Activity Recognition Using Wearable Sensors for Healthcare

Annapurna Soumya Evani*, Bharadwaj Sreenivasan†, Joshi Shruti Sudesh‡, Monika Prakash§, Jyotsna Bapat¶
International Institute Of Information Technology, Bangalore, India
{annapurna.soumya*,bharadwaj.s†,Shruti.Joshi‡, Monika.P§}@iiitb.org
jbapat@iiitb.ac.in¶

***Abstract*—Wireless Sensor Networks (WSNs) formed by wireless sensors can be designed to interact continuously with the real world. WSNs help in communicating accurate real time information and have proliferated from the areas of industrial processing and environmental monitoring to science and healthcare. Today's healthcare systems are facing two serious challenges: rapid growth in adult population and severe nursing shortage. As per United Nations (UN) statistics, the number of people in the world aged 60 years and above are expected to increase from 605 million to 2 billion by 2050. Nursing shortage has been identified as a global crisis since 2002 and India has a nurse density per thousand population of 0.80. These statistics suggest a urgent need for automated monitoring systems to aid the healthcare industry. In this paper, we describe the implementation of a patient activity monitoring system using wearable flex sensors. Patient activities are classified as standing, sitting, or walking using a lightweight, low latency algorithm. Our approach features a unique sensing technique and facilitates a cost effective and energy efficient solution for healthcare.**

***Keywords*—Healthcare; activity recognition; flex sensor; wireless sensor networks.**

I. Introduction

A. Motivation

The increase in the number of people availing healthcare services has stressed the need for a larger nursing pool. According to global statistics, the demand for registered nurses is expected to grow from 2 million to 3.2 million between 2008 and 2018, a 60% increase [1]. In the Indian healthcare sector, there is a shortage of 350,000 nurses, with a nurse to patient ratio of 1:1205 [2]. As per World Health Organization (WHO), India is ranked 52 out of 57 countries facing Human Resources for Health (HRH) crisis [3]. With this global shortage, patient care is expected to be compromised. There have been reports of nurses being stressed and overworked resulting in significant attrition. In such a grave scenario, it is necessary to think of alternatives for taking care of the elderly population. One approach is to reduce the need for around-the-clock care givers and automate the monitoring processes in the healthcare industry.

B. Background

Applications of WSNs (Wireless Sensor Networks) in healthcare has been an area of interest in recent years. These applications require collecting large data sets from multiple sensors and manipulating the context to find the patterns pertaining to the medical aspect being monitored. The parameters such as security, privacy, user friendliness, scalability, context-awareness are critical in designing healthcare monitoring application [4]. There have been significant contributions in the area of vital sign monitoring in hospitals by providing assistance to patients with declining sensory and motor capabilities, at-home assistance to patients suffering from Alzheimer's disease, and depression for the elderly population and many more [5]. The sensors in smart health systems are capable of sensing heart activity, temperature, brain activity, glucose levels, behavioral patterns, etc. [6]. Researchers in computer, networking, and medical fields are working together to create intelligent healthcare monitoring systems. In the future, personal area network technologies such as radio frequency identification (RFID), Bluetooth, ZigBee, and wireless sensor networks are expected to work together with infrastructure based networks to provide context-aware applications [4].

In this paper, we propose an approach in-line with one of the current on-going research interests and design principles, i.e., activity detection for patients. Activities such as sitting, standing, and walking are recognized by the system using wearable sensor. This activity data can be further analyzed to know whether the patient is healthy and is following his/her routine day-to-day activities without constant vigilance by a real person. Also, it is possible to detect inactivity, which can be treated as an abnormal behavior and an alarm can be triggered alerting concerned people.

C. State of the Art

Existing activity recognition systems can be broadly classified into video sensor-based activity recognition and physical sensor based activity recognition [7]. Video sensor-based activity recognition is a traditional method, which was extensively used [8][9][10][11]. It involves continuous capture of human activities through cameras; however, the video method raises privacy issues and requires the individual being monitored to either remain within the vicinity of the camera or to have a video recorder attached onto the body [12]. Moreover, the extraction of features from the captured images requires complex computations. Due to these limitations, wearable sensor based activity recognition, which requires less data processing (physical sensor based activity recognition) is recommended. Inertial sensors - accelerometer and gyroscope are the most widely used body worn sensors for activity recognition [12][13][14]. Although these sensors are accurate in monitoring activities, the proposed solutions using them are complex and expensive.

To overcome these challenges, we propose a novel method of human activity recognition using a low weight wearable flex

 ISBN: 978-1-61208-296-7

sensor. This low cost high resistance sensor enables the product to be an affordable solution in detecting patient activities in hospitals.

This paper is organized as follows: Section II discusses System Architecture comprising System Design and Operation. Section III describes Implementation Details explaining the Algorithm of the system. Section IV explains the Experimental Setup and Results. Sections V and VI discusses the conclusion and future scope, respectively.

II. System Architecture

A. Overview

The posture recognition system consists of three main components: the Flex sensor, the Controller, and the Wireless Transceiver. The flex sensor is placed on the kneecap of the patient. Based on readings from the flex sensor, the controller can make intelligent decisions about the posture of the patient. This information is transferred to a central base station, which collates the results from different controllers. This allows a centralized database to be created for all patients using the posture recognition system. The doctor or nurse has the freedom of monitoring several patients with the help of a centralized architecture. The patients can conduct their day-to-day activities without being deprived of their privacy.

B. System Design

The Project uses an IRIS - XM210 mote with an MDA100CB sensor board. The Sensor board hosts the flex sensor as shown in Figure 1.The flex Sensor is a resistive device used to detect the flexing of the entity hosting it. The

Fig. 1. Sensor with the sensor mote

specifications of the sensor are shown in Table I.

TABLE I. Flex Sensor Specifications

Manufacturer	Spectra Symbol
Length (inches)	4.5
Flat Resistance	10KΩ
Resistance Tolerance	± 30%
Bend Resistance Range	60KΩ - 110KΩ
Placement	Knee

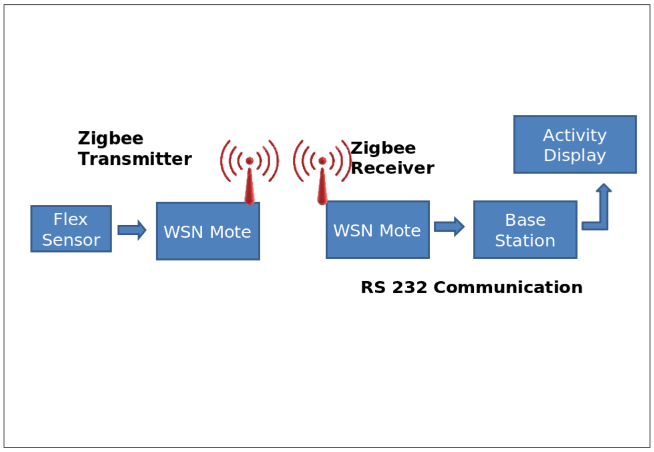

Fig. 2. System Architecture

C. System Operation

The block diagram of the system is shown in Figure 2. The operation of the system can be broadly classified as a three phase phenomenon - Sensor data collection, In-network processing and Activity display.

Sensor data collection

The flex sensor's resistance increases linearly with the bend of the sensor. In order to measure the voltage across the sensor, a voltage divider circuit is constructed as shown in Figure 3.

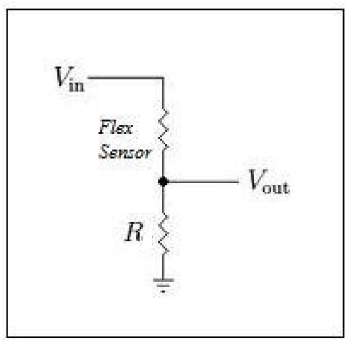

Fig. 3. Flex sensor circuit

$$V_{out} = \frac{R * V_{in}}{R + R_{flex}} \tag{1}$$

The output V_{out} is given by equation (1). The 10 bit Analog to Digital Converter (ADC) present in the IRIS mote is programmed to sample the raw sensor data (V_{out}) at regular intervals. The digitized sample values are considered for further processing in the sensor node.

In-network processing

This phase is the most important phase in sensor networks. To minimize the energy expenditure, radio transmissions must be reduced by local processing of the data. The sampled values are processed using a threshold technique to determine the activity of the patient. The number of transmissions is reduced

 ISBN: 978-1-61208-296-7

by detecting only the change in the posture of the patient, which is then communicated. In order to know whether a node is alive, the posture of the person is sent to the base station with a longer periodic interval, regardless of the change in state of the person.

Activity Display

The base station is a ZigBee-compliant device, which operates at 2.4 GHz range. The base station sends the received packets to the central coordinator over a serial link. The central coordinator hosts the application, which interprets information from the received packets and displays the current activity of the patient in a GUI. Each packet is tagged with a 2-byte Mote ID, which is unique for a given sensor mote. By using the Mote ID, the base station differentiates data from different motes and generates activity history of every patient.

III. Implementation Details

The posture classification algorithm primarily classifies the states into a static or a dynamic state. Sitting and standing falls into the category of a static state, whereas walking and activity transitions are part of the dynamic state. The algorithm is maintained asymptotically less complex, as energy consumed for processing is lower compared to transmitting.

Another important parameter considered during the implementation of the algorithm is response time. The finite size of the memory used in storing the samples is a constraint in achieving the required accuracy in real time applications; however, the larger the memory, greater the delay incurred in processing. To maintain this trade-off between accuracy and delay, optimal memory size is chosen.

The flowchart of the system is shown in Figure 4. The

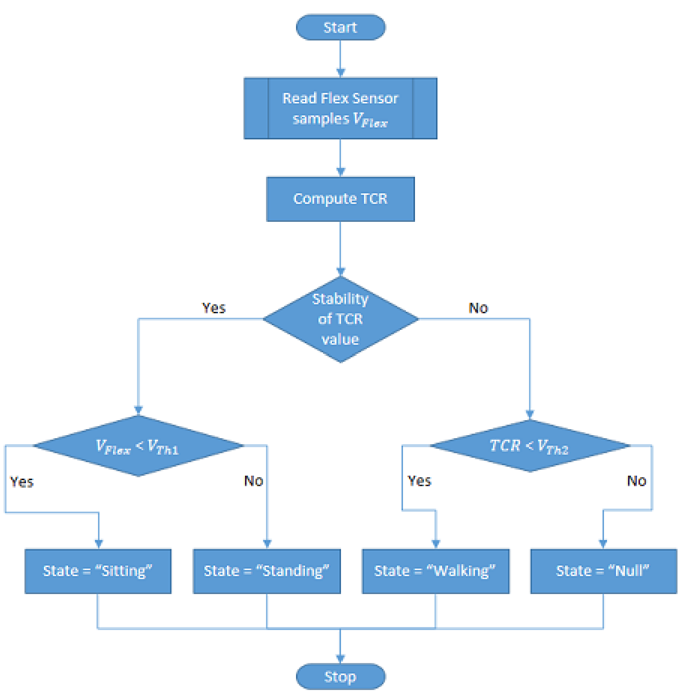

Fig. 4. Flow Diagram at Sensor Mote

postures can be subdivided into two categories: static and dynamic. To classify postures as either static or dynamic, we have created a metric, the Threshold Crossing Rate (TCR). The TCR is computed based on the rate of oscillation of voltage signal V_{flex}, where V_{flex} is voltage measured across the series resistor R as shown in Figure 3. The TCR is further processed to determine between static and dynamic states. It should be mentioned that the walking speed of the patient does affect calculation of TCR. After the determination, we further process the TCR signal to find out whether it is one among the following states: sitting, standing, or walking.

Static postures such as sitting and standing are prone to noise in the V_{flex}. This noise is due to the sensitivity of V_{flex} to the movements of the patient. In order to remove such jitter, we compute the stability of V_{flex} for a window's worth of data. After finding whether the signal is stable, we use a simple thresholding technique to determine between the sitting and standing states. Transitions between activities can cause V_{flex} to look similar to a walking scenario. This introduces false states into the decision system and thus can reduce the accuracy. To remove such transitions, a fourth state is introduced, which is called the "Null" state. All unknown oscillations and transitions in V_{flex} are categorized into this "Null" state. To accomplish this, we apply a threshold on the TCR signal, which is also computed empirically.

IV. Experimental Setup and Results

A. Threshold Determination

As per the algorithm, a threshold is used for classifying the patient postures. The threshold is determined for all postures by sampling the sensor values at regular intervals. The experiment was conducted on 30 people, and the readings were found to be stable throughout the experimental phase.

The pattern observed for the activities, - sitting, standing, and walking is shown in Figure 5. The voltage signal shows the flex sensor readings with respect to time. The system state signal is encoded as 0, 0.5, and 1, where the values refer to sitting, standing, and walking, respectively.

The threshold remained relatively constant due to the casing supporting the flex sensor. It helped in measuring precise readings from the sensor. It saved extra overhead required for computation of adaptive threshold, which would have been mandatory due to fluctuations in readings. The deployment of the sensor mote for the experiment is as shown in Figures 6 and 7.

Figure 8 and Figure 9 show the display at the base station used for monitoring the patients.

B. Range, Delay, and Accuracy Measurements

The experiments for range, delay, and accuracy calculations were conducted in a hospital-like environment. The test environment had rooms located on both sides of a long passage. The base station was located at the extreme end of the passage. The system yielded good results for both line of sight and multipath conditions. The activity detection of patients in the rooms covering the opposite end of the base station was also successful. The indoor line of sight range was approximately 500 meters. The delay observed over this range was between 2 - 4 seconds.

Position of the sensor also influence the accuracy of the system. The flex sensor should be placed on the middle of

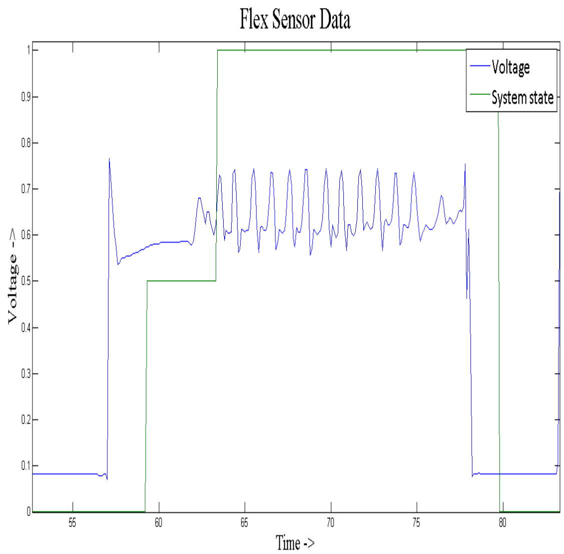

Fig. 5. Threshold Detection Technique

Fig. 6. Sensor view in sitting posture

the person's knee cap so that maximum bend is faced by it. For measuring the success rate, 30 people were asked to perform activities like sitting, standing and walking in a random manner. The percentage of time when the actual posture of the person conformed with decision from the Activity Recognition system was used to compute the success rate. We achieved a success rate of 81% based on the test trails.

V. Conclusion

The project successfully demonstrated the recognition of human activities - sitting, standing, and walking with an accuracy of 81% through a resizable flex sensor band worn on the knee. The developed system is cost effective as only one sensor is required, and also making a flex sensor is feasible through inexpensive materials. Adding to the advantage, the flex sensor is a resistance device that does not require an external power source like active inertial sensors [13]. Also, low energy consumption is maintained by performing in-network processing resulting in long life of the product. Finally, the robust casing and light weight of the product makes it so comfortable that patients would get a feel of just wearing a knee band. Thus, this presents a low cost and a low power solution for remotely monitoring patients in hospitals.

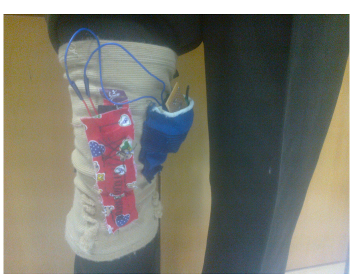

Fig. 7. Sensor View In Standing Posture

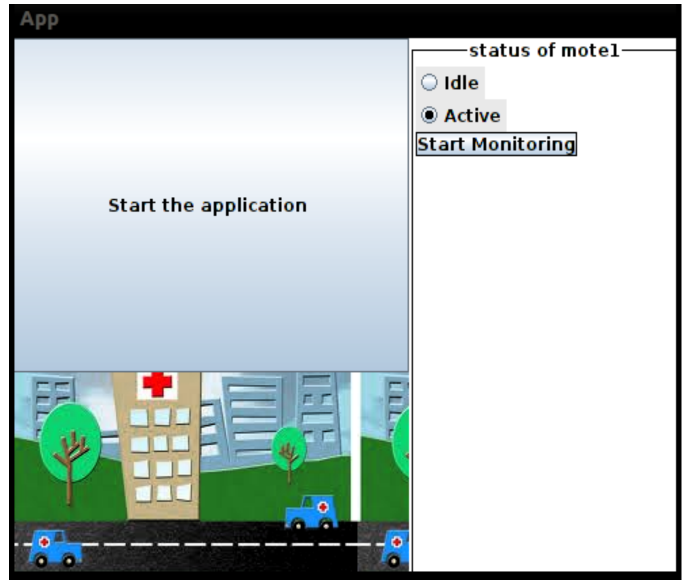

Fig. 8. GUI at the Central Base station

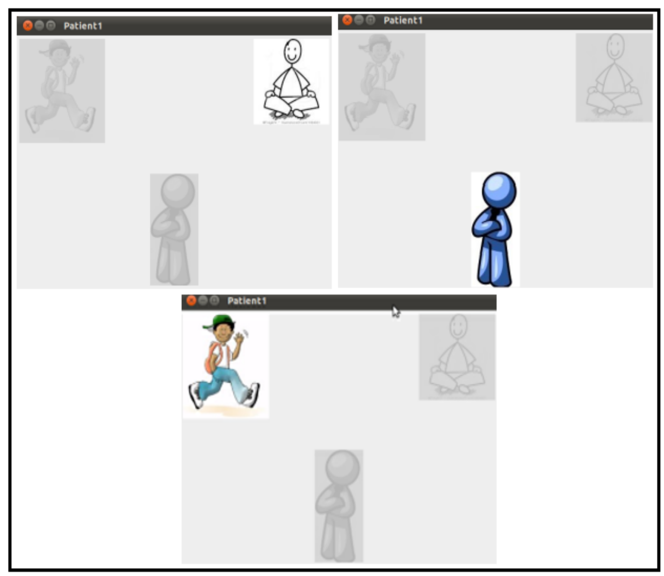

Fig. 9. GUI Depicting Postures

 ISBN: 978-1-61208-296-7

VI. Future Scope

We have proposed a novel activity recognition system using the flex sensor. To make the system cost effective, we propose that the flex sensor be constructed using simple inexpensive materials. The system has the capability of detecting postures such as walking, sitting, and standing. It can be extended to detect the fall and the location of the patient using localization techniques. We also propose that constant human monitoring at the base station can be eliminated by alerting the care giver over SMS.

Acknowledgment

This paper was supported by CEEMS Laboratory at the International Institute of Information Technology, Bangalore funded by the Government of Karnataka. We are grateful to Joseph Jeffrey for his immense support throughout the phase of design and conceptualization of the system.

References

[1] C. A. Holland, N. Ferrell, and D. James. (2009) The nursing shortage: Exploring the situation and solutions. [retrieved: May, 2013]. [Online]. Available: http://www.minoritynurse.com/article/nursing-shortage-exploring-situation-and-solutions

[2] M. Doshi, "Northbridge capital report on hospital sector," November 2010, [retrieved: June, 2013]. [Online]. Available: http://www.northbridgeasia.com/research_reports.aspx

[3] WHO, "World health organisation: World health statistics 2011," 2011, [retrieved: May, 2013]. [Online]. Available: http://uhc-india.org/uploads/ThammaRaoD_HumanResourcesforUniversalHealthCoverage.pdf

[4] H. Alemdar and C. Ersoy, "Wireless sensor networks for healthcare: A survey," *Computer Networks*, vol. 54, no. 15, pp. 2688 – 2710, 2010. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1389128610001398

[5] P. Neves, M. Stachyra, and J. Rodrigues, "Application of Wireless Sensor Networks to Healthcare Promotion," *Journal of Communications Software and Systems (JCOMSS)*, vol. 4, no. 3, 2008.

[6] K. Grgić, D. Žagar, and V. Križanović, "Medical applications of wireless sensor networks - current status and future directions," *Medicinski Glasnik*, vol. 9, 1840-0132. [Online]. Available: http://hdl.handle.net/10400.11/548

[7] A. Jehad Sarkar, D. Guan, T. Ma, W. Yuan, and Y.-K. Lee, "Review of Sensor-based Activity Recognition Systems," vol. 28, no. 5, 2011, pp. 418–433.

[8] X. Xu, J. Tang, X. Zhang, X. Liu, H. Zhang, and Y. Qiu, "Exploring techniques for vision based human activity recognition: Methods, systems, and evaluation," *Sensors*, vol. 13, no. 2, pp. 1635–1650, 2013. [Online]. Available: http://www.mdpi.com/1424-8220/13/2/1635

[9] P. Turaga, R. Chellappa, V. S. Subrahmanian, and O. Udrea, "Machine recognition of human activities: A survey," *Circuits and Systems for Video Technology, IEEE Transactions on*, vol. 18, no. 11, pp. 1473–1488, Nov.

[10] R. Bodor, B. Jackson, N. Papanikolopoulos, and H. Tracking, "Vision-based human tracking and activity recognition," in *Proc. of the 11th Mediterranean Conf. on Control and Automation*. Kostrzewa Joseph, 2003, pp. 18–20.

[11] C. N. Joseph, S. Kokulakumaran, K. Srijeyanthan, A. Thusyanthan, C. Gunasekara, and C. Gamage, "A framework for whole-body gesture recognition from video feeds," in *Industrial and Information Systems (ICIIS), 2010 International Conference on*, 29 2010-Aug. 1, pp. 430–435.

[12] O. Lara and M. Labrador, "A survey on human activity recognition using wearable sensors," *Communications Surveys Tutorials, IEEE*, vol. PP, no. 99, pp. 1–18, 2012, [retrieved: June, 2013].

[13] H. Junker, O. Amft, P. Lukowicz, and G. Tr "Gesture spotting with body-worn inertial sensors to detect user activities," *Pattern Recognition*, vol. 41, no. 6, pp. 2010 – 2024, 2008, [retrieved: June, 2013]. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0031320307005110

[14] B. Florentino-Liaño, N. O'Mahony, and A. Artés-Rodríguez, "Hierarchical dynamic model for human daily activity recognition." in *BIOSIGNALS*, S. V. Huffel, C. M. B. A. Correia, A. L. N. Fred, and H. Gamboa, Eds. SciTePress, 2012, pp. 61–68, [retrieved: June, 2013]. [Online]. Available: http://dblp.uni-trier.de/db/conf/biostec/biosignals2012.html#Florentino-LianoOA12