs (McLaws, 2015). Adhering to the hand hygiene recommendations would significantly reduce the number of HAIs per year saving the public economy millions of dollars (Larson, 2013). Raising awareness of proper hand hygiene practices amongst healthcare workers (*HCW*) became essential, as a result, it is mandatory to have a way of measuring how well healthcare providers understand and follow the correct procedure to take care of their hand's hygiene (Sax, et al., 2009).

In healthcare environments, the ordinary common-sense approach to hand cleanliness that one uses while growing up does not apply (Larson, 2013). The World

Health Organization (*WHO*) defines five moments for hand hygiene in healthcare environments which constitute the elective based clean hands definition (Sax, et al., 2009). These moments are:

1. Before touching a patient.
2. Before clean/aseptic procedures.
3. After body fluid exposure/risk.
4. After touching a patient and
5. After touching patient surroundings.

Infection control and prevention groups in most hospitals are constantly striving to improve their healthcare providers' hygiene behaviors. This can be approached using methods such as educational training and campaigns; posters and reminders in the healthcare environment; increasing the number of available sinks, alcohol-based hand rubbing dispensers and hand hygiene products near the patients and in the corridors; and/or by monitoring, tracking and modulating staff behaviors on the floor.

Any attempts to improve the healthcare providers behaviors' and increase their compliance will most likely fail without having a reliable and consistent way to estimate how much do they comply to the hand hygiene standards (Larson, 2013). The ultimately approved way to measure hand hygiene compliance in a healthcare environment is direct observation in which a trained individual manually monitors and audits the *HCW*s' behaviors (Morgan, et al., 2012).

Although the direct observation method might initially seem accurate, when closely inspected the results may be far from reality. Additionally, direct observation has an inherent problem. The observer can identify individual behavior instead of whole group compliance which violates the privacy of the *HCW*s and might not promote the spirit of working as a team to improve the behaviors (Morgan, et al., 2012).

Another approach to gathering compliance data would be automated hand hygiene monitoring systems. Such systems are technology enabled to constantly monitor the behaviors of the selected healthcare workers. Available automated systems rely on a variety of technologies and approaches to count the number of times a healthcare provider follows the hand hygiene recommendations and how many hand hygiene opportunities he/she misses.

Automated hand hygiene monitoring systems overcome most of the weak points of the direct observation method. Human factors such as biasing are not a problem in this case as the system should be able to gather the data without any alteration from any individual. There is no selection involved if the system is deployed and installed in the entire healthcare environment (Morgan, et al., 2012).

Hand hygiene monitoring systems are not only helpful in collecting data and measuring compliance, they can provide real-time information and statistics to the staff and the management team. Periodically sharing feedback regarding the change in staff behavior is a strong intervention tool and could significantly help in improving adherence to expected hand hygiene standards. It is essential, however, that this feedback always be presented in a constructive motivational way; the staff should also be well aware of the importance of hand hygiene, understand that an improvement is required and willing to work on this improvement (Larson, 2013).

While in direct observation the Hawthorne effect reduces the integrity of the measured compliance, it helps improve compliance when an automated hand hygiene monitoring system is used. This is because the healthcare providers would be constantly under constant observation, which could lead to an intentional performance improvement. This intentional improvement may become normal behavior in the long term leading to higher compliance rates and lower HAIs.

1.2 **Objectives**

The work done during this thesis aimed to achieve the following:

1. Design and implement an automated hand hygiene monitoring system based on Bluetooth low energy technology and imagery sensor.
2. Install and monitor the designed system as a pilot project running in real healthcare environment in the Hematology and Oncology Department in the Health Sciences Centre, Eastern Health.
3. Provide real-time hand hygiene compliance feedback for healthcare workers.
4. Verify that the use of hand hygiene monitoring systems with real-time feedback will help increase hand hygiene compliance.

1.3 Thesis Contribution

The main contribution of the conducted research can be summarized as follows:

1. Design a hand hygiene monitoring system based on BLE.
2. Implement and test a computer vision algorithm for hand detection and segmentation.
3. Test and verify the system performance in different setups, namely a simulated lab environment and a real healthcare environment.
4. Optimize both the system hardware and software to achieve the required accuracy and sensitivity.
5. Provide the data gathered by the system to the Infection Prevention and Control Team at Eastern Health to perform the required analysis. The data verified that initial assumption that a hand hygiene monitoring system with real-time feedback will increase hand hygiene compliance.

1.4 Thesis Outline

The remainder of this thesis is organized as follows. Chapter 2 presents a literature review of hand hygiene monitoring techniques. Chapter 3 discusses in detail the design of the proposed system. Chapter 4 presents the pilot study and the implementation at the Health Sciences Centre. Chapter 5 presents the results acquired from lab and field-testing. Chapter 6 concludes the thesis and briefly proposes future improvements to the system.

Chapter 2

Literature Review

Tracking and monitoring healthcare providers behaviors was found to be very effective in improving hand hygiene compliance rates and hence, reducing the number of HAIs. In this chapter, a literature review of the following is presented:

1. Hand hygiene compliance monitoring techniques
2. Automated hand hygiene monitoring systems
3. Hand detection using imagery sensors
4. Indoor localization using imagery sensors
5. Wireless technologies for indoor localization and proximity

2.1 Hand Hygiene Compliance Monitoring Techniques

Measuring hand hygiene compliance rates for healthcare workers could be achieved using one of the following techniques:

1. Direct observation
2. Self-auditing
3. Monitoring of hygiene products consumption
4. Automated hand hygiene monitoring systems

2.1.1 **Direct Observation**

Direct observation is considered the gold standard for hand hygiene monitoring. In this method, a trained professional is assigned to closely monitor the healthcare providers behaviors. The observers could use a software to record the number of hand hygiene instances performed and the number of hand hygiene opportunities. The compliance percentage is the result of dividing the former by the latter.

Direct observation is considered accurate because a trained professional is assumed to see all the circumstances surrounding the hygiene opportunity. According to Morgan, et al. (2012), this method, however, has some drawbacks:

1. Intentional or unintentional bias - as hard as anyone may try to be just and fair, there will always be a desire to have better results, especially in cases where the auditing person belongs to the managerial team and wants to show that the behavior is improving.
2. There is no way that anyone could constantly monitor the behavior as it is costly to do so thereby reducing the reliability of data due to low sample numbers.
3. The process of manual auditing involves some sort of selections such as which room or *HCW* that will be monitored at any time.
4. The change in *HCW* behavior from the normal as they tend to be more careful with the hand hygiene procedures during the time they are being observed or what is called the "Hawthorne effect" (Morgan, et al., 2012).

If the observers measuring the compliance are not sufficiently trained, their understanding of what is compliant and what is not may not be very accurate. Training enough observers to constantly monitor every room at all times is not economically realistic (Boeker, Kelly, & Steed, 2010).

Niles and Johnson (2016) conducted a study from July 2015 to December 2016 to investigate the Hawthorne effect in the compliance rates obtained from direct observations. The study involved training volunteers that do not belong to health institution to be able to identify and count the hygiene moments defined by the *WHO*. The data collected by the volunteers was compared to that found by the members of the Infection Prevention Group. The aggregated compliance found by the Infection Prevention Group was 57.42% while that found by the volunteers was 21.94% for the same period.

According to Dhar, et al., (2010), unit-based observation in which professionals observe the hand hygiene compliance in the same unit in which they work, always have higher compliance rates, while non-unit based observation leads to lower rates and possibly more accurate measurements. For this reason, the affiliation of the observer should always be factored in the hand hygiene compliance calculations to account for this bias.

2.1.2 **Self-Reporting**

A self-reporting hand hygiene monitoring method uses questionnaires that include questions about individual practices answered by healthcare providers to determine their compliance rates. The questionnaires are distributed regularly to the staff either electronically or in hard copy format. The question response should make it possible to determine the compliance rate.

The compliance percentage found by the self-auditing or self-reporting method is subject to bias. In a study performed by Al-Wazzan, et al., (2011) the compliance percentage calculated from self-reporting and direct observation varied significantly. The observed compliance rate was found to be 33.4% while the compliance rate found through self-reporting was 73.8%.

At the organizational level, the World Health Organization (*WHO*) developed a survey based system to permit healthcare institutions to assess their own hand hygiene compliance rates (WHO Hand Hygiene Self-Assessment Framework, 2017). The questionnaire is based on five sections and leads to one of four levels:

1. Inadequate means that not enough effort is being put into hand hygiene practice improvements.
2. Basic means that some measures are being taken but further improvement is still required
3. Intermediate means that there is a proper hand hygiene promotion strategy and the focus should be on developing a long-term plan to sustain that improvement.
4. Advanced - means that the hand hygiene practices are consistently followed and sustained.

2.1.3 Monitoring of hygiene product consumption

In the monitoring of hygiene product consumption, the amount of alcohol-based hand rub solution and soap consumed during a specific period is monitored. Unlike direct observation, this method provides 24/7 hand hygiene monitoring. This method uses an estimate for the patient-staff product used as a denominator for the calculation. The fact that patients and their visitors use the same hygiene sources as the healthcare providers make it difficult to determine an accurate compliance rate (Pettis, 2013). The amount of fluid used is related to the compliance rate.

2.1.4 Automated Hand Hygiene Monitoring Systems

Another approach for monitoring hand hygiene is the use of electronic automated systems. Automated hand hygiene monitoring systems have the following advantages:

- The ability to provide 24/7 monitoring for hand hygiene practices.
- The ability to monitor all the rooms as well as the full staff.
- Real-time feedback for staff hygiene compliance is achievable.
- Not subject to any bias.

Automated hand hygiene monitoring systems vary in the technologies employed, the methods of measuring compliance and their ability to identify the hygiene moments. They can be used to send reminders to healthcare providers if a hygiene opportunity is missed. This acts as a positive intervention. Several studies proved that the use of electronic hand hygiene monitoring systems provide improved monitoring in comparison with direct observation and can help in meeting the targeted 95%+ compliance rate (McCalla, Reilly, Thomas, & McSpedon, 2017).

In a study conducted by Lisa H. Moore RN, CPHRM (2013) at Baptist Memorial Hospital from March 2012 to October 2012, it was found that the use of an automated hand hygiene monitoring technology along with further education for healthcare providers increased hand hygiene compliance rate by 35.3% with an associated cost savings of greater than $300,000 USD in treating healthcare-associated infections.

Another study conducted at Robert Packer Hospital for 21 months between March 2012 and November 2013 presented in (Klee & Onofre, 2014) found a significant improvement in the healthcare providers monthly hand hygiene compliance rates when technology was integrated with other hand hygiene improvement tools.

The accuracy of a specific hand hygiene monitoring system may be affected by several factors. Mawdsley, M. Limper, Pineles, Weber, & Morgan (2011) presents an attempt to validate the accuracy of a commercial hand hygiene monitoring system installed in the University of Maryland School of Medicine. In the study, the collected information from the automated hand hygiene monitoring system was compared to data collected through the direct observation method. The badge orientation and position were changed and the performance was assessed in each case. It was found that system behaviors change with the placement of the badge.

Cheri Plasters and Domeka Casey (2013) conducted a study at the University of Alabama at Birmingham Hospital to understand if automated hand hygiene monitoring systems have a positive effect on the individual's hand hygiene compliance. It was found that the use of such systems provides a safer environment for patients and enhances clinical outcomes. Constant monitoring of hand hygiene behaviors and performance feedback for staff provided enough motivation for the staff to adhere more to the recommended hand hygiene techniques hence increasing the compliance by 36.9% (Plasters & Casey, 2013).

Automated hand hygiene monitoring systems have a direct impact on decreasing health-care-associated infections (HAIs). Sanders, Cole, & Brown (2014) in a study conducted at Brookwood Medical Center raised the hand hygiene compliance, rates from 36.06% to 81.30% achieving a 125.47% increase. The economic savings for treating HAIs during the study period was $121,511 USD.

Susan Blumstein (2014), Manager of Infection Prevention in Shelby Baptist Medical Center, reported the use of radio-frequency identification based hand hygiene monitoring system in two adult units from May 2011 to October 2013 (Blumstein, 2014). It was found that the automated system is more accurate and easier to implement than direct observations, self-auditing, and hygiene products consumption monitoring. The economic saving in the treatment of HAIs during this period was $476,697 USD. In one of the two units, the compliance rate increased from 20.2% to 80.4% while in the other unit the compliance rate increased from 44.2% to 63.4% during a shorter period.

2.2 Existing Automated Hand Hygiene Systems

Automated hand hygiene monitoring systems vary in their method of counting and the technology used to identify the hand hygiene moments. According to Ward, et al. (2014), electronic hand hygiene monitoring systems can be classified into:

1. Electronically assisted/enhanced direct observation systems.
2. Video-monitored direct observation systems.
3. Electronic dispenser counters.
4. Fully automated hand hygiene monitoring systems.

In this section, existing hand hygiene monitoring systems are presented. The systems are identified by the last name of either the system developer or the publication's first author. The systems are introduced and classified based on their monitoring method to one of the previously stated categories defined by Ward, et al. (2014).

2.2.1 Polgreen

Class: Fully automated hand hygiene monitoring system.

The system presented in (Polgreen, Hlady, Severson, Serge, & Herman, 2010) consists of 4 main components:

- Badges
- Beacons
- Triggers
- Recorder

Badges, beacons, and triggers are implemented using the same hardware designed by the research team called Mote. Mote is a relatively small battery-powered wireless active device that uses the free Wi-Fi range to send and receive information. Each mote is configurable to act as a badge, beacon or a trigger.

Badges are enclosed in old pagers cases. They were designed to be carried by the healthcare providers. Badges capture and store the wireless signals sent by the beacons and the triggers with a timestamp. The data stored in the badges is transferred to the recorder. Analyzing the data would establish the number of hand hygiene opportunities as well as the missed hand hygiene moments.

Figure 2-1 Mote badge enclosed in a pager case

Image from (Polgreen, Hlady, Severson, Serge, & Herman, 2010).

Beacons are installed in the patient rooms, while the triggers are installed in the dispensers. Triggers are configured to only broadcast when the dispensers are used. Beacons and dispensers broadcast their unique identifiers and a timestamp at which the message was sent. The badge measures the received signal strength and stores it with other associated information.

The system claims 91.1% sensitivity and 100% specificity in one configuration and 97% sensitivity with 100% specificity in another configuration using an extra beacon outside the room. The system suffers from some challenges such as:

- High power consumption for a non-rechargeable device.
- The need for an onboard storage in the motes.
- Single dispenser usage could be detected by more than one healthcare providers.

2.2.2 MedSense Clear®

Class: Fully automated hand hygiene monitoring system

MedSense Clear® uses a custom proprietary 2.4 GHz wireless protocol. The system can detect moment 1 and moment 4 from the *WHO* hand hygiene recommendations. MedSense consists of wireless badges, that detect the proximity to beacons installed in the patients' environment at the head of the bed, and to on-press activated beacons installed in the dispensers.

The badges store the information captured from the beacons, sends the information to a network-connected base station which in turn uploads the information to a server. The server processes and analyzes the information to extract the hygiene compliance percentage.

The system was implemented in the neurosurgical intensive care unit of Queen Mary Hospital in Hong Kong. The data collected by the system was compared to data collected by human observers during the same period. It was found that the system missed around 1.9 scenarios per hour. During this test, the compliance found by the system was 88.9% and the compliance calculated by the observers was 95.6%. The 6.8% difference in compliance corresponds to 7.1% error.

The system was also installed in the coronary care unit of Salmaniya Medical Complex in the Kingdom of Bahrain. The study conducted by Al Salman, Hani, Marcellis-Warin, & Fatima Isa (2015) included 16 one-patient rooms and 28 distributed dispensers. The system helped raising the average hand hygiene compliance from 60% to 71% in the

28 days of the experiment. During this study, the main disadvantages of the system were found to be:

1. Poorly defined patients' area, which caused a false signal for a missed hygiene opportunity.
2. The system cannot adapt to the pre-installed alcohol and soap dispensers.
3. The system generated uncomfortable vibrations, strong enough to cause the badges to fall.

2.2.3 Sahud

Class: Electronically assisted/enhanced direct observation systems

The system as explained in the study performed by Sahud, et al. (2010) consists of two components:

- Readers, which are 8 cm x 3 cm x 1 cm coin cell battery powered devices that should be carried by healthcare providers.
- Triggers, placed in the room and inside the dispensers.

The reader records all room entries when the healthcare worker approaches the patient by 1.83 m. The reader detects the room exits when the healthcare provider moves away from the patient vicinity and stay away for 5 mins. The reader sometimes fails to detect very quick approaches to the patients. It detects the triggers whether it is inside a room or inside a dispenser, counts the scenarios, displays them on a liquid crystal display and internally stores them to be manually gathered by the research team through a USB port. The reader and the trigger placed in a dispenser are shown in Figure 2-2.

Figure 2-2 Sahud Hand hygiene reader and trigger.

Sahud's system assumes two hand hygiene moments per room entry, hence the compliance is calculated by (Swoboda, Earsing, Strauss, Lane, & Lipsett, 2014):

$$Compliance = \frac{Recorded\ hand\ hygiene\ events\ count}{2\ \times Number\ of\ room\ entries}$$

Sahud, et al. (2010) claim to detect 98% of the room entries and 95% of the dispensing events after having to do some post-installation system tweaks. The operation of the system was interrupted for 1 week due to flat batteries in the reader. The study which lasted for 4 weeks involved nurses and interns. The compliance reported for the last 3 weeks of the experiment rate for the nurses was 28.8% and 19.1% for the interns.

2.2.4 **Third-Party Remote Video Auditing**

Class: Video-monitored direct observation systems.

Motivated by traffic light cameras and their impact on raising the awareness of the drivers, in the study conducted by Armellino, et al., (2011) cameras were used to monitor hand hygiene compliance rates and identify poor techniques in hands washing. The system uses cameras, which are focused on the sinks and ABHR, and door motion sensors to detect the entries into the rooms. The feedback was given through light emitting diode (LED) boards, email summaries, and weekly reports.

For the first 16 weeks of the experiment the results were not shared with the staff. Compliance rates varied between 3.5% and 9.8%. After that duration, the aggregated compliance percentage rose to 81.6%. The weekly results of the experiment are shown in Figure 2-3.

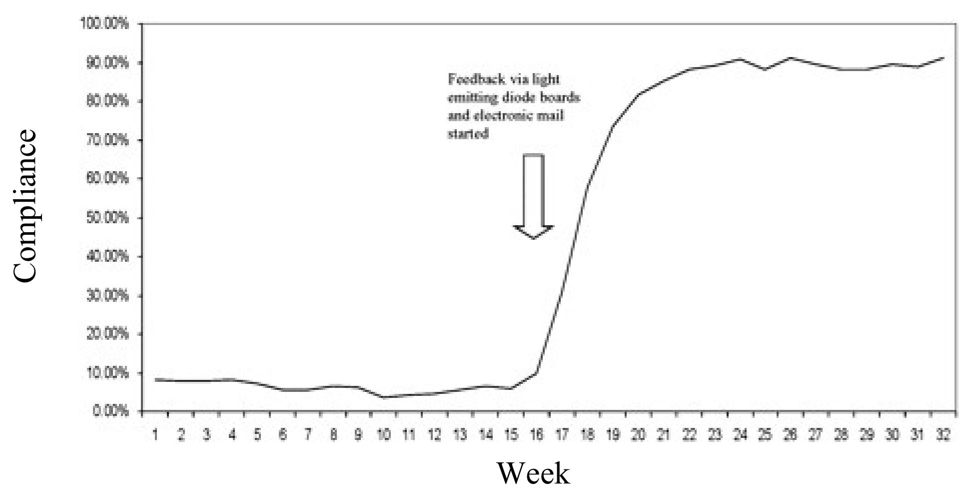

Figure 2-3 Video-Auditing hand hygiene monitoring weekly results

The main disadvantages of such systems are related to privacy violation, and the inability to differentiate between healthcare workers, patients and visitors. Installing a camera in a healthcare environment puts the patients' privacy at risk, as the system examined in Armellino, et al.'s study as stated in *"Automated and electronically assisted hand hygiene monitoring systems: A systematic review"* used cameras with wide angle of view.

2.2.5 **Amron**

Class: Fully automated hand hygiene monitoring system.

The study conducted by Swoboda, Earsing, Strauss, Lane, & Lipsett (2014) used an electronic hand hygiene monitoring system capable of generating voice prompts as a behavioral intervention. The electronic hand hygiene monitoring system was designed by Amron corporation and its exact topology is not included in the publication but it was noted that the system does not differentiate between healthcare providers, patients, and their visitors.

The study reports compliance determined by the direct observation for a short period to be 20% with a maximum of +/-2% difference from the electronically calculated compliance (Swoboda, Earsing, Strauss, Lane, & Lipsett, 2014). The improvement in hand hygiene compliance resulting from using an electronic hand hygiene monitoring system was 44%.

2.3 Hand Detection using Imagery Sensors

Hand detection and recognition is very beneficial for hand hygiene detection. Cameras installed at the sink or near ABHRs, could be used to verify if the *HCWs* follow the proper recommendations while washing their hands with soap and water. Hand detection and segmentation acts as the first step in hand recognition. In general, objects detection algorithms could be classified into three categories (Uijlings, Sande, Gevers, & Smeulders, 2013):

1. Exhaustive search.
2. Segmentation.
3. Other sampling strategies.

2.3.1 Exhaustive Search

Exhaustive search algorithms hunt for the object everywhere in the image; this is achieved by applying sliding window techniques. In each window, image features are extracted and classified. As the probable number of windows in a given image is huge, exhaustive search algorithms enforces some constraints such as the windows aspect ratio.

Harzallah, Juri, & Schmid (2009) proposed a sliding window-based object detection algorithm. The algorithm represented each window on two levels: Shape descriptor, and appearance descriptor. Harzallah, et al. used a variation from histogram of gradient (HoG) for their shape descriptor, the windows are scaled into 3 levels and represented by scale-invariant features transform (SIFT). The calculated SIFT descriptors are transformed into bag of features (BOF) descriptors.

The method developed by Harzallah, et al. (2009) searches the image by using two stages cascade classifier. The first stage is a linear support vector machine (SVM) classifier. The classifier is applied to all the window proposals in the image, significantly reducing their number to only the strong candidates. The second stage is a strong nonlinear SVM classifier. Only the strong candidates are classified in the second stage generating a score for each candidate. Non-maxima suppression is applied to identify the candidates that contain objects.

2.3.2 Segmentation

In contrast to exhaustive search algorithms, which output a bounding box containing the object, segmentation algorithms extract only the object pixels. Segmentation algorithms starts by randomly selecting seed pixels, which are then expanded to regions (bottom-up model), and each region is reasonably classified into foreground and background segments. The likelihood of a foreground segment to be a complete object is calculated and used to rank the segments. Segmentation methods mainly vary in the algorithm used to identify a good region. As some objects consists several inconsistent regions, bottom-up approach alone might not be enough. Some algorithms incorporate a top-down model to extract the full object.

Carreira & Sminchisescu (2010) proposes a segmentation method in which the foreground seeds are regularly distributed in a 5 x 5 grid, and background seeds either cover the full image boundary, the image vertical edges, the image horizontal edges or all the edges except the bottom edge. The seeds are used to generate pool of segments using constrained parametric min cuts. A threshold is applied to reject small segments, the ratio cut presented in (Wang & Siskind, 2003) is calculated to keep the segments with highest scores. Segments with 95% overlap are grouped and the segment with lowest energy in each group is selected.

To estimate the likelihood of a segment to an object, random forests regressor (L. Breiman Breiman, 2001) is used. The regressor learning included 34 features. It was found that the regressor generates adjacent ranks to similar segment, so a maximal marginal relevance was used to diversify the ranking and enhance the quality of the top ranked segments.

2.3.3 Other Sampling Strategies

This category includes methods that does not completely belong to neither the exhaustive search nor segmentation. As an example, selective search proposed by Uijlings, Sande, Gevers, & Smeulders (2013) is a hybrid method from exhaustive search and segmentation. Selective search uses a bottom up graph-based image segmentation to create regions. The grouping is done in a hierarical manner, each layer of the hierarchy is created by grouping the two most similar neighbor regions, the process is repeated untill the entire image becomes a single region which is considered the top of the hierarchy.

The grouping is done using 3 diverstifying strategies: complementary color spaces, complementary similarity measures, and complementary starting region. Complementary color spaces negates the effect of lighting conditions. The complementary similarity measures between two neigbhor regions is calculated based on color similarity between regions; texture similarity calculated using SIFT features; size similarity which represents how well the two regions fit each other; and fill similarity which indicates how tight is the box bounding the two regions.

The generated regions are then combined and ranked based on the order in which they were generated. The regions are ordered such that each location is assigned a number equals to its rank multiplied by a random number between 0 and 1.

2.4 Indoor Localization Using Imagery Sensors

As wireless signals are always subject to interference, some attempts to achieve indoor localization using cameras do exist. With the recent advancements in computer processing units (CPUs) and graphical processing units (GPUs), computer vision techniques are able to process more frames per second, achieving real-time performance.

2.4.1 General Methodology

Most imagery sensors-based localization algorithms could be applied indoor, and outdoor. In either case, all the current methods require visual fingerprinting for the environment, in which, the visual features of the environment are associated to geolocations. Visual localization algorithms are similar in their basic architecture. The algorithms start by:

1. Features extraction – in this step, robust distinctive features for the image are extracted using a state of the art algorithm.
2. Features compression – the extracted features are represented by a feature descriptor such as Scale-invariant feature transform (SIFT) or Histogram of Gradients (HoG).
3. A visually similar image is recognized from the fingerprints database using content-based image retrieval (CBIR).
4. The current location is determined based on the location associated with the recognized image.

2.4.2 Schroth Algorithm

Schroth, et al. (2011) proposes a visual localization algorithm. They used Google Street View 360° panoramic images as their fingerprinted dataset. The algorithm was also successfully applied on the indoor dataset proposed in (Huitl, Schroth, Hilsenbeck, Schweiger, & Steinbach, 2012). Schroth, et al. method uses maximally stable extremal regions (MSER) (Matas, Chum, Urban, & Pajdla, 2004) as a feature detector. The algorithm tracks the features, solid features persistent in several frames to speed up the feature extraction process. The extracted features are compressed using compressed histogram of gradients (CHoGs) introduced in (Chandrasekhar, et al., 2009). The image retrieval is based on a variation of bag of features algorithm (Schroth, Al-Nuaimi, Huitl, Schweiger, & Steinbach, 2011). The method performance was evaluated by the mean average precision (mAP). The mAP for the indoor experiment was found to be 0.18.

Visual indoor localization might not be suitable for use in Healthcare environment. The usage of a camera continuously capturing videos for the environment might not be allowed. The high dynamic environment enforces the use of robust computationally expensive descriptor to overcome problems like occlusions, overlaps, shadows and reflections (Schroth, et al., 2011).

2.5 Wireless Indoor Proximity and Localization Technology

To reliably capture hand hygiene moments using electronic hand hygiene monitors, detecting the location of the healthcare provider is necessary. Some electronic monitoring systems such as dispenser counters (Moore, 2013) and the system designed by Amron

(Swoboda, Earsing, Strauss, Lane, & Lipsett, 2014) fail to differentiate between healthcare workers, patients, and their visitors thereby leading to lower confidence in the numbers generated. In the following subsections available wireless technologies that could be used for proximity detection and localization are discussed. These include:

1. Radio frequency identification
2. Wireless local area networks
3. ZigBee
4. Bluetooth low energy.
5. Near field communications

2.5.1 Radio Frequency Identification

Radio Frequency Identification (RFID) has many applications in healthcare environments ranging from assets and personnel tracking to patient and healthcare identification. RFID systems consist of tags and readers. RFID tags are classified into two groups:

- Passive RFID tags which are low in cost, but have a very low range as they can only operate when they are within the magnetic or electrical field of the reader. The main advantage of passive RFID tag is that they do not need batteries.
- Active RFID tags which can provide longer range than the passive RFID tags, but they require a power source to operate.

Active RFID is mainly used for personnel and equipment tracking (Yao, Chu, & Li, 2010) although some localization systems use passive RFID (Ma & Shi, 2011). The range of active RFID tags could exceed 100 m. based on the design of the antenna (Ni, Zhang, & Souryal, 2011).

Indoor localization using active RFID is based on having more than one reader placed in specific locations. The active RFID tags will broadcast their unique identifiers. The readers will detect this identifier with different received signal strength values. The values are then sent to a processing unit which processes the information to localize the target (Ni, Zhang, & Souryal, 2011).

RFID based localization suffers from several problems such as:

1. Sources interference with RFID system - RFID systems are prone to interference from other unlicensed systems as they operate in a free frequency band (Ni, Zhang, & Souryal, 2011) and to interference from other RFID devices such as tag-to-tag, reader-to-tag and reader-to-reader interferences (Zhang, Ferrero, Gandino, & Rebaudengo, 2016).
2. RFID system interference with other systems - high-power RFID readers could lead to failures of medical devices in the healthcare environment (Yao, Chu, & Li, 2010).
3. Readability of RFID tags by the readers depends extensively on the placement of the RFID tags (Yao, Chu, & Li, 2010).
4. The cost of deploying RFID systems on a large scale could reach $600,000 USD (Yao, Chu, & Li, 2010).

2.5.2 **Wireless Local Area Network**

Wireless local area networks (WLAN) are considered the most popular wireless networks. Nowadays, WLANs are everywhere, making them a very strong candidate for indoor localization applications (Khalajmehrabadi, Gatsis, & Akopian, 2017).

WLAN localization algorithms are classified into 3 categories:

- Direction of arrival (DOA) methods
- Time of arrival (TOA) and time difference of arrival (TDOA) methods.
- Model-based and model-free fingerprinting.

In DOA methods, the object to be localized sends a wireless signal. This signal is picked up by at least two access points of known locations having antenna arrays to be able to find the incident angle of this signal. The calculated angles could be used to plot two lines, the intersection of these two lines is the location of the object (Khalajmehrabadi, Gatsis, & Akopian, 2017).

TOA is similar to the GPS theory of operation. The travel time of the wave is used to find the distance between the object which acts as a radius of a circle around the access point. This method requires at least three access points to draw three circles. The intersection of these circles determines the location of the object. TDOA is slightly different from TOA. In this method the time difference of arrival is calculated relative to a source signal (Khalajmehrabadi, Gatsis, & Akopian, 2017).

Fingerprinting methods use the received signal strength from the available access points to find the location. Model-based fingerprinting method factors in a model for the signal loss to determine the path length while model-free fingerprinting methods require a radio map to detect the location (Khalajmehrabadi, Gatsis, & Akopian, 2017).

WLAN was found to be unsuitable for hand hygiene monitoring systems for the following reasons:

1. Received signal strength is subject to shadowing due to the presence of walls and doors in the healthcare environment (Khalajmehrabadi, Gatsis, & Akopian, 2017).
2. Surveying the healthcare environment for fingerprinting algorithms is logistically very hard to achieve.
3. Wireless LAN indoor localization systems are not easily scalable, as any change in the indoor environment would require constructing a new model (Ding, Zhang, Zhang, & Tan, 2013).
4. According to Phil Smith (Smith, 2017), WLAN is a power demanding technology. WLAN chips consume 0.21W when the output throughput is 40 Mbps and cannot be powered by a coin cell battery.

2.5.3 **ZigBee**

ZigBee is a low cost, low power consumption 2.4Ghz wireless protocol. It is defined by the IEEE 802.15.4 standard (Niu, Wang, Shu, Duong, & Chen, 2015). The main purpose of designing the ZigBee protocol is for use in low data rate applications that requires extended battery operation in which the WLAN is not a good candidate.

The same indoor localization methods discussed in 2.5.2 could be applied to ZigBee. ZigBee devices have the advantage of much lower power consumption than

WLANs but they are not as common as WLANs, hence a special hardware is required for indoor localization.

The main drawback of using ZigBee in hand hygiene monitoring systems is that the ZigBee standard does not include any frequency hopping technique which introduces challenges in deploying large numbers of nodes in a limited space. (Smith, 2017)

2.5.4 Bluetooth Low Energy

Bluetooth Low Energy (BLE) is a standard maintained by the Bluetooth Special Interest Group (SIG). It uses three 2 MHz channels in the 2.4 GHz band. BLE was designed to provide ultra-low power consumption so that the BLE devices could potentially last for years on a single battery. BLE power consumption can go as low as 0.147 mW (Smith, 2017).

The BLE stack defines four Generic access profiles (GAP):

- Broadcaster profile in which the device transmits unconnectable advertisement packets that could carry information in its payload.
- Peripheral profile which is a connectable profile that could run one or more generic attribute (GATT) service.
- Observer profile which is a profile capable of performing a device scan to detect the surrounding BLE profiles but cannot connect to any device.
- Central profile in which the device can perform a scan and connects to the detected target if possible.

The stack also defines two generic attribute profiles:

- GATT Server which contains one or more GATT services each defined by a universal unique identifier (UUID).
- GATT Client which access the information from the GATT Server.

BLE stack V4.0 only allows for only one GAP role to run on the device, while V4.1 and V4.2 allow any combination of GAP roles. Any connectable GAP role can be either a GATT server, a GATT client or both. Two connected central and peripheral devices could be both clients and servers for each other simultaneously. It also allows multiple connections initiated from the same central device. Connectionless data transmission is achievable through the advertisement packets of any device running the broadcaster GAP role or the peripheral GAP role.

According to Smith (2017), BLE was found to be the second least expensive technology compared to ANT, Nike+, RF4CE, ZigBee and NFC with NFC being the least expensive technology. However, in regard to indoor localization purposes, NFC is only used for corrections in IMU-based dead reckoning indoor localization systems (Strutu, Caspari, Pickert, Grossmann, & Popescu, 2013).

Chapter 3

3 System Design

In this chapter, the proposed system will be discussed in detail. All the system components, as well as, the way in which they interact together to achieve accurate compliance measurement will be presented. Two hand detection algorithms using imagery sensors are also presented in this chapter.

3.1 System Overview

The proposed hand hygiene monitoring system is based on BLE technology for the following reasons:

1. Low power consumption:

   Bluetooth Special Interest Group (*SIG*) assures that the average BLE power consumption is lower than half that of the ZigBee (Habbal, 2012) and definitely lower than wireless LAN based on (Smith, 2017).

2. Availability of software development tools and resources.

   There are a variety of System-on-chip (SoC) integrated circuits available that support prototype development of BLE-based systems. The SoC CC2650 offered by Texas Instruments (TI) was selected because (1) it provides 75% lower power consumption than the available development hardware, (2) rapid software development using the BLE-Stack provided by TI, and (3) its capability of running real-time operating system TI-RTOS.

3. Suitability for the application

    BLE is increasingly used for many applications in healthcare environments such as heart rate sensors and blood flow meters. Also, the BLE standard uses 40 channels with adaptive frequency hopping to reduce collisions which enables the use of a high number of devices (Tosi, Taffoni, Santacatterina, Sannino, & Formica, 2017).

4. Low implementation cost compared to the other available technologies

    Utilizing a cost-efficient technology will enable a faster spread for electronic hand hygiene monitoring systems in healthcare institutes.

The CC2650 is a multi-standard 2.4Ghz wireless low power microcontroller unit. It features an advanced yet low power ARM Cortex-M3 microcontroller with a maximum operating frequency of 48 Mhz. CC2650 has a very generic 2.4Ghz RF module that could be configured to implement Bluetooth, ZigBee or 6LoWPAN applications (Texas Instruments, 2016).

The proposed system is designed with the assumption that *HCW*s will comply with hand hygiene protocols using one of two dispenser-based approaches:

(1) Alcohol-Based Hand Rub (*ABHR*): which is considered a fast and more convenient hand hygiene option as it suits the busy environment of the *HCW*s and is usually located in the hallways; or

(2) Traditional the soap and water approach: using the sink in the nursing station or in any of the patient rooms.

The proposed system consists of 5 components:

- Badges
- BLE-enabled dispensers
- Bedside Beacons
- Data Collection Nodes (DCN)
- Charging Stations

The core component of the system is the badge that the *HCW* will either have to hang to their scrubs using a clip or put in their pocket. This badge can detect two main events: the dispenser usages, whether it is soap or alcohol-based; and the proximity to a patient bed through the bed side beacons. A finite state machine is implemented to properly detect how many times the *HCW* performs the correct hygiene action (correct scenarios) and how many missed hygiene opportunities (wrong scenarios) occurred based on the two discussed events.

The collected information is transmitted to the data collection nodes through BLE advertisement packet which in turn sends the information to a server using the file transfer protocol (FTP) located on the healthcare provider's network. The data is then parsed and stored in a database. The information stored in the database is presented on a screen to the

*HCW*s and could also be used to better analyze the improvements in staff hand hygiene performance.

Figure 3-1 demonstrates the system components and their interactions when the HCW adheres to the hand hygiene recommendations, while Figure 3-2 demonstrates the interactions if the *HCW* missed a hygiene opportunity.

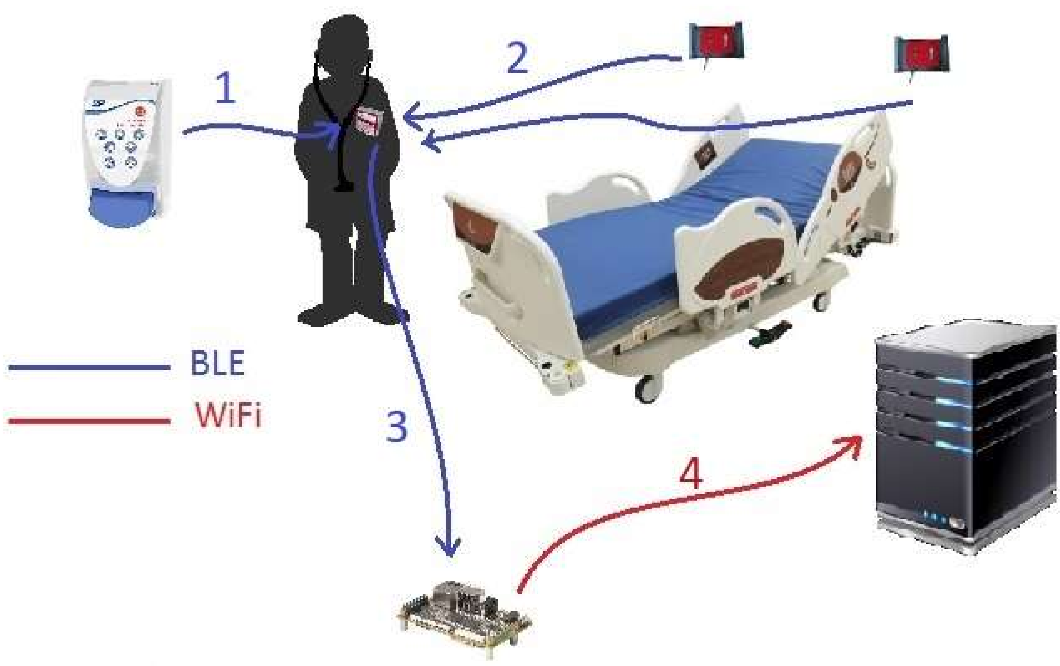

Figure 3-1 System components and their interaction in a correct scenario.

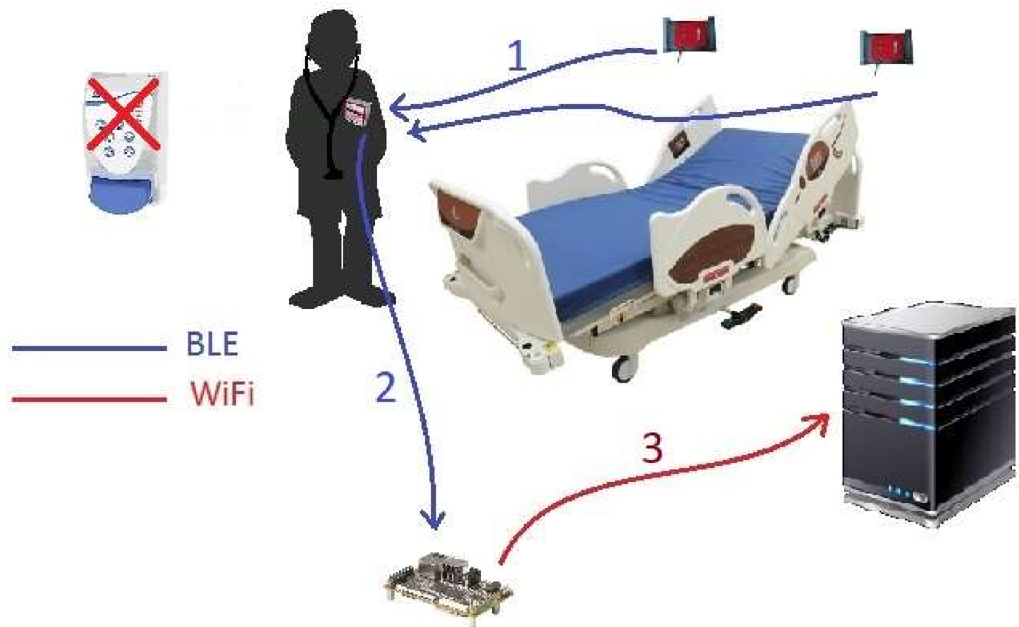

Figure 3-2 System components and their interaction in a wrong scenario.

3.2 Badges

They are considered the main component of the system as they count the scenarios. The badges are based on BLE implementing two BLE profiles: central profile; and broadcaster profile. The badges (Figure 3-3) are powered by rechargeable lithium polymer batteries. They count the scenarios with the aid of a finite state machine (FSM) which will be explained in detail in the following section. The badges automatically transmit the collected information to the data collection nodes.

Figure 3-3 BLE badge

3.2.1 Badges Hardware Design

The badge consists of (1) the CC2650STK, (2) a lithium polymer battery with a protection circuit, and (3) a voltage regulator board. CC2650 (1) is the main component of the badge. It runs on an 890 mAh lithium polymer single cell battery (2). The output of this battery ranges from 4.2 volts when it’s fully charged down to 3.0 volts when it is completely depleted. The protection circuit ensures that the battery never goes to a deep discharge cycle which will make it unusable. The CC2650 absolute maximum input voltage is 4 volts, hence a voltage regulator circuitry (3) was designed and implemented to ensure a stable and safe operation for the board. The regulator board was designed on Eagle software and sent for fabrication in a facility in China. The components were connected as shown in Figure 3-4.

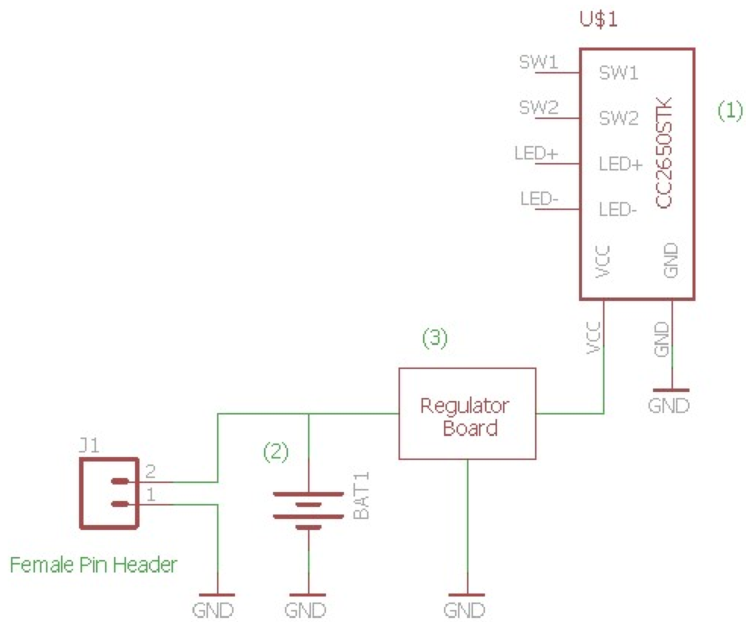

Figure 3-4 Badge connection diagram

For the case, a model was designed with the aid of SolidWorks® and a prototype was constructed using 3D printers. During the prototype testing phase, increased fluctuations were observed with the presence of metal objects close to the antenna of the CC2650STK. Also, the original size of the case was not suitable for a portable device. The badge case was carefully redesigned to keep the antenna away from the battery and the regulator board to avoid the additional fluctuations while significantly reducing the overall case size through the rearrangement of the components.

3.2.2 Badge Software Design

The software of the badge runs two BLE profiles: (1) Central profile, which acts as a foundation for detecting the *HCW* behaviors. It provides the means to scan for available

BLE devices, but it cannot send information without initiating a connection. However, collected data, along with debugging information, is transmitted to the DCNs in the BLE advertisement packet by means of (2) Broadcaster profile.

The badge software is based on the standard BLE-Stack. The Texas Instruments APIs were modified to expose the received signal strength for the surrounding BLE targets. As the badge performs different time-critical tasks related to the stack and the application itself, the software was implemented in a real-time operating system (*RTOS*) environment.

In this section, a detailed description of the developed software is provided. A typical scenario for a healthcare worker is to either wash or not to wash his/her hands, and then approach the bed of a patient. These two steps are handled in the developed software by (1) proximity detection stage. This leads to (2) event generation in which one event is triggered that conveys more information about the action of the *HCW*, followed by (3) scenario detection in which the developed software analyzes the actions of the *HCW* through a finite state machine and counts the number of correct and incorrect scenarios. Finally, the gathered data is sent to the data collection nodes in the (4) data transmission stage. details on each of these stages is provided in the following subsections.

3.2.2.1 Proximity Detection

Proximity detection is based on the received signal strength from either the dispenser or the bedside beacons. The badge performs an active BLE device scan. The devices are filtered based on a stream of bytes sent in their advertisement packet to determine whether this device belongs to the HHMS or not. devices belonging to the system are then placed in an array of structures. Each entry in this array represents a location of either a dispenser or a patient environment. These location entries will have information about the devices either extracted from the advertisement packet or calculated by the badge. One location array entry is demonstrated in Figure 3-5.

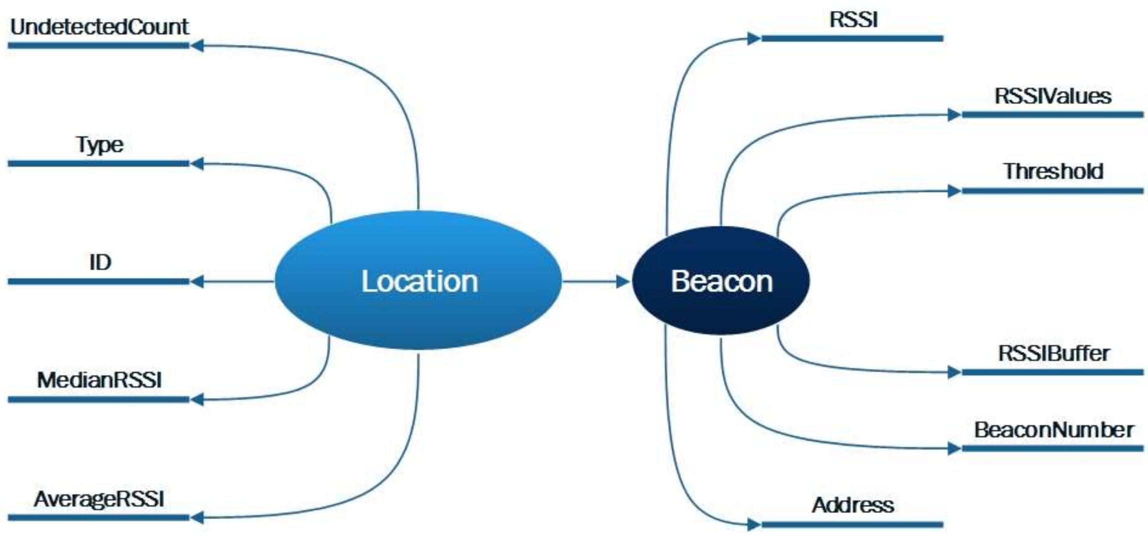

Figure 3-5 One entry from the location array.

Each entry in the location array contains the following:

1. Beacon which represent a BLE target.
2. ID which is a unique number for each BLE device belonging to the HHMS.
3. Type which could be either Bed or ABHR.
4. Median RSSI which is the middle value of the RSSI Buffer in the beacon associated with a specific location entry.
5. Average RSSI which is the sum of the RSSI Buffer entries divided by the RSSI values.

6. Undetected Count, which represents how many times the beacon did not show in the scan results.

The software transverses through the location array and attempts to detect the proximity to a specific location using the median value in case of bed BLE devices and using the latest RSSI value in case of dispensers. The detection threshold varies based on the room topology and will be set during the installation of the system. The following pseudo code snippet explains the proximity detection algorithm.

```
//Search for ABHR first
foreach (Location loc in LocationsArray) do:
      if (loc.type == ABHR) :
            if (loc.beacon.rssi >= loc.beacon.threshold) :
                  return loc;

//NO ABHR found, search for a bed
maxRssi = LocationsArray[0].RSSIMean;
maxRssiIndx = 0;

//Find maximum RSSI mean.
for (int i = 1; i < LocationsArray.Length; i++) do:
      if (LocationsArray[i].type == BED) :
            if (LocationsArray[i].RSSIMean > maxRssi) :
                  maxRssiIndx = i;
                  maxRssi = LocationsArray[i].RSSIMean;

//Check if that maximum is above the threshold
if(maxRssi > LocationsArray[maxRssiIndx].beacon.threshold)
      return maxRssiIndx;
else:
      if (isOutside())
            return 254;
      else return 255;
```

3.2.2.2 Event Generation

After performing a BLE scan, populating the locations array and determining the proximity to a specific location, the software has enough information to generate an event. There are five events, described below, that determine the behavior of the system:

1. *Dispenser* - generated when a soap or an ABHR dispenser is used.
2. *Bed* generated when the *HCW* becomes in close proximity to a patient.
3. $\overline{Bed}$ - generated when moving from the proximity of one patient to another.
4. *Outside* - generated when the *HCW* leaves the room.
5. *Inside* - generated when the *HCW* is inside the room but not close enough to the patient.

Due to the busy work environment of the health workers, it is expected that health workers will be close to the dispensers for a very short time. Therefore, there is little time available to search for the dispensers in the location array. Hence, the algorithm was developed such that the *Dispenser* event could be generated before any other events would be considered. Dispenser proximity detection is based on receiving a BLE signal from a dispenser stronger than the specified threshold for this dispenser.

The *Bed* event is generated if and only if the median of the most recent five RSSI values of the BLE signal broadcasted from a bedside beacon is higher than its own threshold and the last determined location was not a bed. The generation of $\overline{Bed}$ event is also based on the median RSSI value, except that the last determined location in this case was another bed with a different ID, indicating that the *HCW* moved from the proximity of one bed to another.

Generation of the *Outside* event is not as straightforward as the other three events. This is because a signal from any beacon will always be received even if one is outside the room. The *Outside* event is generated when the average RSSI signal of the most recent five RSSI values falls below a certain configurable threshold for a specified period. To make outside detection more reliable, any RSSI signal less than -62 dBm is converted to -127 dBm as shown in Figure 3-6.

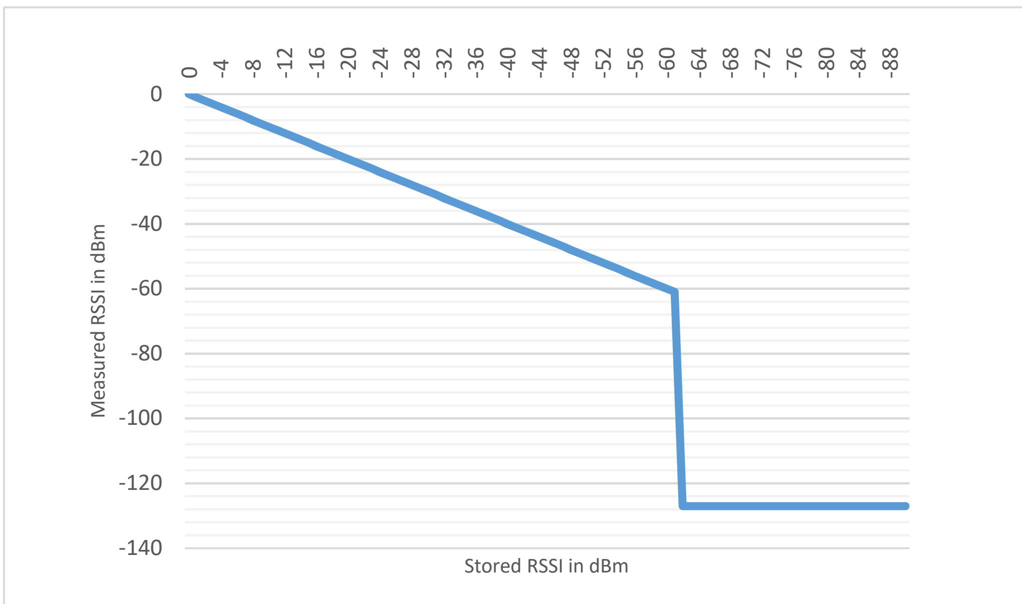

Figure 3-6 RSSI Values clipping

Inside event is generated when the received signal strengths are not high enough to trigger either *Bed*, $\overline{Bed}$ or *Dispenser* events and not low enough to trigger the *outside* event. This event is normally generated when the HCW is inside a room and not facing the patient. Figure 3-7 presents the flowchart of generating the events.

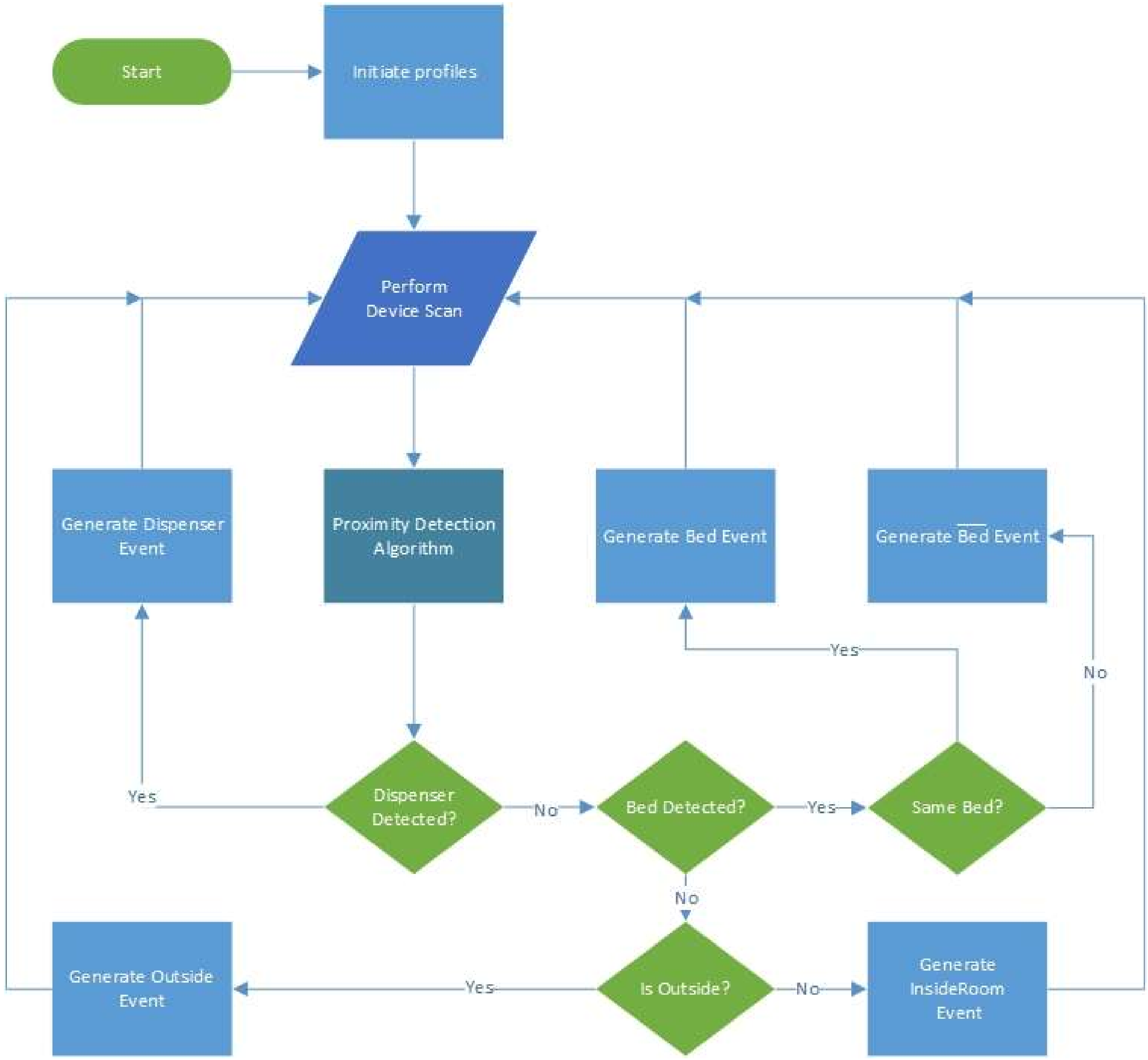

Figure 3-7 Event Generation Flowchart

3.2.2.3 Scenario Detection

The system core is a finite state machine (FSM) that consists of six states: Idle, System on, Armed, Normal, Triggered and Alarm. The transition between the states is based on the events generated and software timers. Figure 3-8 illustrates the FSM and the hopping between the different states based on the events. In the next subsection, the timers and the states is discussed in detail.

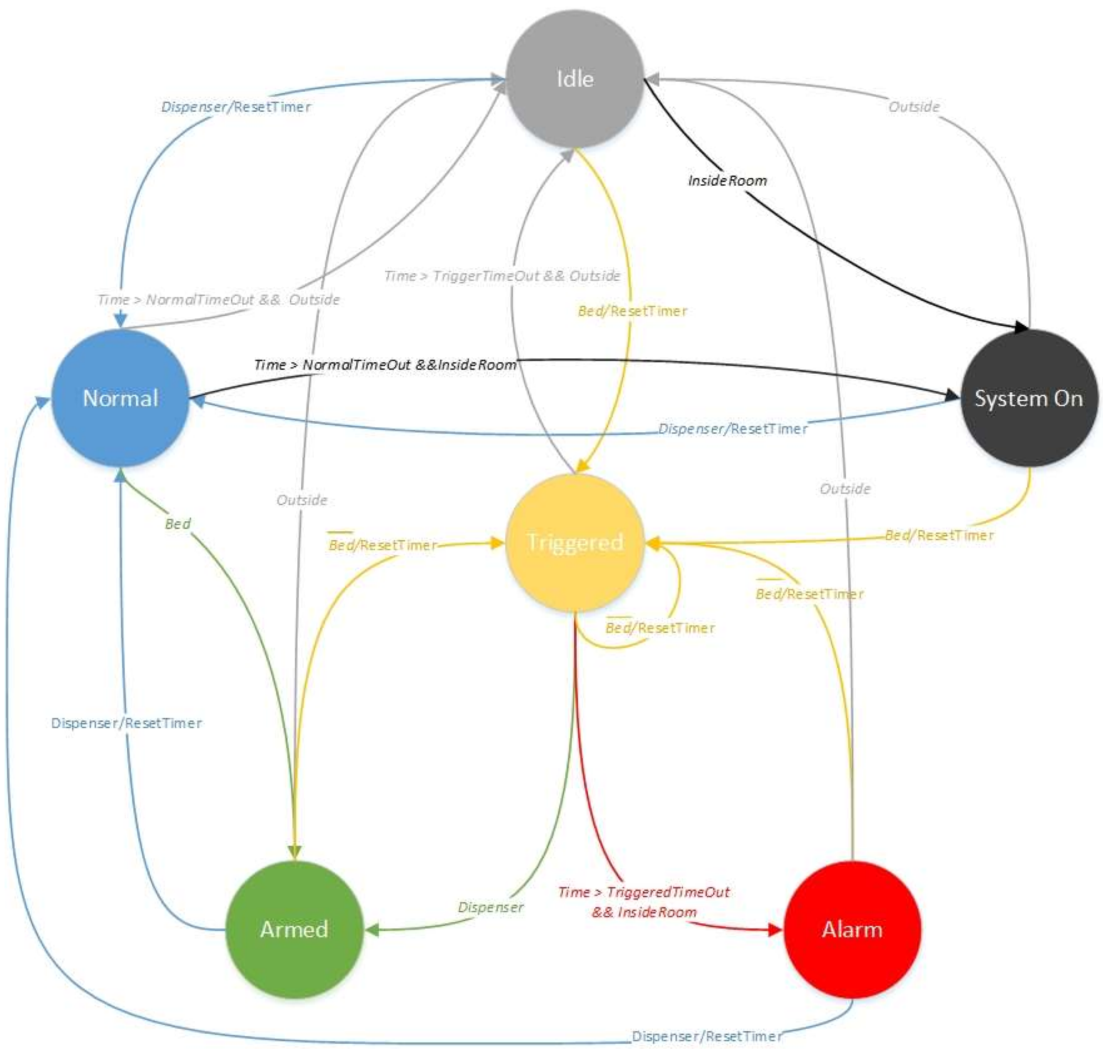

Figure 3-8 Finite State Machine

The system starts in the Idle state. The system will also switch to the Idle state from any other state when an *Outside* event is generated. In this state, all the system global variables are either reset or modified, this includes: hits count, which is the number of correct scenarios that occurred in this room entry; misses count, which is the number of missed hygiene moments in this room entry; and entry number, which is a counter to differentiate between room entries to avoid data duplication.

The system switches to the System On state when the location is undetermined for a specified configurable time. This happens if the health worker is inside the patient room but not close enough to the patient to be interacting with him/her. It can also indicate being in a room with more than one bed but not close to any of them. In this case, the entry number is not increased.

Whenever a HCW enters a room and gets to the vicinity of the patient, either Bed or $\overline{Bed}$ will be generated. If the HCW did not use a dispenser before entering the room, this will switch the system to the Triggered state. The system does not count the incorrect scenario, instead, it will remain in this state enabling a timer. When the timer times out a decision will be made.

The Triggered state is included to avoid falsely counting a high number of incorrect scenarios as it was noted that the HCWs might just enter the rooms to ask the patients if they need anything without actually interacting with them. It also serves to tackle the challenge of having a sink inside the room and very close to the patient vicinity.

When the triggered timer times out, if the HCW is still in the same room and never washed his/her hands the system will switch to the Alarm state. Every entry to the Alarm state increases the misses count by one. If the *HCW* moves to another bed the system will revert to the triggered state again.

Normal state indicates that the *HCW* has used the ABHR or the sink dispensers and that he/she is at an adequately hygienic level to deal with a patient. The Normal state is associated with a predefined timer to give the health worker enough time to start dealing with the patient. The expiration of the specified duration indicates a high probability that the health worker dealt with the environment before dealing with the patient, so the system switches back to Idle and it is expected that he/she washes his hand again.

The system will stay in the Normal state either until the expiration of the Normal timer or until an interaction with a patient. The latter case will switch the system to the Armed state in which the hits count is increased by one. The Armed state could also be reached if the health worker uses a dispenser before the expiry of the Triggered timer. Being in the triggered state means that the health worker is inside a patient room so using a dispenser, in this case, provides good evidence for hitting a hygiene moment.

Each time the system switches to either the Armed or Alarm state, it broadcasts the information to the DCN, the advertisement packet will carry the scenario information along. It will keep broadcasting for five seconds to ensure the reception of at least one packet to the DCN.

3.3 **BLE-enabled Dispensers**

Healthcare workers must use dispensers to get more hygienic hands, whether it is soap or alcohol-based hand rub solution. The dispensers were modified to broadcast a

Bluetooth Low Energy signal whenever they are used. Fortunately, the mechanical design of the soap and ABHR is the same. The signal broadcasted from the dispenser when pressed is picked up by the badge and handled to generate the proper event. In the following two sections, the dispenser's hardware and software are explained.

3.3.1 Dispenser Hardware Design

As part of this project, the dispensers used in the 4 North A branch of the Health Sciences Centre of Eastern Health, originally supplied by Deb®, were modified to make them BLE enabled. Deb® dispensers do not come with any circuitry, and there is not much room inside creating a challenge when trying to fit a battery, circuitry and a switch inside.

The modifications involved (1) A limit switch, (2) a CC2650STK board, (3) lithium polymer battery, and (4) a voltage regulator circuit. To detect the usage of the dispenser, the limit switch (1) was carefully placed so that it is triggered when the dispenser is pressed. To add BLE functionality to the dispensers, CC2650STK board (2) was installed. The board is powered by an 8000-mAh lithium polymer battery (3) through a voltage regulator circuitry (4) to ensure stable operation of the circuit. A charging DC jack was installed in the back of the dispenser to provide a means to recharge the battery if required. The battery after a full charge cycle provides 3 months of continuous operation. Figure 3-9 shows the schematics for the circuitry that was installed inside each dispenser.

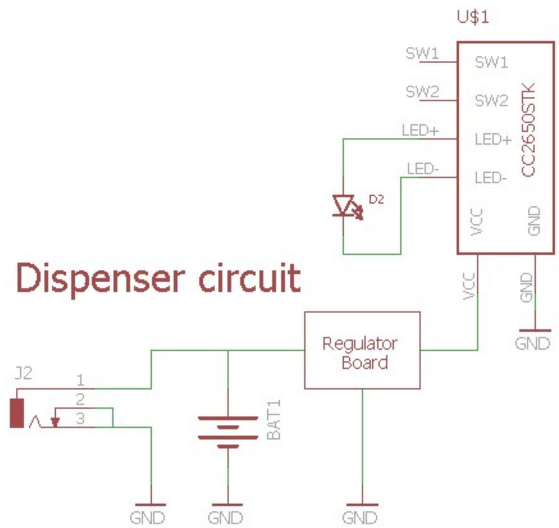

Figure 3-9 Dispenser circuitry schematics

Due to the presence of a liquid inside the dispenser and as a safety measure, all the electronics including the battery were waterproofed. This acts as a line of defense against any leakage from the soap or ABHR bottles. The waterproofing was achieved using silicon insulation and a 3D printed cover that has grooves to accommodate the circuit and the battery. To ensure ultimate safety, the battery terminals were placed on a level higher than the bottles to avoid any liquid contact in case of a leakage. The terminals of the limit switch did not constitute a threat even in the case of leakage due to its location, so heat shrinks were used to cover them.

3.3.2 **Dispenser Software Design**

The software duties for the CC2650STK installed inside the dispenser are very straightforward. It runs a connectable peripheral BLE profile with a Generic Attribute Service (GATT). It is based on the stack provided by TI. The GATT service provides 3 characteristics that are discussed more greater detail in the following paragraph.

The first characteristic value is a Threshold, this defines a value transmitted with each Advertisement packet sent by the dispenser, the threshold is used by the badge to determine the proximity of the dispenser. This helps with system optimization, eases the manufacturing process and speeds up the installation process. The second characteristic is an echo for the Threshold characteristic value, to make sure it is properly configured. The last characteristic value is to give the dispenser a unique number, which facilitates maintaining the system.

To comply with the BLE standard, each characteristic value is assigned a universally unique identifier (UUID). The UUID is used to access the values from other central BLE devices. The access policy for each characteristic value could have one or more of the following (1) Writable (WR), which means that the value is settable, (2) Readable (RD), which means that the value could be read, and (3) NOTIFY, which is a value that gets pushed to the central device whenever it is updated. The following table describes the services.

Table 3-1 GATT service characteristics

GATT Characteristics	**UUID**	**Properties**
Threshold	0xEE01	WR
Threshold Echo	0xEE02	NOTIFY
ID	0xEE03	RD, WR

3.4 Bedside beacons

To detect the proximity to a patient environment, two BLE beacons were installed on the two sides of each room. Each beacon has unique identifiers and a specific configurable threshold. The beacons advertisement packets are picked up by the badges and analyzed to generate the proper scenario. Figure 3-10 presents a bedside beacon.

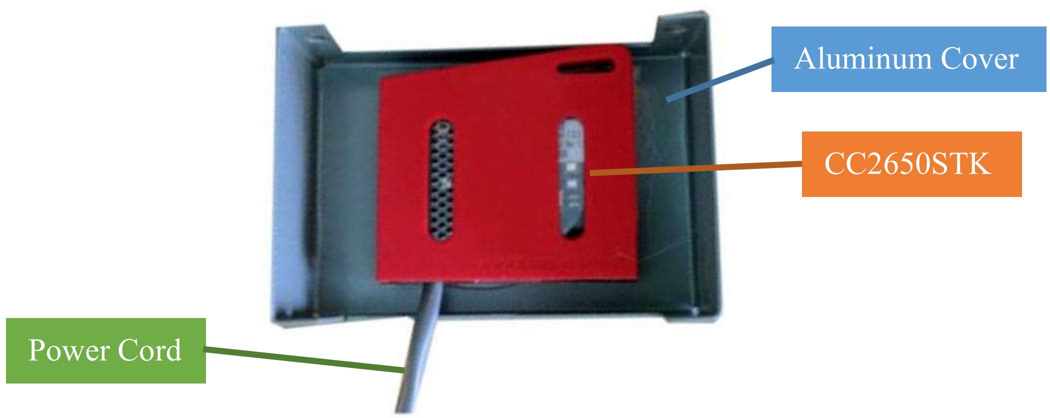

Figure 3-10 Bedside Beacon

3.4.1 Bedside Beacons Hardware Design

The designed beacons consist of (1) CC2650STK boards, (2) power adapter, and (3) metal reflector. After obtaining the CC2650STK and the aluminum cover, the design was implemented such that the beacons could be fed directly from the wall outlet. The CC2650STK BLE-enabled board runs on a 3.3v CSA certified DC power adapter as it was feasible to provide wall outlets close to the patient's beds through a 2.5 mm DC jack.

Due to the topography of the rooms in the hospital, some beds are placed head to head with a thin wall separating the two rooms. This causes strong BLE signals from the adjacent room, which could lead to false detections. To reduce the cross-talk between any two adjacent rooms, an Aluminum cover was installed between the wall and the antenna of each CC2650STK board. The cover acted as a strong signal reflector, which reduced the BLE signal strength in the adjacent room significantly, eliminating the cross-talk. Figure 3-11 shows the connection diagram for the beacons.

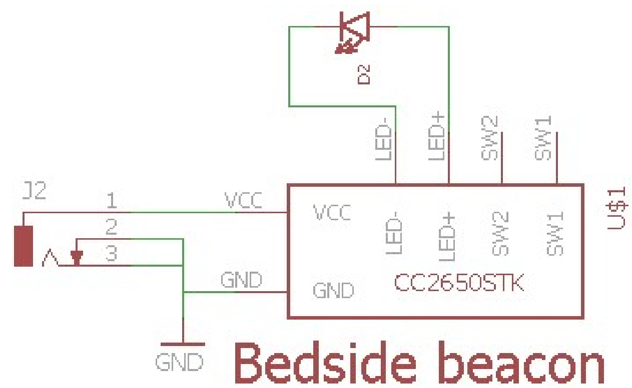

Figure 3-11 Bed-side beacon wiring diagram

3.4.2 Bedside Beacons Software Design

The CC2650 inside the bedside beacons runs a Peripheral BLE profile with a GATT service that has four characteristic values. Like the other project components, it is based on the BLE stack provided by TI. The application is developed in a real-time operating system (RTOS) environment provided by TI as well.

Each bedside beacon poses a unique identifier which is a combination of the room number, bed number, and the beacon number. The number of beacons designated to any specific patient is configurable as well as the threshold value for each patient. The threshold is configured through the implemented GATT service which echoes back that threshold in another characteristic value. Room number, bed number, and beacon number are also configurable through the GATT service. This alleviates the need for having to specify the identification number during the manufacturing phase.

Table 3-2 Bedside beacon characteristic values

GATT Characteristics	**UUID**	**Properties**
Threshold	0xEE01	WR
Threshold Echo	0xEE02	NOTIFY
Room Number	0xEE03	RD, WR
Bed Number	0xEE04	RD, WR
Beacon Number	0xEE05	RD, WR

3.5 Data Collection Nodes

A Data Collection Node (DCN) was installed in each room to collect the information sent by the badge. Inforce 6309 (Figure 3-12) was chosen for its BLE capabilities, reliability and its reasonable price. The board was installed in a custom-made box with enough ventilation to suit the healthcare environment.

Figure 3-12 Inforce 6309

3.5.1 **DCN Software**

The Inforce 6309 supports both Linux and Android operating systems. An Android operating system was installed on all the boards as it has direct support for Bluetooth Low Energy. The boards are responsible for collecting the advertisement packets sent by the badges, extracting the information from the packets and forward the information to a server in the healthcare provider's infrastructure.

An Android application was developed in Java using Android Studio IDE. The application constantly scans for BLE devices. The detected devices are filtered to extract the badges only. The information is extracted from the advertisement packets for each badge. As the badge sends more than one advertisement packet for each scenario, several packets are read by the DCN. Also, a single advertisement packet could be read by more than one DCN causing duplication in the data accumulation. To prevent this, two techniques were used. Firstly, Entry Number which is a number set by the badge that changes every time a healthcare provider enters a room thereby preventing duplicate counting of the same detection result by the same board. Secondly, Room Number which is stored in the application settings. The badge is only registered if the stored room number matches the number sent in the advertisement packet of the badge. This prevents the same scenario being picked by more than one DCN at the same time. Figure 3-13 shows the GUI for the developed application running on the Inforce 6309.

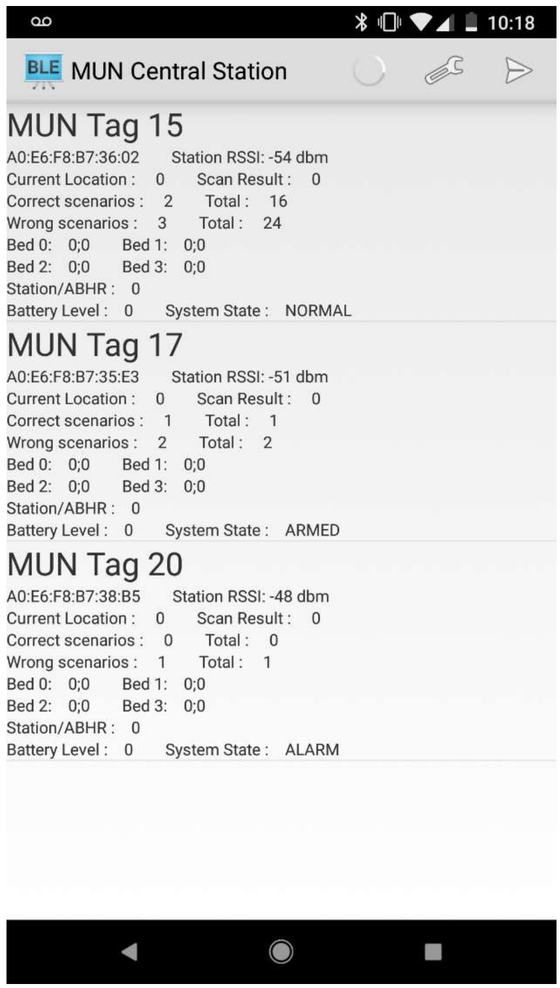

Figure 3-13 Android Software

The information collected is stored in a directory structured by year, month, day and badge. The application accesses every file in that directory, calculates the totals in one file and finally that file is sent to the server via file transfer protocol (FTP). The file name signifies the time in which it was generated and the room number. The duration between each file transfer to the server is configurable in the application settings menu along with the server IP and the FTP credentials. The locally stored files act as a back-up in case of any break-down in the connection to the server.

To facilitate debugging and optimizing the system, a log file is generated that contains every advertisement packet sent by any badge regardless of the room and entry number. This file is also sent to the server and act as a redundancy to the information transmission technique. A proper inspection of this file could generate the total number of scenarios. To protect the anonymity of the information, the badge number and MAC address were discarded before the transmission.

3.6 Charging Docks

The badges run on rechargeable lithium polymer batteries. To facilitate the recharging process, charging docks were designed and manufactured. Each dock provides five charging slots for the badges (Figure 3-15). The badges use unpolarized female pin headers to connect to the charger, so the slots were designed to allow for only one placement for the badges. This prevents any reverse polarity connections.

Figure 3-14 Charging Station

Each slot is associated with two LEDs: Red and Green. These two LEDs indicate the state of charging as shown in Table 3-3:

Table 3-3 Charger LED indications

	RED LED	**GREEN LED**
NOT CONNECTED	Off	Off
CHARGING	On	Off
BATTERY FULL	Off	On

Each charger slot is connected to a charging board designed by Adafruit (Figure 3-16). These boards are based on a configurable battery charger controller Microchip MCP73833. The MCP73833 was configured to output 200 mA fast charging current. It could also monitor the temperature of the battery during charging using thermistor but since it was difficult to have the thermistor close to the battery, this feature was not used.

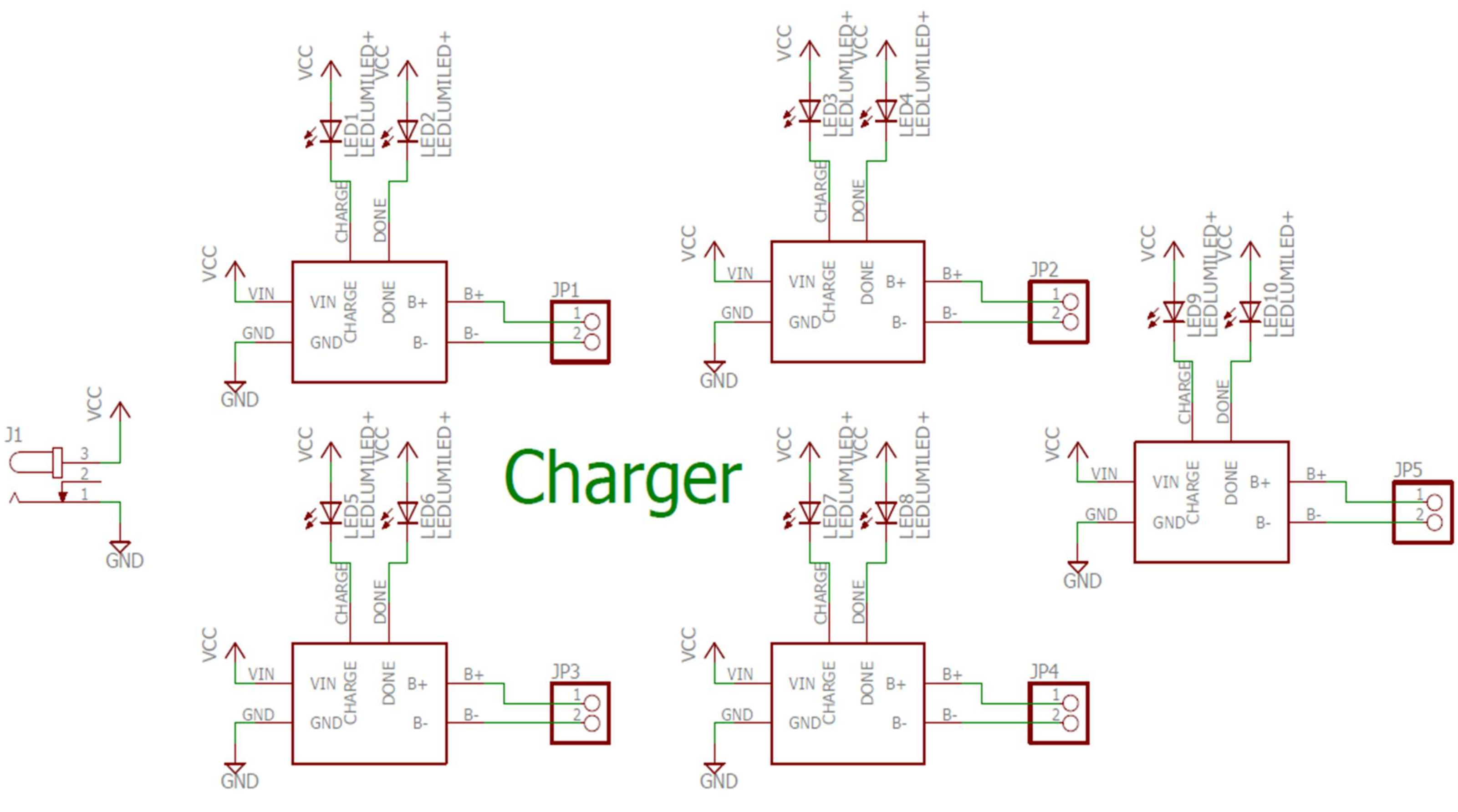

Figure 3-15 Charger station wiring diagram

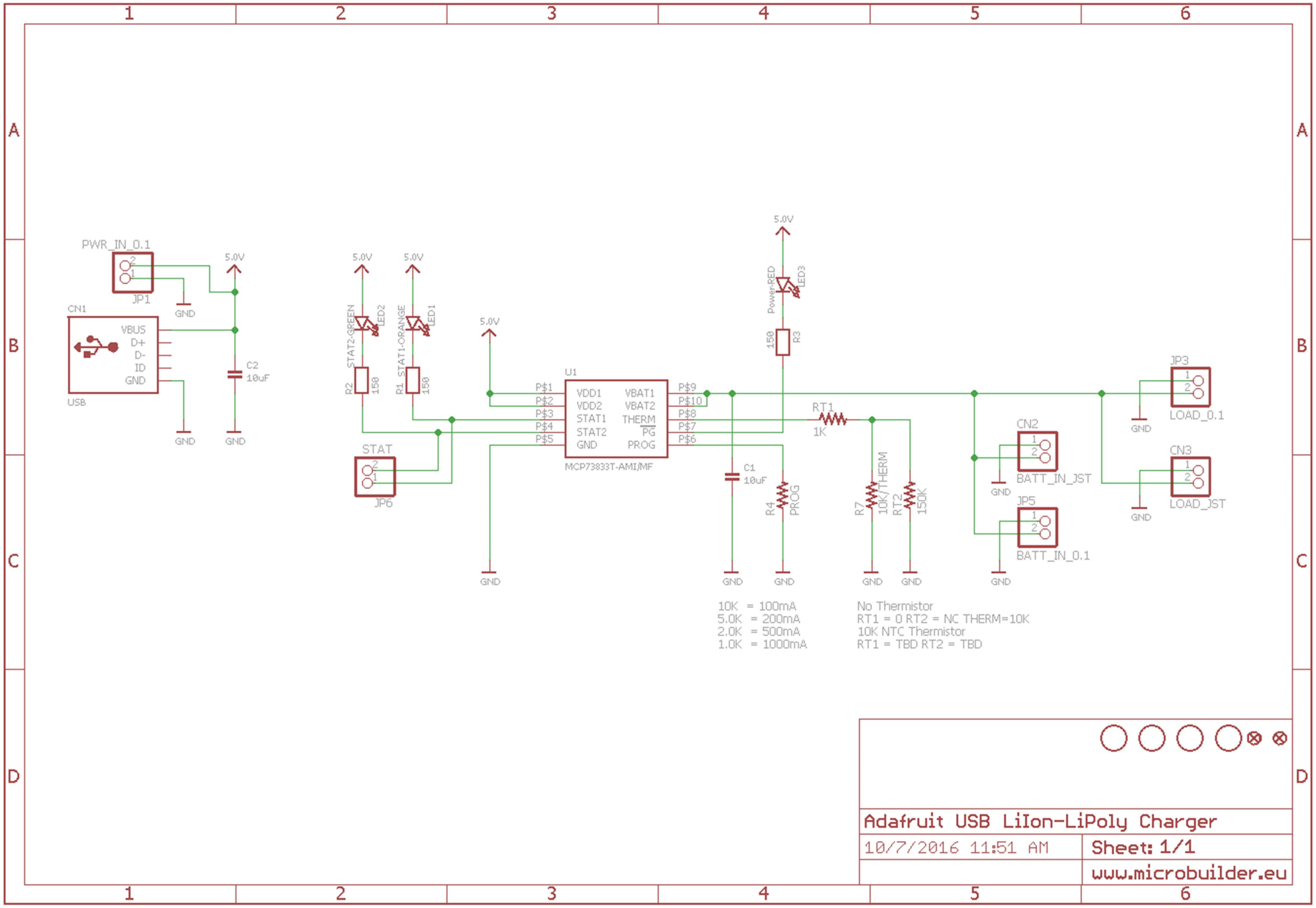

Figure 3-16 Adafruit LiPo charger schematics

3.7 Safety Certifications

As a part of Eastern Health regulations, it was mandatory to acquire certifications ensuring that the proposed system is safe for installation in the patient environment. The project components were subject to field evaluation performed by QPS evaluation services. The proposed system was inspected to meet CSA 22.2 No. 14, CE code 2015 and CSA Model Code SPE 1000.

During the certifying process, the system successfully passed a flame test, a dielectric strength test, an accessibility to live parts test, a leakage current test and a functional test.

3.8 Hand Detection and Segmentation using Imagery Sensors

As a part of hand hygiene detection, proper washing for hands using soap and water should be detected. To achieve that, the first stage is to detect hands using a camera. During this thesis, two hand detection algorithms were implemented and tested. The first algorithm is based on direct sampling algorithm introduced in (Bambach, Lee, Crandall, & Yu, 2015) and the second algorithm is based on object detection algorithm developed by (Dollar & Zitnick, 2014). The algorithm was tested as provided by Bambach et al., we did not contribute to the algorithm.

3.8.1 Direct Sampling

The method can be summarized as follows:

1. Generate window proposals using direct sampling.

2. Resize the generated samples to a specific size.
3. Classify the samples using a convolutional neural network (CNN).
4. Apply non-maximum suppression to find the best proposal.
5. Apply semi-supervised segmentation algorithm to extract hands pixels.

Bambach et al. (2015) method uses direct sampling to generate window proposals. The proposed method assumes that in egocentric videos, hands will most likely appear in the center of the field of view. For our purposes, this claim is still valid as hands are normally washed above the sink. The size of hands in the picture depends on the camera parameters and location with respect to the sink. Hence, strong spatial biases to hands location and size do exist. For rectangular window proposals, 4-dimensional kernel density estimator is used to sample the video frame.

The generated samples are resized to 227 x 227 pixels. The resized samples are then classified using a convolutional neural network (CNN). CaffeNet framework was used to implement and train the CNN. Bambach et al. (2015) trained two classifiers: general hand classifier that detects if the window proposal contains a hand, and four hands classifier. The four hands classifier can determine if the proposed window contains own left hand, own right hand, other left hand, or other right hand. In our project, we were only interested in the first two categories.

If pixel-wise hand segmentation was required, Bambach et al. proposed an algorithm in the same research. The main object in a given detected window proposal is a hand, so it fills most of the window pixels. A skin color model is used to generate an initial estimate for hand pixels. The threshold is adjusted to assume that a given pixel is a hand pixel except if it is highly probable that it is a background pixel. The generated pixels are provided as a seed to a segmentation algorithm called GrabCut (Rother, Kolmogorov, & Blake, 2004).

3.8.2 Edge Boxes

Edge Boxes is generic object detection algorithm based on edge detection developed by Dollar and Zitnick (2014). The algorithm generates a score for each window proposal based on the number of closed contours included in that window and does not overlap with the box boundaries. The algorithm was adopted to generate hand proposals. The edge boxes will be briefly introduced in this section.

The first step in the algorithm is edge detection. Edge boxes uses structured edges detector to find the edge response of each pixel. Structured edge is based on a random forest regressor which detects good object boundaries very efficiently. The regressor was trained to hand edges contours. Edge peaks are detected by applying non-maximal suppression is perpendicular to the edge points. Weak edge points are discarded based on a defined threshold.

Edge groups are formed by combining edges if they are 8-connected and the sum of their orientation differences is less than or equal 90°. Small adjacent edge groups are combined. The affinity between each two edge groups is then calculated. Calculating the affinity is summarized in Algorithm 1.

The affinity of each edge group is used to calculate the box score. Each group s_i is assigned a weight $w_b(s_i)$ based on its location with respect to the box. If s_i is entirely located inside the box, $w_b(s_i) = 1$. If s_i is either entirely outside the box or overlapping with the boundaries, $w_b(s_i) = 0$. $s_i \in S_b$ if it entirely overlaps with edge boundaries. Edge groups partially located inside the box, i.e. the edge intersects one or more of the box boundaries, are assigned a continuous value $w_b(s_i) \in [0,1]$. In this case, $w_b(s_i)$ is calculated based on a continuous ordered path of edge groups T. The path begins at some $s_i \in S_b$ and ends at $s_i = |T|$, where $|T|$ is the length of the path. The scoring algorithm is further explained in Algorithm 2.

Algorithm 1: Edge Groups Generation and Affinity Calculation

Input: image
Output: affinity between edge groups
Begin:
Foreach pixel p:
    Compute edge response using structured edge (m_p *and* θ_p)
    Perform non-maximal suppression
    If $(m_p < 0.1)$ $m_p = 0$

$i = 0$
Foreach pixel p:
    If (p **is** *8-connected)* $p \in s_i$
    Else $i = i + 1$

$S = \{s_1, s_2, s_3, \ldots\}$
Foreach $s_i, s_j \in S$:
    $x_i = mean\_angle(s_i)$ and $x_j = mean\_angle(s_j)$
    $\theta_i = mean\_angle(s_i)$ and $\theta_j = mean\_angle(s_j)$
    $\theta_{ij} = angle(x_i, x_j)$
    $a(s_i, s_j) = |\cos(\theta_i - \theta_{ij})\cos(\theta_j - \theta_{ij})|^\gamma$

Algorithm 2: Box score calculation

Input: Bounding Box b, Edge groups S
Output: Box score h_b
Begin:
Foreach edge group s_i:
    $m_i = 0$
    Foreach pixel $p \in s_i$:
        $m_i = m_i + m_p$
    If each $p \in s_i$ is contained in *b*:
        $w_b(s_i) = 1$
    Else if each $p \in s_i$ is not contained in *b* **or** $s_i \in S_b$:
        $w_b(s_i) = 0$
    Else:
        $w_b(s_i) = 1 - \max_{T} \prod_{j}^{|T|-1} a(t_j, t_{j+1})$

$b_w = width(b)$ and $b_h = height(b)$
$k = 1.5$
$h_b = \frac{\sum_i w_b(s_i) m_i}{2(b_w + b_h)^k}$

Edge Boxes search for proposals in a sliding window scheme. Unlike exhaustive search methods which generate high number of boxes, edge boxes algorithm selects only the boxes with high scores. The sliding window parameters are determined based on the desired output intersection over union (IoU) γ. For higher IoU, the algorithm generates more high-density candidates around the probable object; while for low IoU requirements, the algorithm will propose sparse candidate boxes.

The window is slid over the position, size and aspect ratio. The steps are defined using a defined parameter α, which represents the IoU between the current and the next window. To reduce the number of boxes, non-maximal suppression is applied for sorted boxes such that a box is removed if the IoU with a higher ranked box is more than β.

As in Bambach et al. (2015) method, the proposals are resized to 227 x 227 pixels, and classified using the same CNN. It was found that to achieve comparable IoU from the two detection methods, fewer number of proposal is required when edge boxes algorithm is used. The number of proposals generated from edge boxes depend on the parameters γ, α and β with a defined maximum. The following images were captured from a camera installed above a sink. The two algorithms were applied on the same set of images with different parameters.

In figures 3-17, 3-18, 3-19 and 3-20, direct sampling results are displayed on the left, and edge boxes results are displayed on the right. Figures 3-17, 3-18 and 3-19, displays the output proposals in the top row and the output of the classifier in the bottom row. In these figures, direct sampling was configured to output 2500 proposal, while edge boxes algorithm was configured with $\alpha = 0.65, \gamma = 0.7$ and $\beta = 0.75$ with maximum of 1500 sample. The execution time 62 seconds per image using direct sampling, and 16 seconds using edge boxes.

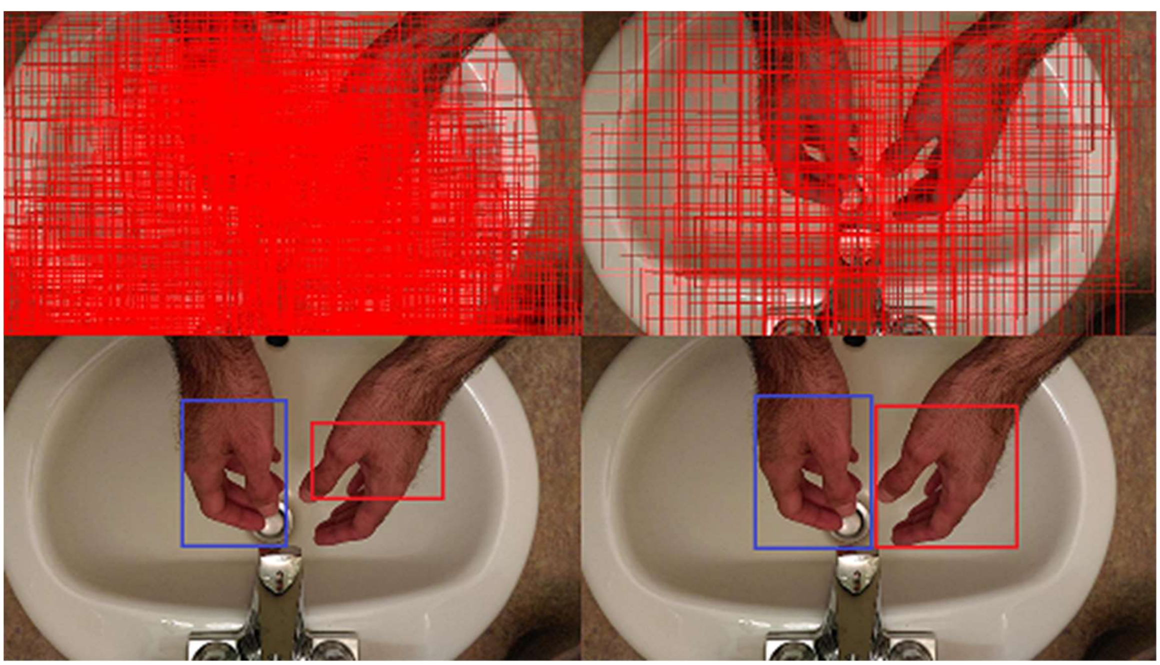

Figure 3-17 Direct sampling vs edge boxes sample 1

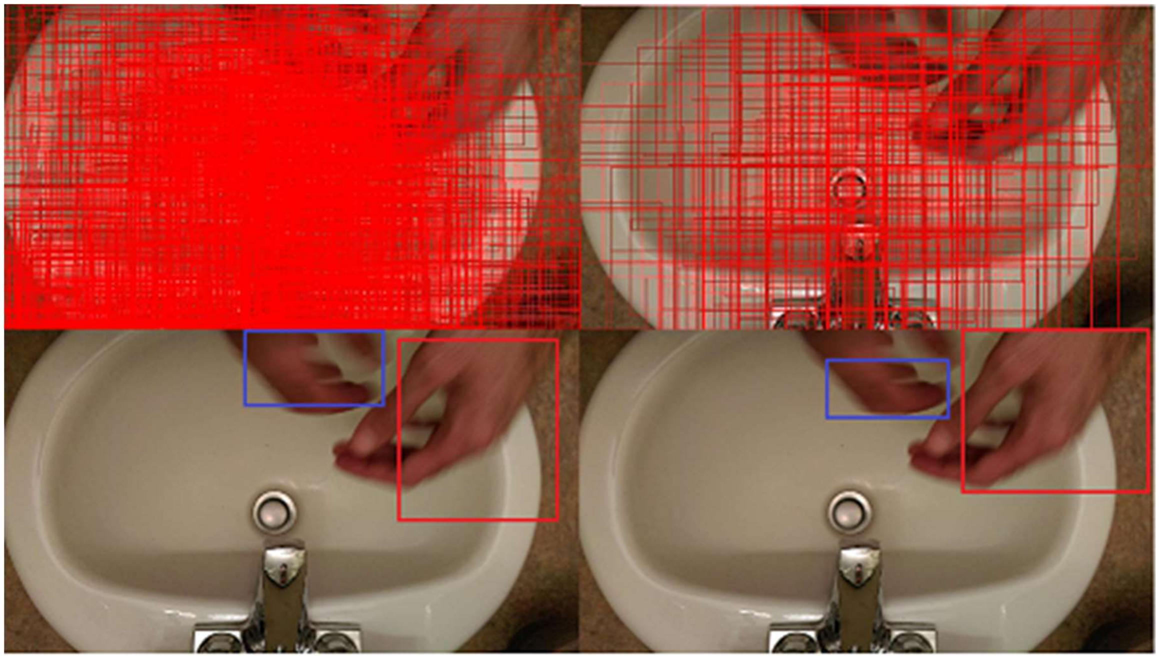

Figure 3-18 Direct sampling vs edge boxes sample 2

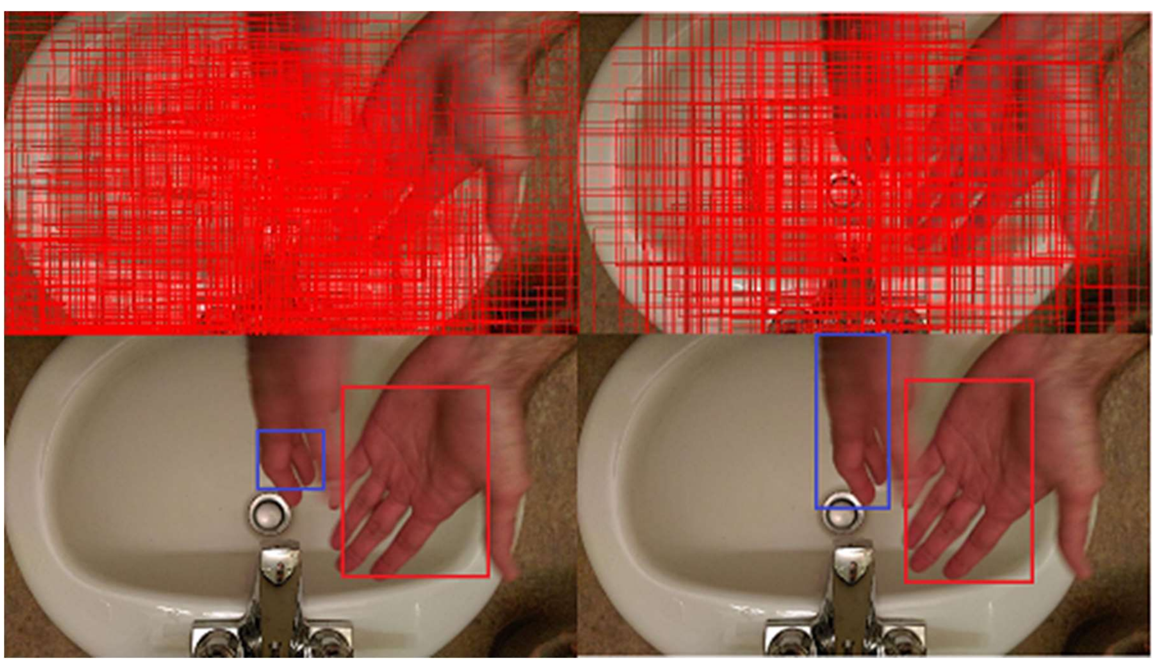

Figure 3-19 Direct sampling vs edge boxes sample 3

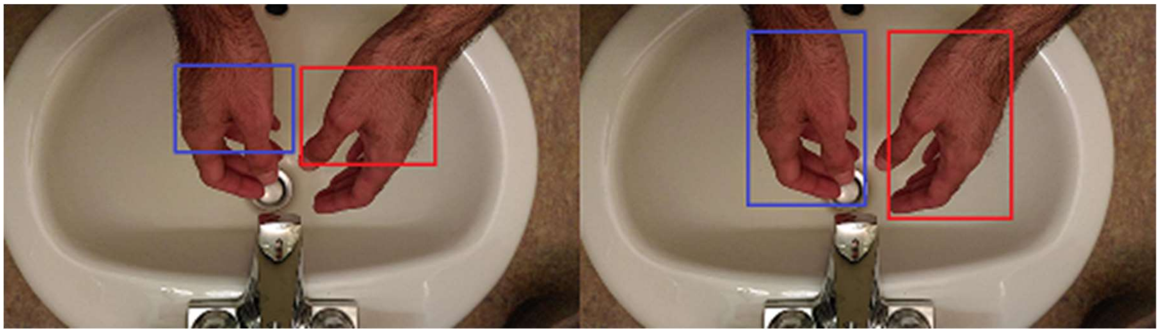

Figure 3-20 Direct sampling vs edge boxes sample 4

In Figure 3-20, direct sampling was configured to generate 1500 sample, while the parameter α was increased from 0.65 to 0.75. Both implementations performed at a comparable rate, the execution time was around 52 seconds.

Chapter 4

4 Experiment Design

The proposed system was subject to several testing stages. Two experiments were conducted to verify the system behavior before the final installation in the Hematology-Oncology unit in the Health Sciences Center to be used in a pilot study. The following chapter presents the details of the experiments and the pilot study.

4.1 HELPS lab experiment

4.1.1 Purpose

The first experiment was conducted in the Human Experiential Learning Performance and Safety (HELPS) lab to achieve the following:

1. Adjust the detection sensitivity of the proposed system
2. Identify possible system limitations
3. Tweak the system to overcome limitations
4. Verify the behavior in different scenarios
5. Determine the system accuracy in terms of false positives and false negatives

4.1.2 Experiment Setup

The system was installed in the HELPS lab in the medical school at Memorial University of Newfoundland. The setup involved 1 Bed, 1 DCN, 2 dispensers and 10 badges. Volunteers with different heights and shapes were invited to test the project. They were asked to simulate the behaviors of healthcare workers and to behave as naturally possible. The DCN was connected to a monitor that shows live results but these results were not shown to the volunteers until the end of the experiment to avoid any bias in their behaviors. Figure 4-2 demonstrates the setup in the HELPS lab.

The volunteers were asked to perform 100 scenarios each. They randomly switched between complying with the hygiene recommendations and intentionally not follow the proper hygiene procedure. They recorded every scenario as they did it. Each volunteer was given a special badge that broadcasts its identity to be able to better analyze the performance. They were also instructed to enter the room in groups or individually given that at any entry all the group will be doing the same correct/wrong hygiene scenario.

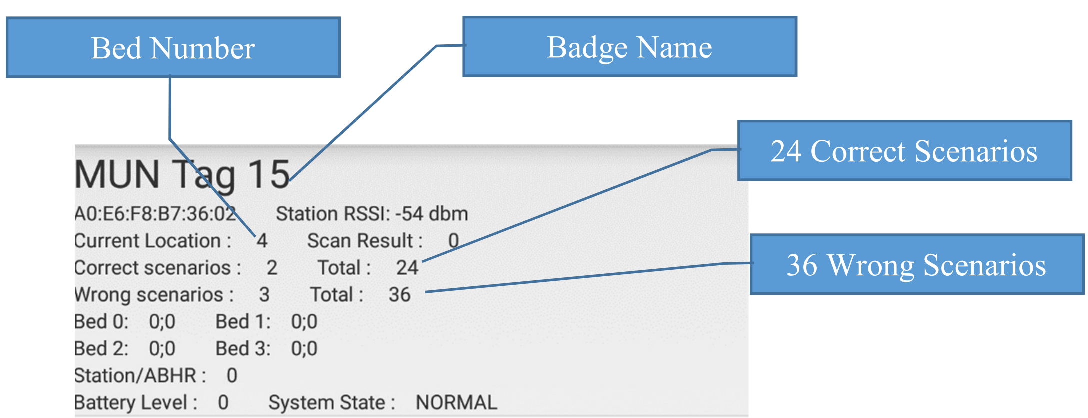

Figure 4-1 Detected scenarios for a badge during the experiment

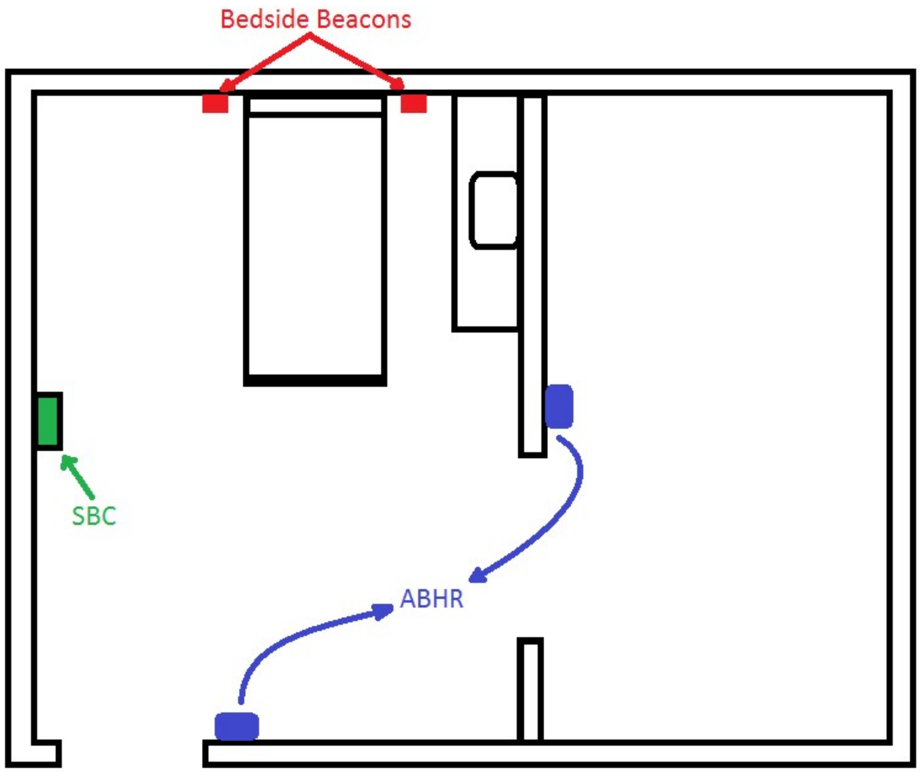

Figure 4-2 HELPS Lab experiment setup

4.2 Semi-private room experiments

4.2.1 Purpose

Three experiments were conducted during the development of the project to address situations where there is more than one bed in the same room, as the previous experiment included rooms with one bed only. The experiments were conducted in a room in the Waterford Hospital, in the Sim lab and in four-bed rooms at the Janeway Hospital.

4.2.2 Experiments Setup

The semi-private rooms in the three locations had a very similar layout (Figure 4-3). The idea was to split the room into two mirrored halves, each half consisting of two beds.

The area around the beds in each half was categorized as In-Between (beds) and Outside (beds). Two bedside beacons were installed on each bed splitting the area into 4 regions. Two regions represent Outside, for which the threshold was set to a specific value. The In-Between area was split into two regions each belonging to one of the beds.

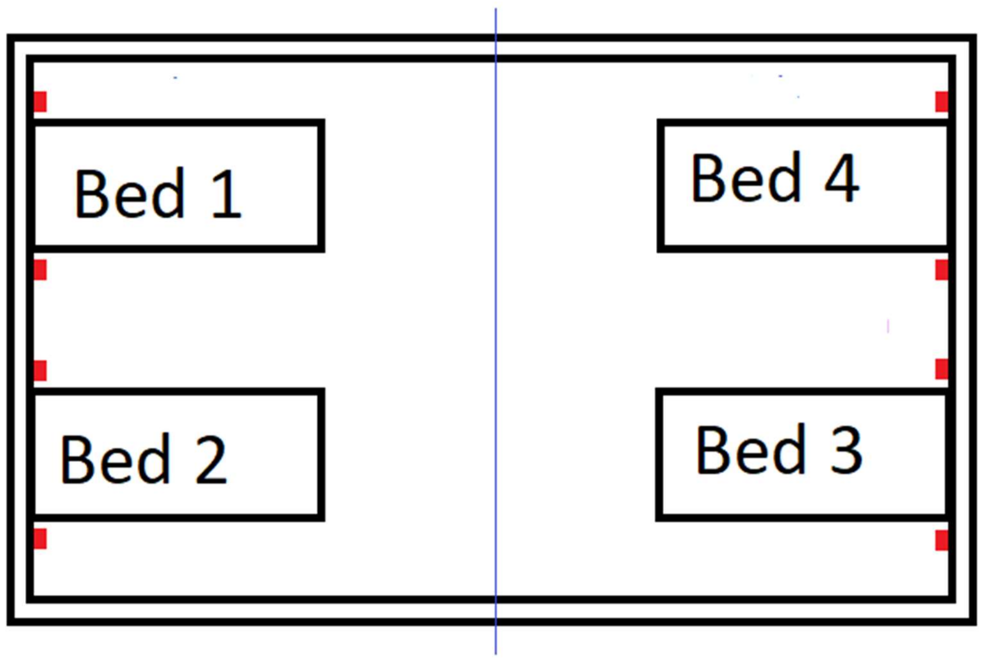

Figure 4-3 Semi-private room layout

The person performing the scenarios was given a badge and was asked to perform 20 scenarios for each attempt switching between the In-Between and Outside regions for the different beds. The tester was also asked to stay in the middle of the room for a period while switching between beds to simulate a possible situation where the healthcare provider might stand there before moving towards the patient.

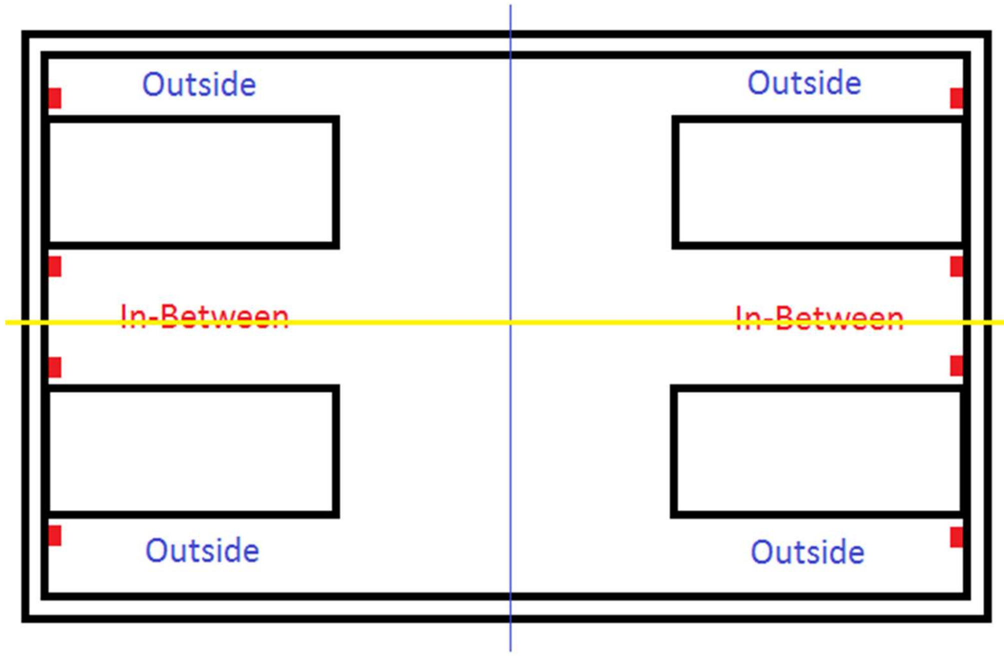

Figure 4-4 4-Bedroom regions division

4.3 **Pilot study**

4.3.1 **Purpose**

The proposed hand hygiene monitoring system was used in a pilot study that took place in the Health Sciences Center in Eastern Health. The study aimed to:

1. monitor the improvement in the hand hygiene compliance using an automated electronic system
2. observe the variations of a specific group of healthcare providers during the weekdays and on weekends
3. determine the acceptability of an electronic hand hygiene system to healthcare providers

4. assess the accuracy and the reliability of the proposed hand hygiene system in a very busy healthcare environment.

4.3.2 Experiment Setup

This section presents the design and the circumstances for the pilot study. The experiment was coordinated by the system developers and the Infection Prevention and Control team in Eastern Health. The baseline rates for the study were collected by the IPAC members using the direct observation method.

4.3.2.1 Location

The proposed system was installed in the Hematology-Oncology unit in the Health Sciences Center. The study included all private rooms in the aforementioned unit. This unit was specifically chosen due to its nature and the adequate size of the staff. All the soap and ABHR dispensers were replaced by the designed BLE enabled dispensers discussed in section 3.3, including the soap dispensers by the sink inside each room and the ABHR dispensers in the hallways containing the private rooms.

4.3.2.2 Manufacturing and Installation

To avoid any liability issues, all the system components were manufactured by an ISO certified workshops in the Technical Services at Memorial University of Newfoundland. The system was subject to strict criteria during the design and manufacturing phases in order to meet the required safety standards due to the critical nature of the installation environment. To ensure maximum safety was achieved the system was CSA certified by QPS in Montreal, Quebec, Canada.

4.3.2.3 Duration

The dispensers were designed with 8000 mAh LiPo batteries that could keep the dispensers running with average usage for 3 months on a single full charge. Due to the difficulty involved with charging the dispensers, it was determined that the pilot study should initially last for 3 consecutive months only.

4.3.2.4 Participants

The study was mainly coordinated by the Infection Prevention and Control (IPAC) Team at Eastern Health and the project developer at the Faculty of Engineering at MUN. The entire healthcare staff at the Hematology-Oncology unit at the Health Sciences Center was motivated to participate in the study by conducting focus groups to discuss the study idea, intentions and outcomes.

All the project components were briefly explained to the participants to ensure their familiarity with the project and to prevent any miss-conceptions about the project particurlarly those related to privacy issues.

4.3.2.5 Privacy

The study promotes the anonymity of the data collection. The project was specifically designed to discard any information that could identify a badge holder. Although it was possible, special care was given to not provide any individual statistics or compliance rate. As a second level of protection against identity detection, the badges were randomly picked by the staff at the start of each shift without tracking which healthcare provider had which badge.

4.3.2.6 Ethics

The engineering team participating in the study had to sign an oath ensuring the confidentiality of the patients in order to be on the floor. The study did not require any ethics approval.

4.3.2.7 Components

The study included all 15 private rooms in the Hematology-Oncology unit. This required the design and manufacturing of 30 bedside beacons as each bed required two beacons to fully cover the room. Twenty-four dispensers were required to replace all of the dispensers in the area covered by the study so 26 dispensers were manufactured (including two spares). Each room required a data collection node (DCN) so a total of 15 Inforce 6309 boards were configured and installed in the rooms for the data collection.

It was found that a maximum of eight badges would be required during any shift so twenty badges were manufactured of which fifteen were supplied to the staff and five were kept as spares. Finally, three charging stations were manufactured, each capable of charging five badges at the same time to make sure that there would always be an available charging port when needed. No cameras were installed at the sinks as a part of the experiment, so the hand detection algorithm was not used.

4.3.2.8 Data visualization

To provide feedback on staff performance, a C# desktop application was developed that reads the files from the server, calculates the compliance and displays a pie chart (Figure 4-5) to the staff. The chart presents a daily compliance percentage. The update rate of the chart and the server configurations are configurable through the GUI (Figure 4-6). A validation word is required for any configuration changes. The software could be installed on any computer connected to the Eastern Health network without any special installation requirements.

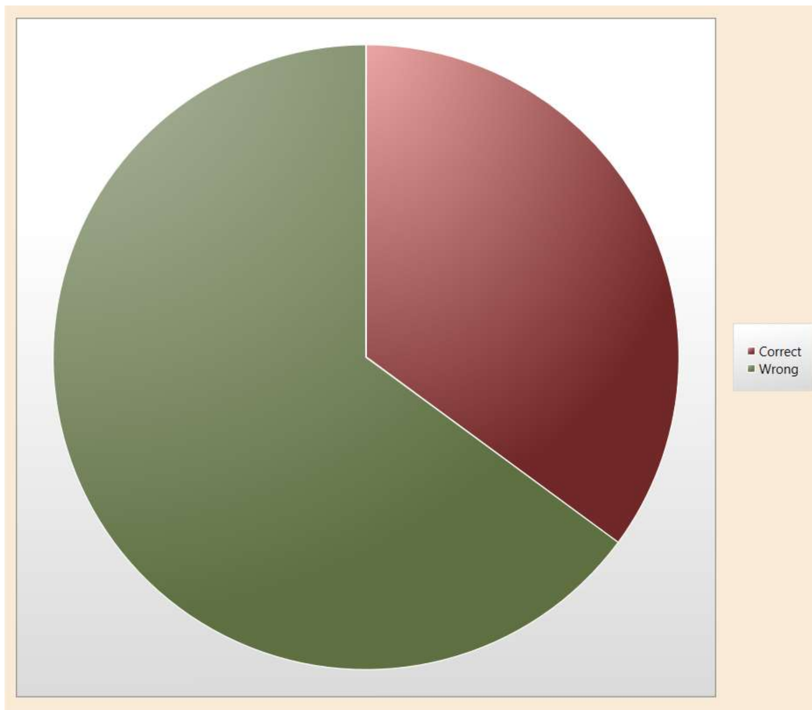

Figure 4-5 Hand Hygiene compliance viewer

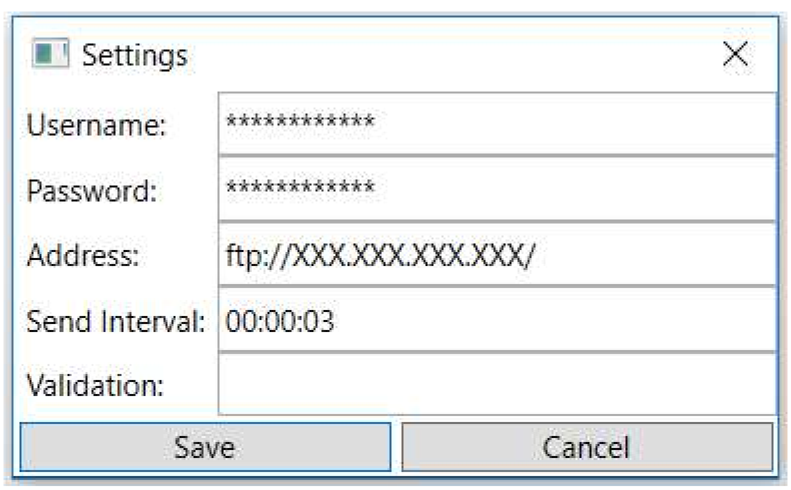

Figure 4-6 Configurations window

Chapter 5

5 Results and Discussion

In this chapter, the performance and the results of the experiments explained in Chapter 4 are presented. The performance of the proposed system was assessed in two setups before its installation in a real healthcare environment. The power consumption analysis of the project components is also discussed.

5.1 HELP lab experiment

5.1.1 Executive Summary

The system was tested in a room-like lab environment to quantify and optimize the performance, identify and if possible overcome the limitations and verify the behavior. The system sensitivity was adjusted by tweaking the system parameters to detect at least 90% of all the scenarios with minimal false negatives and false positives. It was found that the badge orientation affects the accuracy. Sources of false positives and false negatives were identified.

5.1.2 Findings and Discussion

The first attempt of the experiment lead to poor results. The system was not sensitive enough to detect all the proximities to the patient. This was fixed by changing the detection threshold of the bedside beacons to detect at least 90% of the scenarios. Table

5-1 presents part of the data obtained after adjusting the sensitivity. The system had 88% recall and 90.85% precision. Table 5-2 summarizes the experiment results.

Table 5-1 Typical data obtained during the experiment

		MUN Tag 15					MUN Tag 17					MUN Tag 20					MUN Tag 21				
		Actual	Detected	TP	FP	FN	Actual	Detected	TP	FP	FN	Actual	Detected	TP	FP	FN	Actual	Detected	TP	FP	FN
Total	Wrong	48	40	85	4	10	52	42	78	9	13	51	49	87	10	6	53	44	78	10	13
	Correct	51	49				48	45				52	48				48	44			
Entry 1	Correct			TRUE	FALSE	FALSE	1	1	TRUE	FALSE	FALSE	1	1	TRUE	FALSE	FALSE	1	1	TRUE	FALSE	FALSE
	Wrong	1	1																		
Entry 2	Correct	1	1	TRUE	FALSE	FALSE	1	1	TRUE	FALSE	FALSE	1	1	TRUE	FALSE	FALSE	1	1	TRUE	FALSE	FALSE
	Wrong																				
Entry 3	Correct	1	1	TRUE	FALSE	FALSE	1	1	TRUE	FALSE	FALSE			TRUE	FALSE	FALSE			TRUE	FALSE	FALSE
	Wrong											1	1				1	1			
Entry 4	Correct	1	1	TRUE	FALSE	FALSE	1		FALSE	FALSE	TRUE	1	1	TRUE	FALSE	FALSE			TRUE	FALSE	FALSE
	Wrong																1	1			
Entry 5	Correct	1		FALSE	FALSE	TRUE			TRUE	FALSE	FALSE	1	1	TRUE	FALSE	FALSE	1	1	TRUE	FALSE	FALSE
	Wrong						1	1													
Entry 6	Correct	1	1	TRUE	FALSE	FALSE			TRUE	FALSE	FALSE			TRUE	FALSE	FALSE		1	FALSE	TRUE	FALSE
	Wrong						1	1				1	1				1				
Entry 7	Correct	1		FALSE	FALSE	TRUE		1	FALSE	TRUE	FALSE	1	1	TRUE	FALSE	FALSE			TRUE	FALSE	FALSE
	Wrong						1										1	1			
Entry 8	Correct	1	1	TRUE	FALSE	FALSE			TRUE	FALSE	FALSE			TRUE	FALSE	FALSE	1	1	TRUE	FALSE	FALSE
	Wrong						1	1				1	1								
Entry 9	Correct	1	1	TRUE	FALSE	FALSE	1	1	TRUE	FALSE	FALSE	1	1	TRUE	FALSE	FALSE			TRUE	FALSE	FALSE
	Wrong																1	1			
Entry 10	Correct	1	1	TRUE	FALSE	FALSE	1	1	TRUE	FALSE	FALSE	1	1	TRUE	FALSE	FALSE			TRUE	FALSE	FALSE
	Wrong																1	1			
Entry 11	Correct		1	FALSE	TRUE	FALSE			FALSE	FALSE	TRUE	1	1	TRUE	FALSE	FALSE	1	1	TRUE	FALSE	FALSE
	Wrong	1					1														
Entry 12	Correct			TRUE	FALSE	FALSE	1	1	TRUE	FALSE	FALSE	1	1	TRUE	FALSE	FALSE	1	1	TRUE	FALSE	FALSE
	Wrong	1	1																		
Entry 13	Correct	1	1	TRUE	FALSE	FALSE			TRUE	FALSE	FALSE	1	1	TRUE	FALSE	FALSE			TRUE	FALSE	FALSE
	Wrong						1	1									1	1			
Entry 14	Correct			TRUE	FALSE	FALSE			TRUE	FALSE	FALSE			TRUE	FALSE	FALSE	1	1	TRUE	FALSE	FALSE
	Wrong	1	1				1	1				1	1								
Entry 15	Correct			FALSE	FALSE	TRUE	1	1	TRUE	FALSE	FALSE	1	1	TRUE	FALSE	FALSE	1	1	TRUE	FALSE	FALSE
	Wrong	1																			

Table 5-2 Adjusted-system performance metrics

	Actual	Detected	TP	FP	FN	Recall	Precision
Wrong	204	175	328	33	42	88.648649	90.85873
Correct	199	186					

1. Initially the proposed system used the same algorithm to detect both the bedside beacons and the dispensers. Due to the relatively low detection-threshold value for the bedside beacons, if a dispenser located inside a room was used, the badge would sometimes assume proximity to the bed and would not detect the dispenser. This lead to high false negatives (misses). To overcome this, higher priority had to explicitly be given to the dispensers-detection over the bedside beacons. This was done by searching for any close dispenser first, before searching for the bedside beacons. This increased the system accuracy to above 90% by reducing the false negatives.
2. Another finding was the significance of the badge orientation. It was found that it has a huge effect on the detection accuracy. This was nailed down to the field pattern of the microstrip antenna implemented in the CC2650STK. Due to time and financial restraints, unfortunately, there was no way to fix this problem so it was identified that as a system limitation.
3. The accuracy was also affected by having more than one volunteer entering the room at the same time performing different scenarios i.e. One volunteer would use a dispenser before approaching the patient and another volunteer would approach the bed directly. It was found that sometime this lead to false positives. A possible solution would be to let the dispenser identify

who pressed it by broadcasting a signal from the badge and performing a scan in the dispenser, however, this would lead to a significant increase in power consumption.

Repeating the experiment, while considering the system limitations, lead to 100% accuracy in the detection with 0 false positives and 0 false negatives. The system was then subject to an extended period of testing as it was kept running for two weeks performing a couple of trials at random times per day and verifying the behavior which indicated that the system was ready for the deployment. The performance of the system is summarized in Table 5-3.

Table 5-3 System performance metrics after considering the limitations.

	Actual	Detected	TP	FP	FN	Recall	Precision
Wrong	197	197	411	0	0	100	100
Correct	214	214					

5.2 Semi-private room experiment

5.2.1 Executive Summary

The performance of the system in rooms with more than one bed was assessed. The accuracy of the system suffered from a high number of false-negatives due to the instability of the RSS. The orientation of the bedside beacons was adjusted in an attempt to improve the performance. The system accuracy in the 4-bed patients' rooms setup dipped to 80%.

5.2.2 Findings and Discussion

The initial attempts for determining the scenarios in the setup discussed in section 4.2 did not meet the expectations. It was found that:

1. The RSSI values fluctuated drastically for reasons like multipath fading, and shadowing, causing incorrect bed detections. These incorrect detections lead to a high number of false negatives. The system sensitivity was very low as well due to rapidly switching between the beds and very similar RSS values in the In-Between area.
2. The Outside regions did not suffer from this problem because the badge was significantly closer to the beacon placed on the outer side of the bed while in the In-Between regions the badge was close to two beacons from different beds.
3. Different orientations and placement for the bedside beacons were experimented with as an attempt to overcome this problem. It was found that the average RSS values changed with the orientation and the position with respect to the bed.
4. Signal blocking using wave guides was also tested to direct the signal into specific areas. This did not seem to be effective due to the omni-directional nature of the antenna field pattern (Figure 5-1).

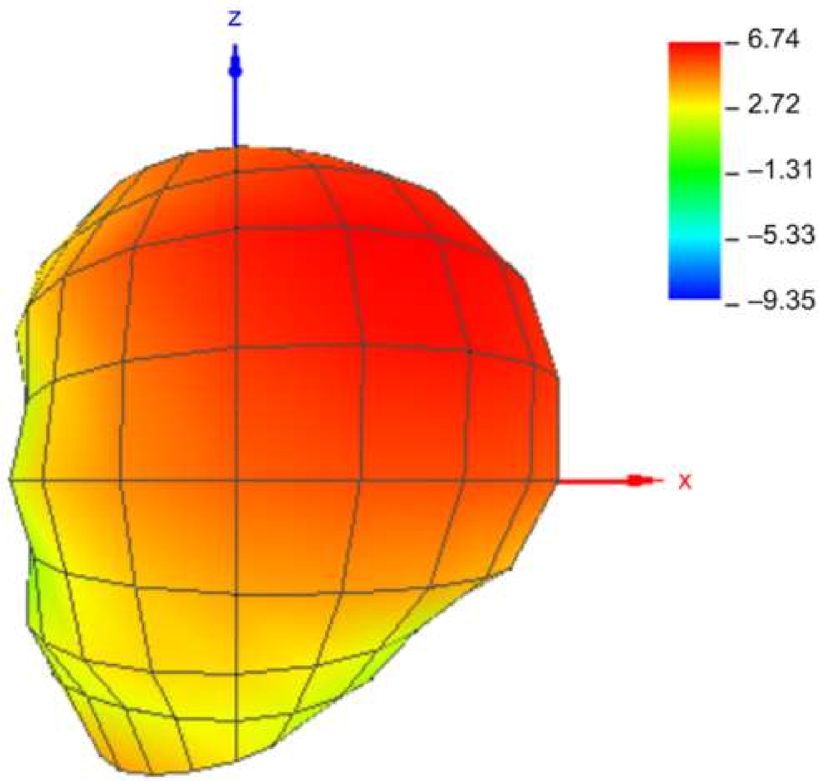

Figure 5-1 CC2650STK Antenna field pattern (Texas Instruments, 2016)

Based on the findings, a working version was achieved after going through several trials and iterations to optimize the system. The system showed 80% precision with few false negatives. The experiment indicated that with further development in the proximity detection algorithm, the system could be improved to be more accurate and stable. The system in its current state is not suitable for deployment due to the amount of per room customization required.

Table 5-4 System performance in semi-private rooms

	Actual	Detected	TP	FP	FN	Recall	Precision
Wrong	100	112	133	33	9	93.66197	80.12048
Correct	75	54					

5.3 Pilot study experiment

5.3.1 Executive Summary

This experiment aimed to assess the performance of the system, improve the hand hygiene compliance rate, observe the variation in the staff behavior on different days (weekdays vs weekends) and determine the acceptance of electronic hand hygiene monitoring systems by the healthcare providers.

5.3.2 Findings and Discussion

5.3.2.1 System performance in real healthcare environment

Maximally, the system was tested in 4-beds room setups. Therefore, the performance of the system on the large scale was not evaluated. This experiment, constitutes the first actual real-life usage for the system. Throughout the duration of the experiment, the following findings were noted:

1. At the first phase of the experiment, the system was detecting the first 5-7 rooms and completely missing the remaining rooms.
2. The system had difficulty detecting the dispensers, so the number of false negatives was high and compliance was much lower than anticipated.

The problem with scaling up the system was the number of Bluetooth Low Energy targets surrounding the badge. As the experiment involved 15 rooms, 30 BLE bedside beacons were constantly advertising their presence and 24 dispensers each started broadcasting when used. The badge was designed to replace the far BLE targets in the location array discussed in section 3.2.2.1 by the closer ones. The original location array size was 12 locations but it was observed that even with the replacement algorithm the array was still so small to handle the BLE targets.

Several code optimizations had to be made to reduce the required data memory for the application. This enabled an increase of the array size from 12 to 30 locations to accommodate all the available targets.

3. Another observation was sluggishness in scenario detections. With the increased number of BLE devices, the system tended to be slower in detecting the bed and the beacons.

It was found that changing the BLE scan window and scan interval in the badge affects the speed at which the scenarios were detected. Scan window represents the time spent in scanning one of the three BLE channels while scan interval is the periodic time of each scan. These two parameters define the scan duty cycle. Increasing the scan duty cycle lead to a faster beacon detection.

4. The measured compliance rates were compared to data collected using direct observation performed by trained professionals from the Infection Prevention and Control team in Eastern Health.

Although the sample for the direct observation was not large enough, the system demonstrated a high correlation to the direct observation numbers. Figure 5-2 presents the direct observation compliance compared to the electronically calculated compliance.

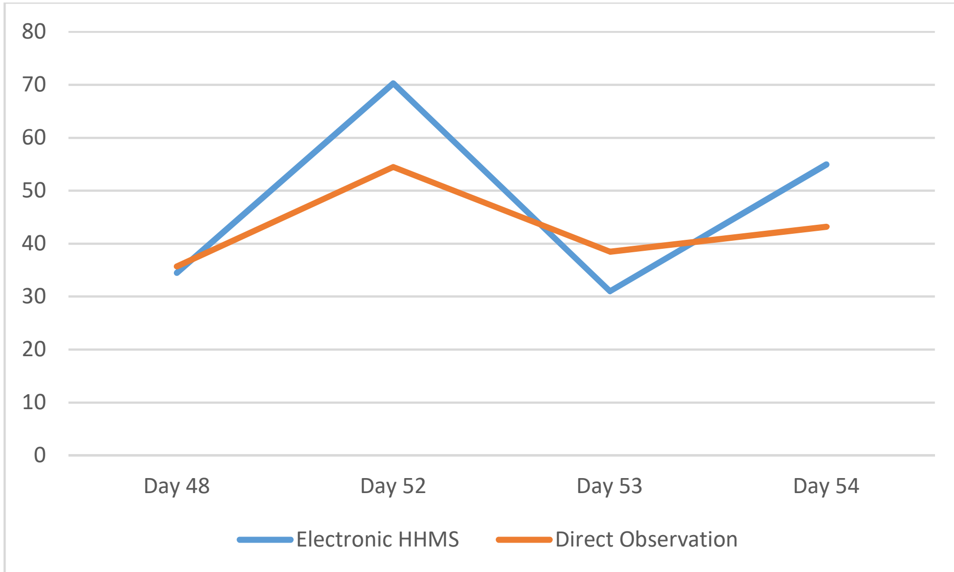

Figure 5-2 Compliance measured by the proposed system against direct observation method

5.3.2.2 Human Behaviors

The experiment investigated the effect of using an electronic hand hygiene monitoring system on the behaviors of healthcare workers.

Table 5-5 shows the collected information using the system. For privacy reasons, the actual dates are not displayed in the table. It shows the difference in the compliance rate between the start of and the end of the experiment. The compliance had a significant increase of 23.5% particularly after displaying daily results to the staff. The Infection Prevention and Control (IPAC) team at Eastern Health is studying the collected data to determine the impact of using an electronic hand hygiene monitoring system on the reduction on HAIs.

The data indicates a change in staff behavior on the weekends compared to the weekdays. The number of detected scenarios on weekends is much lower than on weekdays. This was due to either not using the system or not paying enough attention to using charged badges.

Focus groups were conducted with the participating staff before, during and after the experiment to promote the study and understand staff behaviors and concerns. The focus groups indicated the following:

1. The staff understood the nature of the experiment and the prototype form factor of the system components.
2. The staff showed their acceptance of electronic hand hygiene monitoring.
3. The staff believed that the rates collected by the system are more consistent with the actual compliance rates than the self-auditing method.
4. The staff emphasized that even without using the badges, seeing the other project components in the rooms acts as a reminder to follow the proper hygiene recommendations.
5. The staff recommended future improvements to the system to make it more user-friendly.

Table 5-5 Compliance rate for each day in the experiment

Day	Percentage	Total	Day	Percentage	Total
Day 1	28.5	88	**Day 22**	43	74
Day 2	29.5	147	**Day 23**	41	61
Day 3	30	131	**Day 24**	48	243
Day 4	31	156	**Day 25**	35	152
Day 5	50	212	**Day 26**	36	254
Day 6	35	141	**Day 27**	42	287
Day 7	32.5	95	**Day 28**	47	245
Day 8	36	78	**Day 29**	39	103
Day 9	32	113	**Day 30**	37	89
Day 10	39	188	**Day 31**	45	168
Day 11	32	210	**Day 32**	34	187
Day 12	38	144	**Day 33**	37	171
Day 13	41	284	**Day 34**	42	193
Day 14	37	241	**Day 35**	45	177
Day 15	38	87	**Day 36**	29.5	98
Day 16	43	56	**Day 37**	33	61
Day 17	30.5	124	**Day 38**	38.5	183
Day 18	35	154	**Day 39**	42	210
Day 19	31	189	**Day 40**	39	287
Day 20	32	207	**Day 41**	38	235
Day 21	38	261	**Day 42**	36	190

Day 43	46	78	**Day 65**	42	401
Day 44	35	77	**Day 66**	38	478
Day 45	28	210	**Day 67**	38.5	517
Day 46	39	233	**Day 68**	51	421
Day 47	17	208	**Day 69**	42	520
Day 48	34.5	267	**Day 70**	52	561
Day 49	52	37	**Day 71**	52	452
Day 50	54	29			
Day 51	49	40			
Day 52	70.5	102			
Day 53	31	222			
Day 54	55	178			
Day 55	45	201			
Day 56	41	182			
Day 57	32	138			
Day 58	26.5	187			
Day 59	43	441			
Day 60	45	462			
Day 61	44	422			
Day 62	35	397			
Day 63	34	511			
Day 64	44	321			

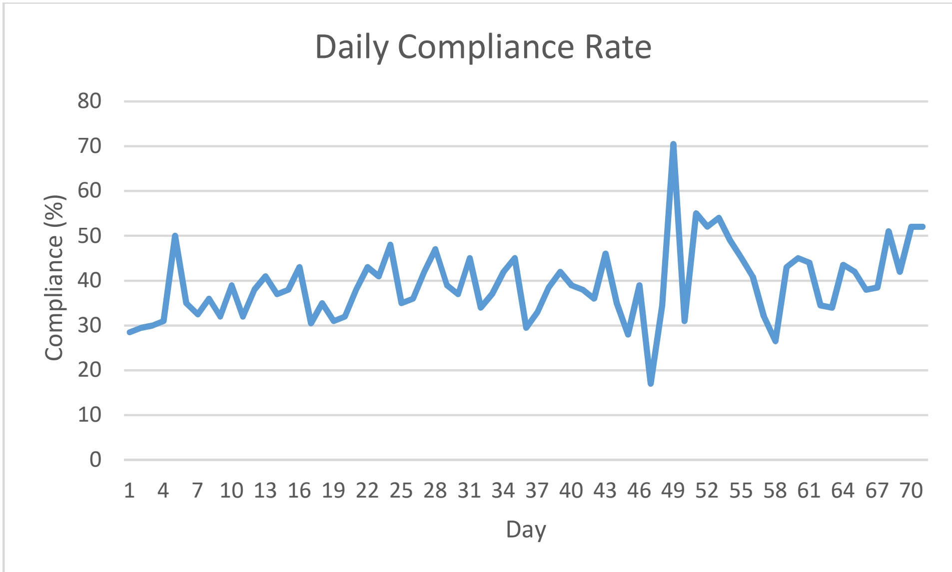

Figure 5-3 Daily compliance chart

5.4 Power consumption measurement

The power consumption for all the project components was determined to estimate the battery life. As the CC2650 consumes very low current, a low noise instrumentation amplifier (INA156) was used to measure the voltage across a resistor connected in series with the CC2650 and the power supply. The amplifier gain was set to 103. Figure 5-4 shows the circuit used for the power consumption measurement.

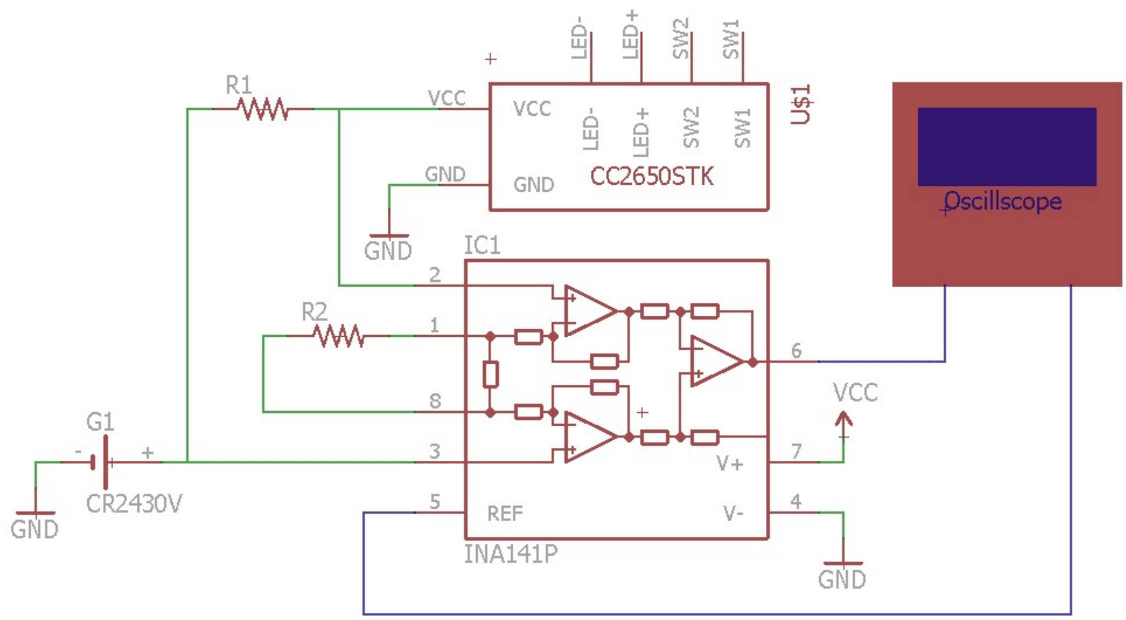

Figure 5-4 Current to Voltage converter circuit

5.4.1 **Badge**

The load current of the badge was measured using the circuit shown in Figure 5-4. The current drawn by the badge running both the broadcaster and central profiles is shown in Figure 5-5. It was found that the badge consumes 8 mA.

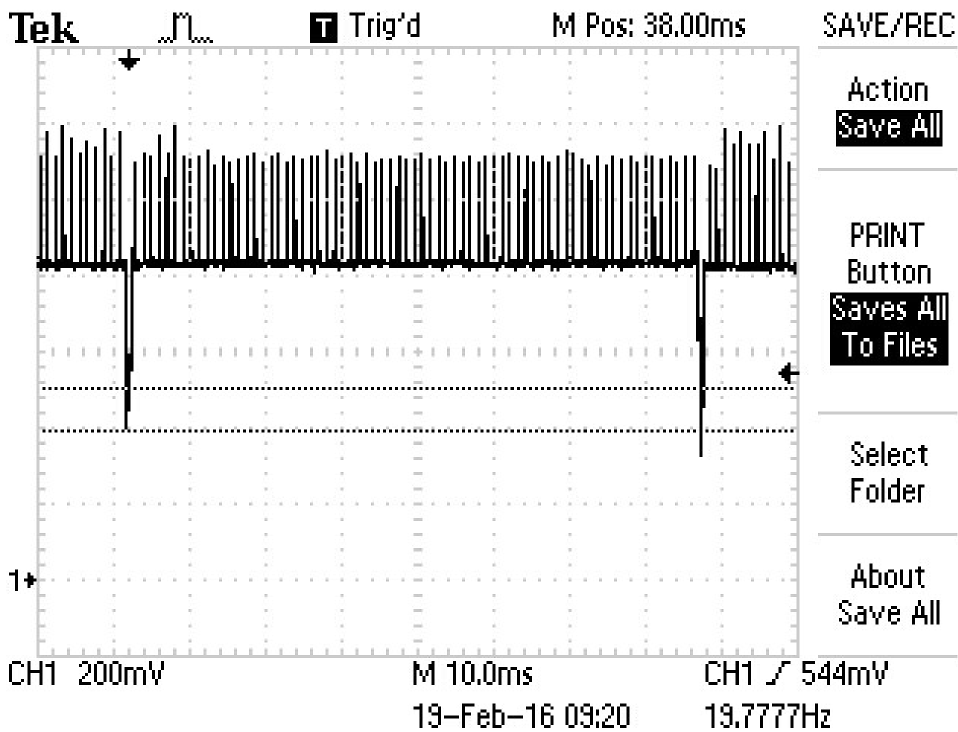

Figure 5-5 Current drawn by the Badge while running two BLE profiles.

5.4.2 **Dispenser**

Unlike the badge, the dispenser is mostly in standby mode. It only starts transmitting for 5 second when it gets clicked. The current drawn by the dispenser while in standby mode is shown in Figure 5-6 while the current drawn during transmission is shown in Figure 5-7, Figure 5-8 and Figure 5-9. It was found the current consumed during standby is around 3 mA.

Figure 5-7 shows that each packet sent during the transmission takes 5.58 milliseconds. The oscilloscope sampling interval was set to 4 microseconds, so the area covered by this packet was represented by 1395 samples. The average current drawn during one packet was found to be 6.2 mA. Figure 5-8 shows that the dispenser sends one packet approximately every 75 milliseconds. Figure 5-9 shows that the full transmission duration is 5 seconds.

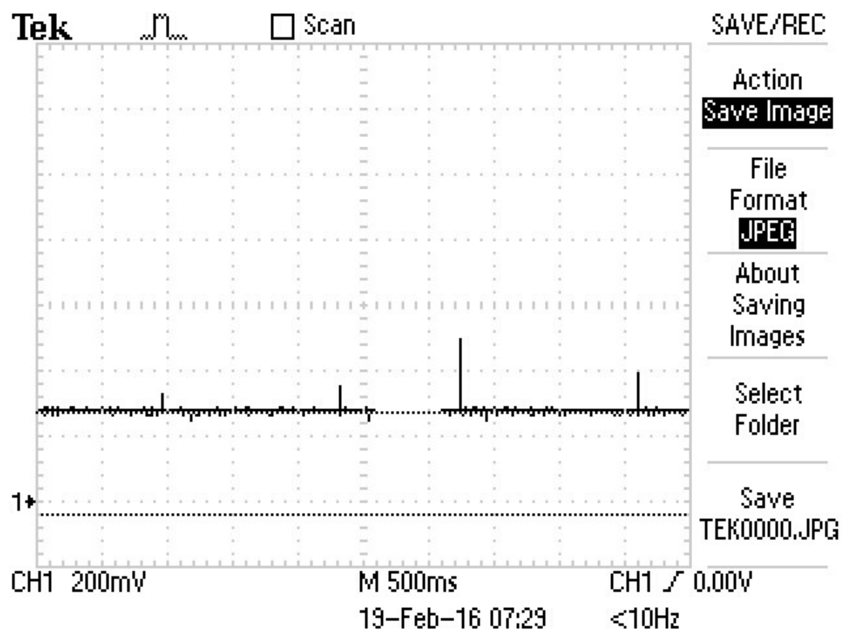

Figure 5-6 Current consumed by the badge in standby mode.

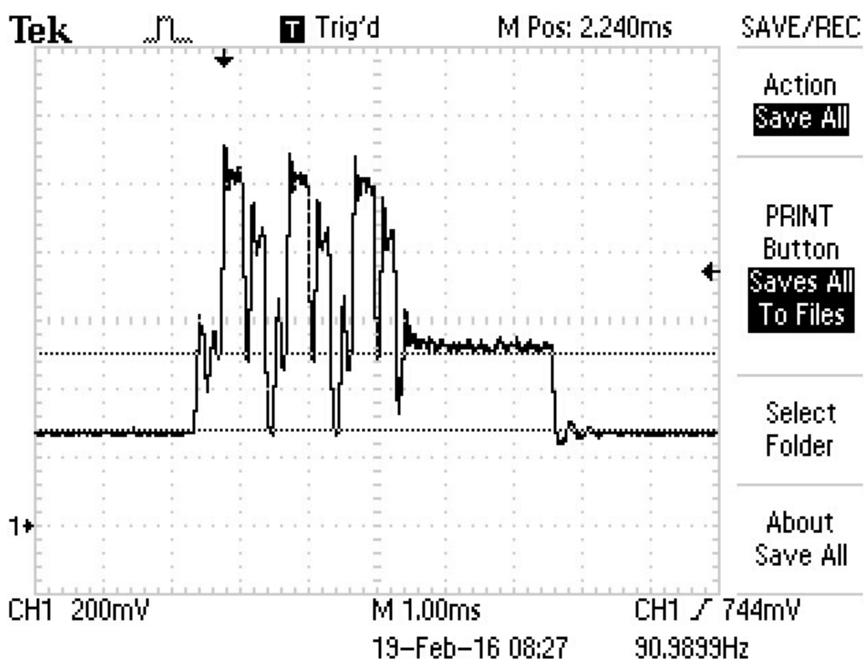

Figure 5-7 Current consumed by the dispenser while transmitting (single packet).

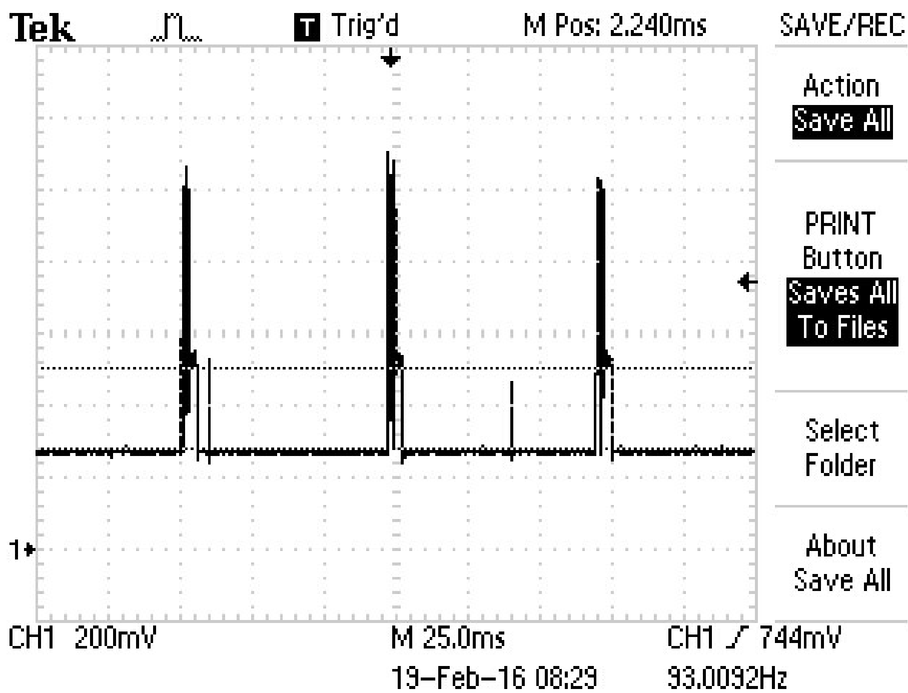

Figure 5-8 Current consumed by the dispenser while transmitting (3 packets).

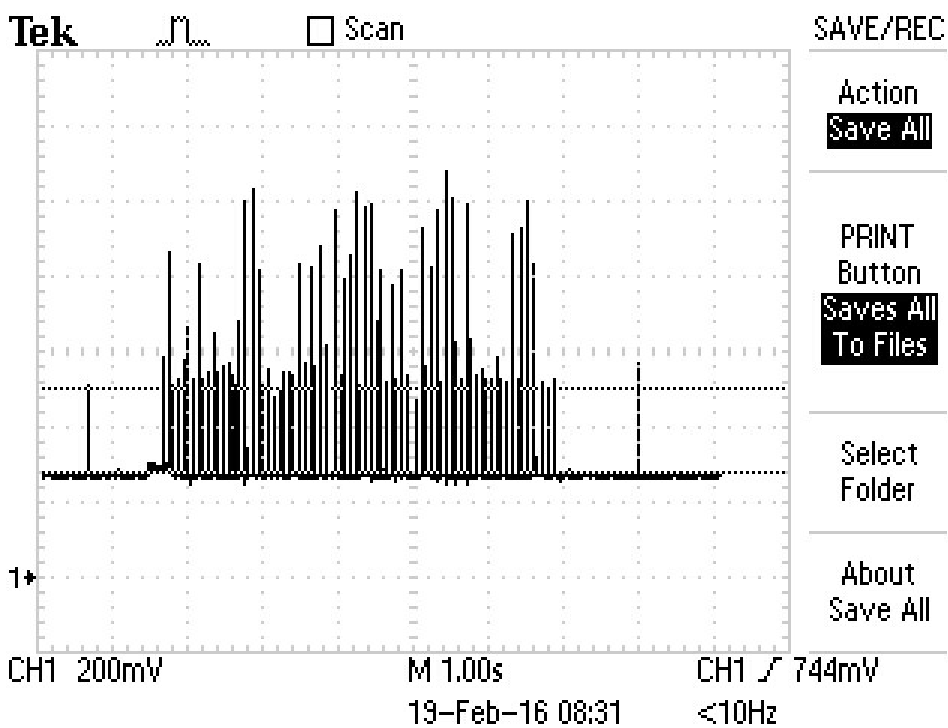

Figure 5-9 Current consumed by the dispenser for each usage.

Chapter 6

6 Conclusion and Future work

6.1 Summary

In this thesis, a real-time hand hygiene monitoring system was designed and implemented. In chapter 1, the motivation for the project was discussed and the importance of electronic hand hygiene monitoring systems was found to be:

- Healthcare-associated infections (HAI) have a significant economic impact.
- Monitoring hand hygiene could tremendously reduce the cost of treating HAIs.
- Direct observation and self-auditing methods might not be very accurate as they are subject to factors as bias and the Hawthorne effect.

Different wireless technologies for in-door relative localization were studied to determine the best approach for the design of a hand hygiene monitoring system. In chapter 2, the technologies were presented and the Bluetooth Low Energy technology was found to be the most suitable technology for the project for the following reasons:

- Low power consumption
- The ability of connectionless information transmission

- Adequate size and wireless range
- Availability of different development platforms and hardware
- More economical solution compared to the other candidate technologies

A BLE hand hygiene monitoring system was designed and implemented based on a System on a Chip (SOC) CC2650. The system consists of badges, bedside beacons, dispensers, data collection, charging station and a configurable windows software to show the results. Chapter 3 discussed the implementation details of the system. The designed system suffers from limitations that were previously discussed.Two hand detection algorithms using imagery sensors were tested.

Chapter 4 discussed a pilot study to determine the feasibility and effectiveness of using an electronic hand hygiene monitoring system. The implemented system was installed in the 4 North A branch of the Health Sciences Centre and focus groups were held to introduce the project to the staff and answer their questions. Compliance was constantly measured for a period and finally, another focus group was held to obtain feedback from the staff.

Chapter 5 presented the results of the lab and pilot study. In the HELPS lab, the system accuracy was found to be 100%. In the 4 North A unit, the data collected using the electronic hand hygiene monitoring system was highly correlated to the compliance found by direct observation. The staff feedback was also presented in that chapter. In general, the feedback was as follows:

1. The system is more accurate than self-auditing.

2. The data should always be anonymous and not presented to individual healthcare providers.
3. The size of the badge should be reduced.
4. A reminder signal might be a good add-on for the project.
5. Even without using the badges, seeing the bedside beacons reminds healthcare workers to follow the proper hand hygiene procedure.

6.2 Future improvements

The study highlighted several opportunities for improvements that would lead to a more accurate and more usable system. The previously discussed system limitations should be addressed for better results. The size and power consumption could also be improved. The following section proposes ideas for development.

To overcome the power consumption problem, a few techniques could be applied to eliminate the need for charging the badge or reduce it significantly. Implementation of energy harvesting from piezoelectric and electromagnetic sources will take care of the charging process. Electro-magnetic energy harvesting perfectly fits the application. The badge can harvest its charging power from the electromagnetic waves emitted from the bed side beacons installed in the environment. These beacons constitute a constant sources of electromagnetic energy.

Application Specific Integrated Circuits (ASICs) is also another approach to address the power consumption issue. General purpose micro-controllers are not very optimized for the power consumption to address a certain application, ASICs are superior in that matter. Moving to ASIC will also reduce the size of the badge. Most of the badge circuitry could be integrated into just one chip, eliminating the need for a bulky printed circuit board PCB.

The field pattern of the antenna created a challenge while implementing the project. The pattern was modified externally to accommodate the room structure and to enhance the performance of the localization algorithm. Custom antenna implementation will lead to a more accurate and flexible system. It will also affect the overall price as at least half the bedside beacons could be removed if we had full control over the antenna field pattern.

The current implementation is based on several components wired together and enclosed in a 3D printed package. The badge form factor can transform from a box to a credit card sized solution when all the parts are combined on one chip. The use of electromagnetic energy harvesting will reduce the size of the required battery. Customized antenna implemented on a flexible PCB will serve for more size reduction.

The relative indoor localization was challenging due to the precision required and the excessive signal reflections to which the badge is subject. The problem was obvious in the case study as well when the system was implemented for testing purposes in a four-bed room with, sink, and multiple dispensers. Higher precision localization is achievable using adaptive and predictive filters to the RSS.

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