RSSI Based Indoor Human Activity Recognition System

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***Abstract*— Being a good reflector, the human body can be recognized with the variation of radio signal. In this work we would show how this can be possible by a sequence of methods. First, we create a wireless sensor network (WSN) in a closed surface area and then we monitor the variation of the signal in that surface in presence of human being. In addition we monitor the radio signal also for the gesture movement. The variations are recorded by received signal strength indicator (RSSI). We then develop another human activity recognition system using radar and compare the accuracy for the two adopted systems. Some interesting results have reported in the paper.**

Keywords—RSSI, WSN, human body, gesture activity recognition

I. INTRODUCTION

We know that human body is a good reflector of radio signal. Hence human activity can be recognized using radio signal. Radio wave (ranges from 3 KHz to 300 GHz) is called electromagnetic wave, when propagates through the earth surface, it will affected by various objects. These effects are reflection, refraction, diffraction, scattering etc. The strength or magnitude of the wave is varied depending on these events. Sometime the wave can directly reach to the destination if no obstacle comes in its path. This is called line of sight (LOS) communication. Our research is based on the monitoring of the fluctuation of the radio wave in presence of any object like human body.

A system can be implemented for tracking of human being with his different gesture position even if when he is standing at a particular point as well as when he is moving through the area. In this case he need not to carry any wireless device like mobile phone, pager etc. This is done by analyzing the radio signal in that area which is varied due to the presence of the Person. Device-free radio-based recognition can extend the awareness of wireless-enabled devices over the device boundaries. It might be applied for mobile phones, laptop computers or consumer products incorporating an interface to the wireless channel.

The system typically employs multiple wireless devices like sensor nodes or Wi-Fi router which are installed around the area. The nodes communicate over one shared radio channel and continuously monitor strength of signals received from other nodes. This is called received signal strength indicator (RSSI). Due to the interactions of radio wave with human body (such as diffraction, reflection, scattering) amplitude of the received signal are measurable changed. Current systems require deployment of multiple wireless devices which actively transmit, receive, and analyze radio signal. Due to radio spectrum recognition these devices are typically limited to only one or few frequency channels in a narrow band frequency spectrum. The frequency modulation technique is used here.

II. BACKBROUND

As a distributed system WSN can be deployed in any physical system for monitoring and tracking purpose. Besides sensing and monitoring another important characteristic of WSN is the defining of the position and the tracking of the static or moving object. Typically location determination system requires the presence of a physical device that is closed to the person that is being tracked. In addition, they usually require the tracked device to participate actively as activity recognition system. The system goes by monitoring and processing changes in the received physical signals at one or more monitoring points to detect changes in the environment. Among traditional localization techniques, the use of global positioning systems (GPSs) is not always the optimal solution because of the huge amount of costs. Moreover, GPS cannot be efficiently used for indoor applications because of interference. A main advantage of radio waves lies in their ability to penetrate smoke, nonmetallic barriers and walls. The standard devices used for tracking and monitoring of an object, may have to face several difficulties for example in a very low light or clumsy closed surface these devices may not work properly. Along with they may get damaged by any unavoidable circumstances. These hamper the efficiency of a tracking system. From this point of view the idea for device-free activity localization has been formulated. Such systems are based on the analysis of the variations of some physical quantities available at the WSN nodes and useful for solving the location and tracking problems. The measurement of the RF signals has been thoroughly exploited since the values of their descriptive parameters (e.g., the RSS) are available at the physical layer of each node without the need of any additional hardware. As a matter of fact, the potential of radio waves to penetrate nonmetallic walls can be very useful also for building surveillance, monitoring, and tracking [1]. Although being a pioneering area of research, some studies have been already carried out.

Activity recognition systems are a large field of research &development for innovation in the field of hardware architecture. Activity recognition aims to recognize the actions and goals of one or more agents from a series of observations on the agents' actions and the environmental conditions. Since the 1980s, this research field has drawn the interest of several computer science communities due to its strength in providing personalized support for many different applications and its connection to many different fields of study such as medicine, human- computer interaction, or sociology. Sensor-based activity recognition connects the emerging area of sensor networks with novel data mining and machine learning techniques to model a wide range of human activities [2]. Activity recognition research sets out to chart a particularly difficult terrain of objects of cognition. When a novel sensor is introduced it is specialized in representing a single facet of the environment at a certain level of details. Due to the highly innovative nature of activity and context recognition, new sensors are continuously being introduced as inputs for activity classification. The sensors themselves vary greatly in terms of physical phenomena measured, data output format, size, accuracy, reliability, and resource consumption. Recognizing an activity in a given situation correctly would therefore mean that a) the activity which has been recognized actually is present in the physical environment at the time, b) that the sensor is able to create and relay a useful and reliable representation of physical parameters of the environment that are affected by the activity, and c) that the classification algorithm is able to decipher these intricacies, yielding a correct activity classification. Our topic is based on Human activity recognition (HAR) system [3]. Human activity recognition (HAR) is a highly dynamic and challenging research topic. It aims at determining the activities of a person or a group of persons based on sensor and/or video observation data, as well as on knowledge about the context within which the observed activities take place. In general, the HAR process involves several steps – from collecting information on human behavior out of raw sensor data to the final conclusion about the currently performed activity [4]. These steps are as follows:
(1) pre-processing of the raw data from sensor streams for handling incompleteness, eliminating noise and redundancy, performing data aggregation and normalization; (2) segmentation – identifying the most significant data segments; (3) feature extraction– extracting the main characteristics of features (e.g., temporal and spatial information) from the segmented data by using, e.g. statistical moments;(4) dimensionality reduction– decreasing the number of features to increase their quality, and reduce the computational effort needed for the classification; (5) classification, the core machine learning and reasoning – determining the given activity. The main goals of HAR systems are to observe and analyze human activities and to interpret ongoing events successfully. Using visual and non-visual sensory data, HAR systems retrieve and process contextual (environmental, spatial, temporal, etc.) data to understand the human behavior [5].

III. Wireless Sensor Network

A wireless sensor network (WSN) is a wireless system consisting of spatially dispersed autonomous devices using sensors to monitor physical or environmental conditions. A WSN system incorporates a gateway that provides wireless connectivity back to the wired world and distributed nodes [6].

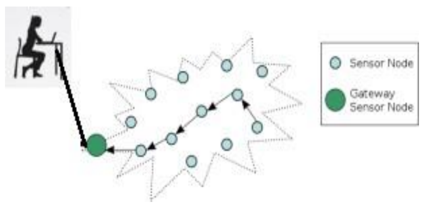

Fig.1. Sensor and gateway sensor nodes

An activity recognition system simply monitor and classify different human action like „walking", „crawling", „siting", "lying", and „standing". Depending on the variation of the radio signal these human gestures are recognized by the RSSI indicator.

IV. Activity recognition systems

Existing activity recognition systems can be classified into four categories: RSSI based, specialized hardware based, Radar based, and CSI based .

IVA. RSSI Based

In case of received signal strength Indicator (RSSI) based human activity recognition systems, the strength or amplitude of received signal changes because of human activities. These systems have limited accuracy. The accuracy may be improved by software implication. As a result the resolution of captured data increases. The accuracy and coverage of CSI based human Activity Recognition and Monitoring system (CARM) is much greater than RSSI based activity recognition systems although the RSSI based system is much simpler than CARM. So it can be easily deployed in any environment [7].

IVB.Specialized Hardware Based

Software defined radios or specially designed hardware can report fine-grained signal measurements. For example, WiSee uses USRP to measure the Doppler shift in wireless signals and achieve an activity recognition accuracy of 95%. Allsee proposes a short range (less than 2.5 feet) solution for gesture recognition by using a special low-power circuit to extract the envelope of the received signal [7]. Wisee explores the possibility of reconstructing an image of the target using the wireless signal received by multiple antennas. WiSee is a novel interaction interface that leverages ongoing wireless transmissions in the environment (e.g., WiFi) to enable whole-home sensing and recognition of human gestures. Since wireless signals never require line-of-sight and can travel through walls, WiSee can enable whole-home gesture recognition using few wireless sources (e.g., a Wi-Fi router and a few mobile devices in the living room). Using WiSee different home allowances like switch on-off of light control of TV without remote and many other is possible by the human being gesture recognition. The results show that WiSee can identify and classify a set of nine gestures with an average accuracy of 94%.

Existing gesture-recognition systems consume significant power and computational resources that limit how they may be used in low-end devices. AllSee is the first gesture-recognition system that can operate on a range of computing devices including those with no batteries [8]. AllSee takes three to four orders of magnitude lower power than state-of-the-art systems and can enable always-on gesture recognition for smart -phones and tablets. It extracts gesture information from existing wireless signals (e.g., TV transmissions), but does not incur the power and computational overheads of prior wireless approaches. AllSee prototypes can identify gestures on RFID tags and power-harvesting sensors. The hardware can be integrated with a smart phone [9]. This enables gesture control such as volume changes while the phone is in a pocket.

IVC. Radar Based

Human activity recognition can also be possible using Radar. Much higher bandwidth is associated with this type of the system, e.g., Frequency Modulated Carrier Wave (FMCW) radar can take up to 1.79 GHz bandwidth while WiFi uses only 20 MHz bandwidth usually. The micro-Doppler information can be extracted and about approximately 20 cm higher distance resolution can be obtained using Radar-based systems [10]. However, specific hardware have been required for both the Radar-based and specialized hardware- based systems, while CARM runs on COTS WiFi devices.

IVD. CSI Based

Recently another recognition system for human activity have be provided by the wireless network (wifi). It is channel state information (CSI) based activity recognition system. In this process CSI values are taken from wifi network interface card to monitor the different human movement activity like presence of person in a particular area, movement in daily living and other home appliances, counting of human number in a crowded area etc. CSI also have the capabilities to detect and monitor a small change in human movement and his gesture position like leap movement, heartbeat etc. The system is very costly and very complex in nature but a greater accuracy level can be obtained.

V. Experimental Processes

We have proposed here a non-adhoc active device free recognition system. For that we have chosen a closed office room surface and place four sensor node in some height towards the ceiling of the room in four corners. These sensors are highly specialize in representing a single facet of the environment at a certain level in detail. We implement our experiment in both RSSI and SDR based device free RF based system [10,11]. The operating frequency for configured WSN is 2.36 GHz. It use IEEE 802.15.4 WSN standard. The distance between two nodes is kept at an average 6m. So that the sensor can detect some human activities if a human being enter into the rom. Four different gestures have been detected by the sensor nodes- walking, crawling, standing, and sitting. All sensors are trans-receiver which can send 100 data packet per second. The sampling rate is 40 Hz.

We examined the variation radio signal both in RSSI and SDR based system. In RSSI, the variation of signal is received by the sensor and we observed the total power of the signal by an indicator called receive signal strength indicator (RSSI) [11]. With the knowledge of node positions and their RSSI level, user‟s location can be directly inferred. There is a relationship between the reduced signal power, node distance and the transmit power.

Here we emphasize the activities not only the position. Therefore four activities are classified and detected by the receiver. When a person is entering in the room, his position is recognized by the RSSI [12, 13]. We made our experiment in four different sequences of activities conducted by the person.

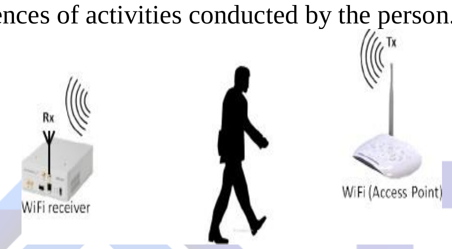

Fig.2. Recognition of human activation in presence of wifi network

Situation 1: In first sequence, the person entering into the room and walking towards the centre of the room and then came back to the entering position and left the room.

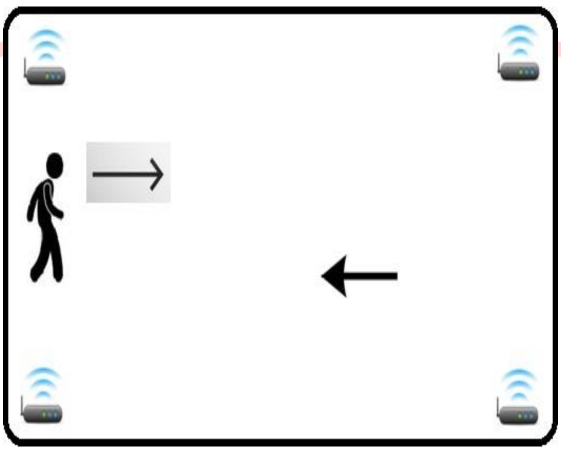

Fig.3. Person entering into the room and walking towards the centre

Situation 2: In the second case the after entering into the room walking up to certain distance then stood for a while and come back. Finally he leaves the room.

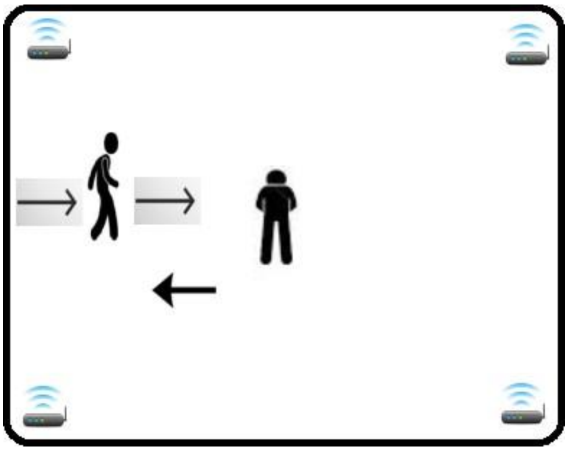

Fig.4. Person entering into the room walking up to centre, stood and come back

Situation 3: In the third case the person after entering walked to the centre. At centre a chair is kept. He sat on the chair for some instance and then stood in front of the chair and finally came back to his entering position.

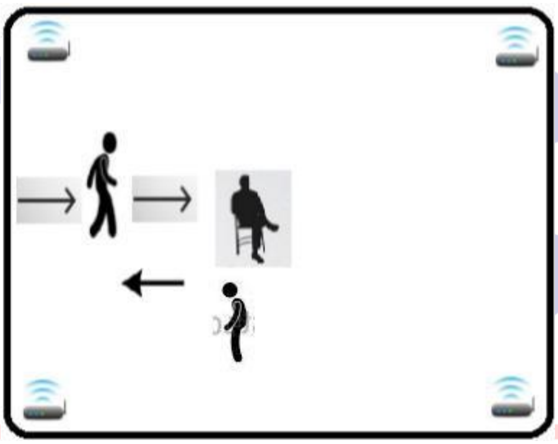

Fig.5. The person after entering walked to the centre, sit and come back

Situation 4: In the fourth sequence the man walking towards the centre of the room and at a point before centre he stopped. The remaining distance he was crawling and reached to centre. He sat on the chair. Again standing up and come back by crawling to the first position and left the room. In each position where the person moved or changed his posture the variation of signal is recorded and shown by RSSI. The signal flowed in all direction in the room as the antenna was Omni-directional.

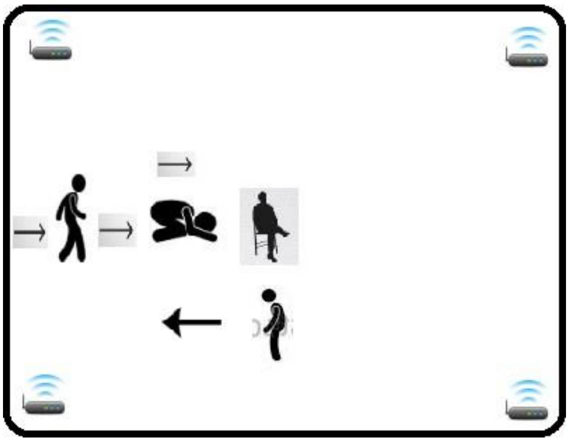

Fig.6. The man walking towards the centre of the room

The case studies were conducted during a period of a period of through a day and the sampled data are continuously collected by the RSSI sensor. For detection the shortest path distance from the object to the sensor is taken and the variation of the signal through this path is observed. As well as the other path of the signal is also considered and the variation is recorded. Then the average value of RSSI is taken as sample data.

VI. RADAR BASED APPROACH

Unlike wireless sensor networks, Radar have been a subject of much interest due to its wide area surveillance. Typically, sensors such as acoustic, seismic, infrared, magnetic, and ultrasonic sensor have been engaged to data transfer [13]. Radar can also be used for such data processing. Ability to operate in all weather conditions and night-time is the added advantage of it. But due to its high power requirements, high cost, and large size it is not much used in these systems. Recently, however, low-cost, COTS radar nodes have been developed so that it can be used as part of a wireless surveillance network [14]. One such example is the BumbleBee Radar which is considered as part of a wireless radar network to monitor the human moving activity within the sensing region of the network. The human micro-Doppler signature measured by the BumbleBee radar is shown for a variety of activities and used as a basis for recognition. Various schemes for fusing sensor data are explored.

In a workshop conducted by the US Army Research Laboratory, it was stated that the sensors with large power supply and communication cannot be used everywhere instead of that simple inexpensive individual devices can be deployed in large number. There is the implication of Radar, possessing important advantages such as being able to operate in all weather conditions and in every time. The BumbleBee Radar is a 5.8 GHz coherent, pulse Doppler radar capable of making measurements at a relative accuracy of about 3 mm for targets lying within a sensing region of 1.5 m to 9.5 m, possessing a radial velocity of 2.6 cm/s to 2.6 m/s, and a maximum Doppler frequency of 100 Hz. Most human motion falls within the operational constraints of the BumbleBee radar. There have been just a few works that have employed using the BumbleBee radars till date. In 2010, the Bumble Bee radar was used to track a non cooperative target based on radial velocity measurements with an Extended Kalman Filter (EKF) by the researchers from Johns Hopkins University [15]. This work was implemented by researchers from Michigan Technological University, who found that the EKF worked well for linear trajectories, but exhibited degraded performance over nonlinear paths. The Bumble Bee, however, is proficient of providing much more target data than just radial velocity, as users are able to directly access the raw data measured by the radar [16]. The micro Doppler signatures of targets were extracted, and it was used as a basis for classification between humans and dogs by the researchers at Ohio State University. In many works Micro-Doppler has been taken as a basis for target identification, with important applications to pedestrian safety using automotive radar networks. In 2010, with a COTS FMCW radar network using human micro-Doppler as a basis, human arm swing was classified by van Dorp and Groen [17, 18]. The purpose of this effort is to examine the application of cheap radar sensors which provide a measure of human micro-Doppler of much poorer quality (lower signal-to-noise ratio, SNR) than conventional military radars, for the purpose of human activity recognition. The micro-Doppler signature for several different human activities (walking, running, and crawling) is presented. Varying the aspect angles relative to the target motion experiment is conducted by using Bumble Bee Radar and then measured data is compared and assessed. Methods for selecting and fusing sensor data for optimal classification performance are discussed here.

VIA. TECHNICAL SPECIFICATIONS

The Bumblebee radar is a battery operated coherent, pulsed Doppler radar for wireless sensor network applications. The central frequency is 5.8GHz while its internal antenna possesses a conical coverage of 60°. Targets with speeds ranging from 2.6 cm/s-2.6 m/s can be detected at a maximum distance of 10 m. The radar provides two outputs as an in-phase signal (I) and quadrature phase signal (Q), which are periodically sent to the Host PC at a frequency of approximately 185Hz. Aside from the center frequency, documentation provides on the

BumbleBee radar provides little information parameters of the transmitted chirp signal, such as bandwidth or chirp slope, pulse duration, and pulse repetition frequency (PRF). Thus, the BumbleeBee radar was identified by making measurements of the transmitted waveform using 700 MHz - 18 GHz horn antenna and feeding the received signal to spectrum analyzer. The frequency domain by the spectrum analyzer of the received signal spectrum is that of corresponds to the Fourier transform of pulsed Doppler envelope. Thus, the bandwidth of the LFM waveform was measured to be 240 MHz [19]. Using the pulse analysis module of the spectrum analyzer, the transmitted waveform was measured. From this measurement it was found that the pulse duration was 40ns, while the pulse repetition frequency (PRF) was 2 MHz.

VIII.CONCLUTIONS

The advantage of RSS-based systems is mainly related to the use of data already available at the WSN nodes without any additional hardware. Indeed, the RSS indicator is available at the physical layer of the node structure and it is not directly concerned with the "quality" of the signal, but to the received power It is a number of 8 or 10 bits depending on the hardware of the WSN node and directly related to the accuracy of the tracking system.

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