Experimental Analysis of a Mobile Health System for Mood Disorders

Tammara Massey, *Member, IEEE*, Gustavo Marfia, Miodrag Potkonjak, *Member, IEEE*, and Majid Sarrafzadeh, *Fellow, IEEE*

***Abstract*—Depression is one of the leading causes of disability. Methods are needed to quantitatively classify emotions in order to better understand and treat mood disorders. This research proposes techniques to improve communication in body sensor network (BSN) that gathers data on the affective states of the patient. These BSNs can continuously monitor, discretely quantify, and classify a patient's depressive states. In addition, data on the patient's lifestyle can be correlated with his/her physiological conditions to identify how various stimuli trigger symptoms. This continuous stream of data is an improvement over a snapshot of localized symptoms that a doctor often collects during a medical examination. Our research first quantifies how the body interferes with communication in a BSN and detects a pattern between the line of sight of an embedded device and its reception rate. Then, a mathematical model of the data using linear programming techniques determines the optimal placement and number of sensors in a BSN to improve communication. Experimental results show that the optimal placement of embedded devices can reduce power cost up to 27% and reduce hardware costs up to 47%. This research brings researchers a step closer to continuous, real-time systemic monitoring that will allow one to analyze the dynamic human physiology and understand, diagnosis, and treat mood disorders.**

***Index Terms*—Affective computing, body sensor networks (BSN), embedded systems, health informatics, medical applications.**

I. Introduction

THE WORLD Health Organization (WHO) estimates that depressive disorders affect approximately 121 million adults and is one of the leading causes of disability in the world [1]. Depression is a chronic mental disorder, where people are usually despondent, lose interest in activities, feel guilty, have feelings of low self-worth, lack energy, lose their appetite, and have trouble concentrating. Bipolar disorders are a subset of depressive disorders, where patients swing between moods of mania and depression. This disorder is also called manic depression and the periods of mania are characterized by a substantial increase in energy, insomnia, racing thoughts, feelings of grandiose, short attention spans, and anxious feelings.

Depression and other mood disorders are difficult disorders to diagnose, understand, and treat due to difficulties in classifying emotion and the fluctuating nature of the disease. Individuals with manic depression continuously have changes in energy, mood, and activity that may not be apparent in office visits. A quantitative method to continuously track patients and provide more data on their moods and emotions could improve how doctors and healthcare clinicians diagnosis and treat the disease.

Recent research has explored the use of noninvasive mobile sensors that can be placed on the human body to measure the vital signs of a patient. These body sensor networks (BSN) allow patients to be continuously monitored remotely and are useful for many medical applications, including manic depression. Previous work by Pentland and coworkers has demonstrated that accelerometer sensors measuring body movements can classify depression states and track the treatment of patients [2]. These sensors can aid in the recognition, interpretation, or inference of human emotion. The ability to classify depression states and emotion can fundamentally improve the treatment of patients with manic depression and mood disorders by being able to detect patterns in the patient and suggest interventions.

However, an open challenge is how to create a communication infrastructure that will allow patients to continuously communicate affective cognitive states through the use of wearable sensors. BSN can consist of wearable systems embedded in cloth or portable embedded systems that can be carried by the patient in a similar manner as the cell phone. In this paper, challenges in connectivity of BSN and interference from the human body itself is addressed.

BSN have different properties than most traditional wireless sensor networks (WSN). A new class of distributed embedded systems BSN, is rapidly evolving and the need to develop architectures from experimental data is needed [3]. Our approach will build upon our growing understanding and experience with wireless *ad hoc* sensor networks. WSN share key features with BSN. WSN and BSN sense, self-configure their resources, and provide actuation under severe communication and memory constraints. In addition, the systems are tightly coupled to the physical world and must adapt and self-organize without human intervention. Due to the dynamic environment that BSN are deployed in, realistic data based on actual events are essential. However, BSNs differ significantly from WSN in that the system must deal with a large amount of interference from the body, the systems are

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inherently mobile, and the system as a whole must integrate into a hospital backbone infrastructure.

Our approach builds upon the growing interdisciplinary field of computer science merged with psychology, cognitive science, biomedical engineering, and medicine. Affective computing and BSN are a subset of these fields, which focuses on the construction of lightweight medical devices, processing of data based on affective states, and the usability of this data within a clinical or everyday settings. In these systems, experimental data are necessary in order to confirm the functionality of these heterogeneous systems. This research specifically addresses the problem of connectivity in a body area network with the optimal placement of sensors in a body area networks that detect the affective states of people.

II. Related Work

As early as 1649, philosopher Descartes proposed the concept of duality or mind-body dichotomy, where the mind controls the body and the body influence an individual's rational reasoning. He proposed that if humans think, than they exist. Descartes incorrectly assumed that emotions stem from the pineal gland and that animals do not feel emotion, since they do not possess this gland [4]. Picard proposed that not only animals but also computers could recognize, understand, and express emotions. She argued that emotion can be detected with sensors that determine the affective state or behavior of a person. This new field affective computing, can aid in learning, information retrieval, communication, interaction, and the health of people [5]. Neurologist Antonio Damasio argued against Descartes philosophy. He suggested that even if a human being can think, he/she can make rational decisions if he/she cannot incorporate emotions into the decision-making process. Damasio gives the example of Phineas Gage, whose brain was damaged in an accident, but his intelligence was not affected. However, Gage's ability to make rational decisions was impaired because his emotions could no longer be included in the decision-making process [6].

Research building on the philosophy of Descartes, Picard, and Damasio use quantitatively analysis techniques to determine how emotions affect reasoning and can advance research in diagnosing, understanding, and treating mood disorders that are driven by emotion. Several researchers have taken various quantitative approaches for studying emotion by analyzing data on people's speech, gestures, or facial expressions. A microphone sensor has been used to infer emotion from voice pitch, speech level, and speed [7], [8]. In addition, vision sensors can capture gestures, facial expressions, and a person's posture to infer emotion [9], [10]. Skin temperature and galvanic resistance can also infer emotion through physiological data, such as heat and sweat.

Affective computing requires that meaningful patterns be extracted from experimental data. Various techniques have been used to process data, such as dynamic-time warping, optical flow, hidden Markov models, corpa models, eigenface, fisherface, dynamic-link matching, and neural network processing. This research does not focus on techniques for extracting patterns from data. Rather, this research explores how this data can be efficiently communicated in a BSN.

Previous work has explored several types of body area communication. Yoo *et al.* proposed four types of body area communication: off-body communication, on-body communication, in-body communication, and through-body communication [11]. Off-body communication uses several mediums, such as 2.4 GHz channel radios, Bluetooth, and ultra wideband, to send data through the air to communicate. The data is usually sent over 30 to 100 ft [12]. The second type of communication is on-body communication that travels on the human skin on the 200MHz band [11]. The range of the communication is the maximum size of the skin around 8 ft. The third type of body area communication is in-body communication and is useful for several *in vivo* sensors communicating with one another inside of a human being. The fourth type of communication investigates through-body communication, where an *in vivo* sensor communicates with an external device [13]. The most common carrier frequency is the 400MHz channel, but the 2.4GHz channel is also used.

Previous work in antenna research with wearable systems has made several important findings. First, the orientation of the antenna and proximity to the human body impacts the communication [14], [15]. Also, the body's biological tissues absorb approximately 30% to 60% of the antenna's power. How well the communication can pass through the human body is greatly affected by what frequency that it is on [14]. Specifically for the 2.4 GHz channel, the permittivity of dry skin is 38.1 S/m and the conductivity is 1.441 S/m. Muscles have a permittivity of 52.7 S/m and a conductivity of 1.705 S/m. The lungs have a permittivity of 34.5 S/m and a conductivity of 1.219 S/m. The overall path loss was 44.2 dB [16]. In addition, the specific absorption rate (SAR), the measure of how much the radio frequency is absorbed by the body, is reduced by lowering the power of the device. As the space between the body and the radio increases, the SAR also decreases [14].

Previous work has specifically investigated the performance of the human body on a 2.4 GHz antenna for wearable wireless local area networks. One study concluded that the radiation characteristics of the antenna were not greatly affected by the human body [17]. However, previous antenna research has focus mainly on one individual antenna and has not taken into account how the combination of distance and a human body affects the communication in the 2.4 GHz channel with wearable devices [14]–[17]. Previous research has also neglected to investigate how the sensor board and processing unit also interact in this system. Also, even though Hao *et al.* discovered that variations due to breathing or small body movements affect the channel, how to quantifiable use or mediate these affects have not been addressed [16]. Previous work has explored using motion capture equipment to characterize movements [18]. However, this research is the first to combine motion capture equipment and communication. In a *people network*, consisting of several devices communicating with one another, these problems are important research topics that should be addressed. This research quantifies the optimal placement of sensors on the

TABLE I
OVERVIEW OF DATA DRIVEN APPROACH TO QUANTIFY LINE OF SIGHT AND RECEPTION RATE IN A MOBILE ENVIRONMENT

Experimentation	Attenuation Measurement Study
⇓ *Modeling*	x,y,z Coordinates to Quantify Mobile Placement
	Line of Sight and Reception Rate
⇓ *Optimization*	Minimal Number of Embedded Systems
	Hardware Cost
	Power Cost

human body and investigates how to make use of this data in the actual systems.

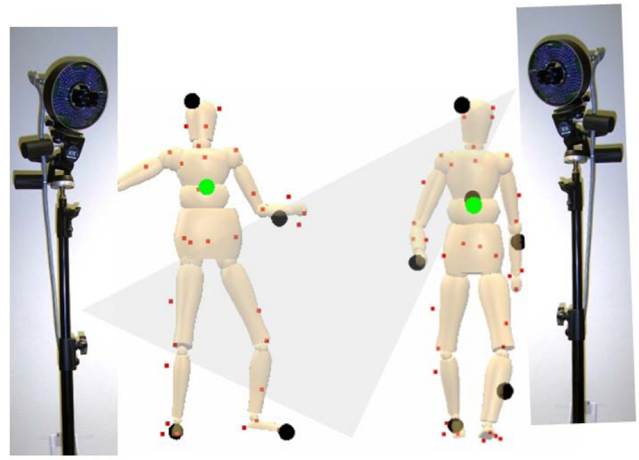

Fig. 1. Setup of the measurement study with seven motes sending and receiving.

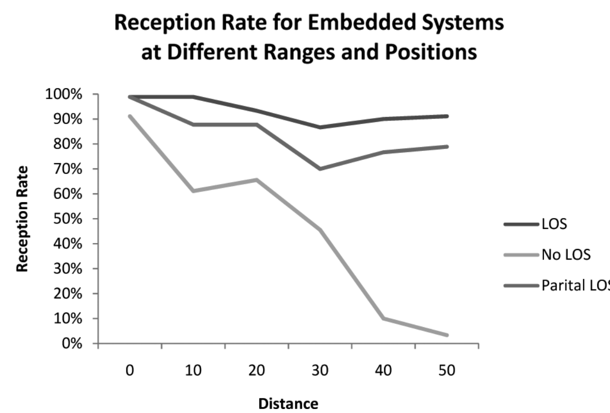

Fig. 2. Reception rate of links in a BSN at various ranges and positions.

III. BSN FOR MOOD DISORDERS

In our proposed architecture, patients suffering from bipolar disorders, move around in their everyday life with embedded systems that have accelerometers, galvanic response, electrocardiogram, or audio sensors. The accelerometer sensors detect the movement of the patient on an x-, y-, and z-plane. Movement is an effective measurement of a bipolar patient's emotion and mood. Recall that bipolar patient swing between states of mania and depression. When bipolar patients are depressed they have less energy and the accelerometers will detect the reduction in movement and physical activity. In addition, the audio sensors can gather data on the patient's pitch, level, and speed of speech. Patients in a manic state usually have racing thoughts and are hyperactive, while patients in a depressed state have reduced social activity and slower speech. These symptoms can be be detected by audio sensors. In addition, galvanic response and electrocardiogram sensors may detect a change in the patient's mental state, metabolism, or sympathetic and parasympathetic responses.

In addition to the vital signs of the patients, data on whom the patient encounters, where he/she goes and his/her reaction to events and people can be recorded. This data can aid patients in identifying what stimuli are triggers to manic or depressive episodes and correlate patterns in their affective state with their surrounding environment. Additionally, patients may even receive feedback from this system to help them deal with their emotions in a healthy way and use their emotions correctly in making rational decisions.

These sensors gather data on the affective state of patient and their surroundings, and can infer their mental state to help them to manage their emotions when making decisions. These sensors will be worn continuously on the patients during their everyday life and data will be continuously uploaded to a central server. In order for this to occur, an efficient communication infrastructure must be in place to gather data pervasively. Our research explores techniques to improve this communication infrastructure taking into account the unique properties of BSN. Our data driven approach is shown in Table I.

IV. MEASUREMENT STUDY

To quantitatively measure communication in a BSN, experimental measurements were conducted. A mobile measurement study was done outside in order to measure received signal strength, delay, and reception rate. Fig. 1 shows the setup of the experiment with seven motes placed on different parts of the body. Two people wore embedded systems on various locations of their body standing from 0 to 100 ft apart from one another. From our experiments, we were able to determine that the body produces a recurring interference that can be predicted, and therefore, mediated to improve throughput. When the systems were in close proximity to each other, they experienced higher throughputs and receive signal strength indicator (RSSIs), as expected from previous work. In contrast, embedded systems whose radio communication traveled through two people's body resulted in a lower receive rate and RSSI. Fig. 2 demonstrates that whenever the medical embedded system deals with interference from the body, the throughput drops significantly. The embedded system placed in the front of the human body during the experiment, usually had a direct line of sight to the remote node. The system placed on the back, usually had no line of sight to the remote node. Finally, the embedded system placed on the arm had partial line of sight to the remote system.

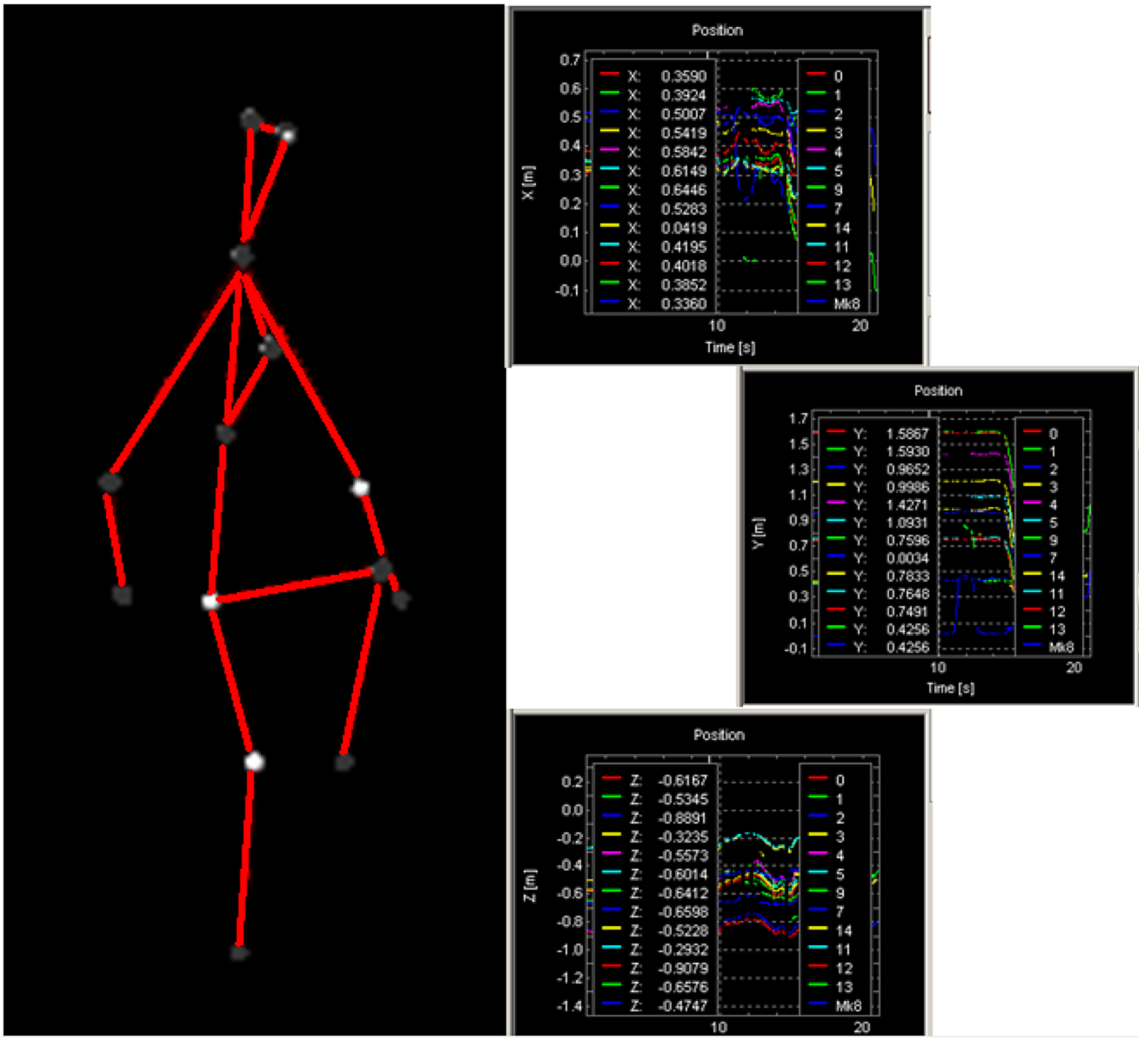

Fig. 3. Quantitative analysis of sensors using motion tracking software. (Left) 3-D image of a person wearing various markers on them. (Right-top) *X* coordinate of all the markers. (Right-middle) *Y* coordinate of all the markers. (Right-bottom) *Z* coordinate of all the markers.

V. Correlation Between Line of Sight and Reception Rate

Experiments in the ambient environment suggested that there was a direct correlation between line of sight and the reception rate. However, in this mobile environment, where the user was continuously moving, it is difficult to determine quantitatively for various individuals the correlation. To order to quantitatively determine the relationship between line of sight at certain time points, a second set of experiments were conducted with motion capture equipment to quantify the degree of visibility of the embedded system at various time instances. Three hundred minutes of experimental data was collected from ten subjects. Subject's weights ranged from 112 to 229 pounds. Subject's heights ranged from 5 ft 5 in to 6 ft 4 in. In these measurements, a sensor board was used with motion capture equipment that could capture the x, y, and z of markers placed on the object. Fig. 3 shows a 3-D image of the human body in the motion capture software [19], [20].

In addition, the base station mote was placed on top of the camera. Therefore, whenever the camera could accurately detect the base station, this quantitatively verified that it was in full view of the base station mote. The quantitative capabilities of the motion capture equipment ensured that the experiments could be reproduced and verified. Reproducibility is a cornerstone of quality research.

Another characteristic that needed to be modeled in the experiment was the fact that the radios could be partially visible to the base station mote. In particular, nodes on the side or on the top of the head often were visible to more angles. However, the entire surface was not visible to each node and the throughput was lower. In order to quantitatively represent this phenomenon, we used a cluster of markers on the embedded medical system. Therefore, the camera had the opportunity to detect multiple markers instead of one. This removed the quantitative 0 or 1 component representing the visibility of a single marker. The test was set up so that two people wearing markers representing embedded system and experiments were run inside and outside. Data has verified that reception rate and visibility of two people at different ranges are directly correlated when the person is outside. Outside it was difficult to setup the motion

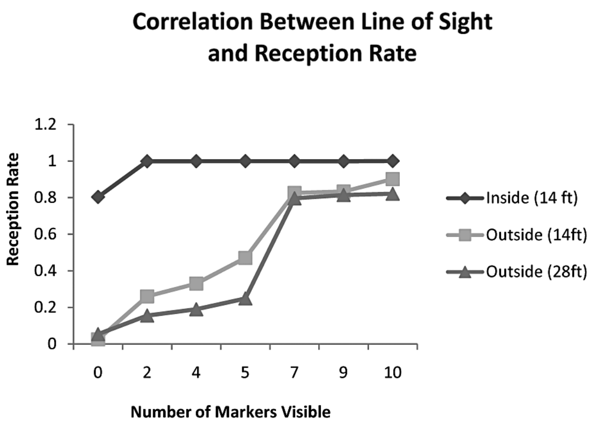

Fig. 4. Correlation between line of sight and reception rate.

capture cameras, but throughout the testing if the person moved minimally, the number of markers stayed the same. The reception rate for markers at various distances indoors and outdoors are shown in Fig. 4. For outdoors, there was a high correlation between reception rate and line of sight of the markers. When the experiments were done indoors, the body also caused interference. However, due to multipath reflections, the signal has a high reception rate. This is an interesting characteristic to discover for later construction of communication.

VI. Minimum Number of Radios for Optimal Coverage

A direct relationship has been established between line of sight, and reception rate. Therefore, one can easily understand that if a radio is always within line of sight of the base station than the throughput will be greater. Assuming that radios are a commodity and can easily be placed on most places on the body comfortably; an interesting research problem is to determine the minimal number of radios for optimal convergence. In this scenario, a radio would always be visible to the base station.

When modeling this data, an essential component to address is whether there are enough markers on the person and if enough data has been gathered. In order to address the first research problem, an abundant number of sensors were placed on the body, and then, patterns of correlations among the sensors were detected. Sensors that are correlated are sensors that appear in every angle together. We then eliminate one of the correlated sensors. In order to address the second challenge of determining if enough data on various movements had been collected, the data was split into two parts. We analyzed the first portion and if all the information in the first portion can be found in the second portion than enough data had been collected. Otherwise, the dataset was doubled and split it again.

Now that the model has been devised, the problem can be formulated as an integer linear program. In our dataset, the human subject is dynamic, and continuously changing positions and orientations. For each body position k that a subject is in at each time instance, the markers *m* that were visible are extracted. The markers ranged between 1 and N, where N is the total numbers of markers. Each marker has an x, y, and z coordinate that is represented by the variable j. In this scenario, there may also be several different types of obstacles o, blocking the radio. Each marker has a position p at an angle k. Embedded devices can also be periodically blocked by the patient's arms or obstacles in a real deployment. In order to quantitatively analyze, how obstacles affected the amount of markers that were needed, obstacles were randomly created in a uniform and random distribution for various percentages of the 3-D space. If a marker and an obstacle were in the same 3-D square, then it was not visible to the camera. Visibility is represented with variable v. The various grid sizes of the obstacle were also modified to represent different sizes of obstacles or different size areas that a marker could cover.

Problem Statement: Given N markers at coordinates x, y, and z, what is the minimal number of markers needed to that each marker is visible regardless of whatever position p and angle k that a person may be in. Also, assume that there are obstacles o that may be blocking communication.

Problem Formulation:

$$\text{Minimize}: \sum_{i=1}^{N} m_i. \tag{1}$$

Subject to the following constraints:

$$0 \leq m_i \leq 1 \tag{2}$$

$$\forall p \quad \forall k \quad \sum_{i=1}^{N} v_{pk} \quad m_{i_{pk}} \geq 1 \tag{3}$$

$$\forall k \quad m_{i_{xyz}} \tag{4}$$

$$\ni k \quad o_{xyz} \equiv m_{ijk} \quad \Rightarrow \quad m_{ijk} \equiv 0 \tag{5}$$

$$\forall p \quad \forall k \quad 0 \geq v_{pk} \leq 1. \tag{6}$$

Constraint (2) ensures that each marker is a binary integer 0 or 1. Constraint (2) guarantees that for all angles k, each marker has an xyz coordinate. Constraint (3) ensures that for all positions p and angles k, there exists at least one marker visible. If obstacles xyz is equal to marker xyz at angle k, then no marker is needed to cover area for angle k (see Constraint 5). Lastly, each marker is visible or invisible for position p at angle k by Constraint (6).

The results of the experiment with various percentages of obstacles are shown in Fig. 5. The dataset of body movement and markers were derived from 300 min of experimental data taken from ten participants. The optimal number of markers or radios was compared with how many randomly added radios would be needed so that any radio is visible at any point and time. The optimal number of markers was derived from the linear program described earlier. A simulation created the random placement of systems on the human body. The systems were randomly placed using a uniform random number generator that choose coordinates on the x-, y-, and z-plane. The embedded radio uses 41 mW of power and cost approximately \$70. Additionally, the power for these systems with a sensor board is 468 mW and the equipment cost approximately \$200. Fig. 6 shows that the power costs between the optimal number of markers or radios and randomly choosing the position of markers is from 16% and 27%. Fig. 7 shows the hardware saving of using the optimal approach is from 37% to 45%.

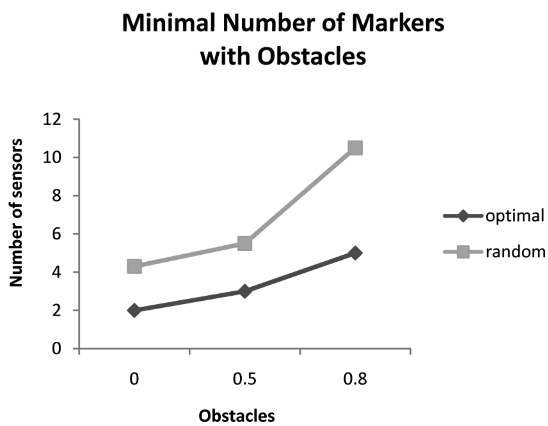

Fig. 5. Minimal number of cameras with markers.

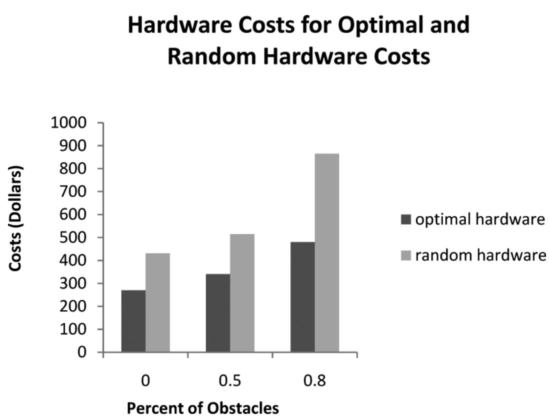

Fig. 6. Power results for optimal and random placement.

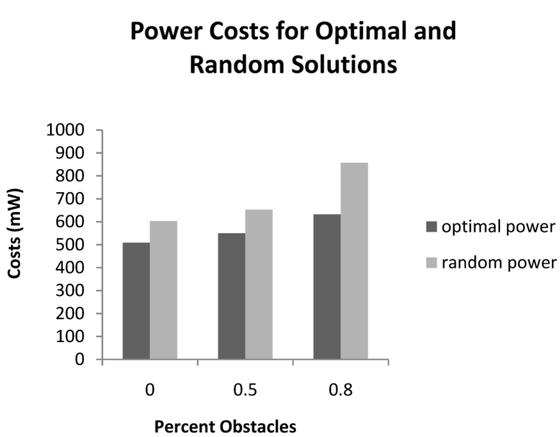

Fig. 7. Costs for optimal and random placement.

VII. Conclusion

BSN can continuously collect data on the affective states of patients. This research specifically investigates communication in a BSN and how to optimally place sensors to improve communication. The experimentation quantified communication in a BSN and analyzed the correlation between line of sight and reception rate. An linear formulation determined the optimal placement and number of sensors so that at any time a radio would be visible to a base station. Portions of the experiments were done in a motion capture laboratory and quantitative data were collected on the xyz coordinates and acceleration of the marker. Further work will determine the optimal number of accelerometers that need to be available to gather data for processing of information to classify the state of depression of the patient. Not only do these approaches save power up to 27% and reduce cost up to 45%, but the experimental analysis results in an efficient BSN that shrewdly makes use of its resources.

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