Walking Parameters Estimation Through Channel State Information

Preliminary Results

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***Abstract*— Stride rate and length are monitored by physicians to identify abnormalities in the patients' gait. These are also important parameters for athletes. Lab based video recordings are used for monitoring while new methods utilize inertial sensors. These sensors require a lot of sensed data processing consequently power is utilized. A new class of methods using wireless sensing has been introduced recently. These methods either require a lot of sensing nodes or are non-ubiquitous while others have used received signal strength as monitoring parameter which is quite unstable. We have proposed a novel ubiquitous node deployment on the human body itself to minimize the environmental noise interference. Walking parameters like stride rate, stride length have been estimated using wireless sensing physical layer channel state information (CSI). The human body acts as an obstacle for the wireless signals due to frequency selective multipath fading. We argue that this fading has a unique signature respective to the activity performed by humans which can be estimated using CSI. This signature should be best observed when both the sender and receiver nodes are deployed on the body due to decreased environmental interference. We have trained the system to identify these signatures and deduce corresponding gait parameters. In this paper we are only able to summarize the new idea with initial findings. We are in the process to understand the signal morphology for finer measurements.**

Keywords—wireless sensing, sensorless sensing, body area sensor network, physical activity monitoring, channel state information, CSI tool.

I. Introduction

Walking is the most common physical activity which is suggested by physicians for majority of medical conditions. Regular walking helps in cardiovascular and neurological disorders management. It prevents obesity, diabetes, etc. by keeping the body weight under control [1]. There is certain need of an automated gait parameters estimation method which can approximately measure stride rate and stride length by counting steps per unit time in subject's daily environment. This can essentially motivate the person to perform the required walking. Current methods for gait analysis are based on video monitoring of the subjects. They require manual observations [2] or involve image processing methods [3] to automatically identify the gait parameters and abnormality. These methods are limited to specific locations and far away from practical use for daily life assisting living as these have only been tested in laboratories where the camera system can be deployed. Another problem is to store and classify large amount of video data.

The other class of methods is based on inertial sensors like accelerometers, gyroscopes, magnetometers and pressure sensors. These use the basic principle of conversion of specific foot movements into electrical and consequently digital data for analysis. Wireless nodes equipped with these sensors are placed on various parts of the subject's body to understand the respective body part's movement and record it digitally [4]. The pressure sensors are mostly placed on the bottom of the foot to estimate the foot pressure [5]. Any abnormality in this pressure can be detected as fall portents. The amount of logged sensor data, because of the mentioned high frequency measurements, is very large [6]. These systems involve sensing and then transferring the sensed data to the data logger wirelessly. Both sensing and communication require power whereas these nodes being deployed ubiquitously are expected to power efficient so they can work for longer without charging [7]. Here, we have planned to eliminate the inertial sensing need from the wireless sensor nodes to identify the human activities by analyzing the parameters of a dummy communication between these nodes. There is no requirement to change the current infrastructure. The humans need to perform the activities in wireless range.

In this paper, we have measured the gait parameters by identifying the unique received signal parameters generated because of frequency selective and multipath fading when a subject performs gait in wireless range. We have measured the step count, stride length and stride rate with sufficient accuracy for 5 subjects at two different locations. We have performed experiments in both indoors and outdoors in presence of another person, environmental instability and in existence of other wireless signals in range. This is not the first time when the wireless sensing has been used for physical activity monitoring but as per our knowledge this is first attempt for ubiquitous gait analysis using physical layer information. Also we are the first to test wireless sensing for gait analysis outdoors in presence of surrounding obstacles and other wireless signals through proposed ubiquitous nodes deployment.

II. Literature Survey

Gait parameter such as stride rate is an important diagnosis parameter for physicians. Assessment of these spatial and

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temporal parameters require expensive equipment like video cameras, on-body placed sensors, which makes this rehabilitation procedure out of scope of pocket of people in developing countries. Before moving further to our proposed method we should discuss previous methods to understand the basic requirements for gait analysis, general flaws in current systems, and inspiring techniques. In the end we also brief out motivations for this work.

A. *Video Based Methods*

Video based methods for gait analysis are most accurate but for indoor, in-home, limited size locations or lab environment only. The subject performs gait in front of video camera while placing some visually identifiable markers on the body. VICON gait analysis system [1], Microsoft Kinect [3], etc. are the most famous gait analysis systems under this category. These systems are expensive due to utilization of high resolution infrared cameras and automated image & video processing software. To assess fall risk, automated gait estimates, and gait parameters like walking speed, stride time, and stride length of elderly subjects, a three-dimensional (3-D) representation of the environment is created using the Kinect depth imagery. Others have used VICON motion capture system by placing markers on human body to capture gait in real-world, dynamic environments for older adults. In video based system effect of sunlight can be seen as decreased accuracy. It lacks daily assisted living features and robustness for real world environmental factors.

B. *Wearable Sensors Based Methods*

The subjects wear sensors and other measurement equipment which are interconnected wired or wirelessly with each other for data collection and interpretation. The inertial sensors are mostly used to gather the movements of the body parts. TailGait [8] is a system which allows measurement of the displacement of trunk as the stepping distance using a 360 pulse/revolution rotary encoder. The wheel will not give accurate results while rotating on different surfaces. Gait counting is done through monitoring heel strike and toe off using pressure sensors placed beneath subject's feet. Pressure sensors are only effective if placed exactly on the contact points on the feet which are different among persons [5]. Inertial sensors require more than 100 Hz sampling rate thus collect a lot of sensor data. The system infrastructure is very complex as the accurate measurement requires node deployed on each moving body part. The inertial sensors cannot avoid the integration error [4]. More details of inertial sensor based systems are given in results comparison section.

C. *Wireless Sensing Based Methods*

Traditionally, the sensors sense the body movements and forward sensed data to a collection sink through wireless connection. Activity monitoring through wireless sensing is different in the way that the inertial sensors and other motion sensing equipment are not utilized for movement pattern generation. The monitoring is done through analysis of the wireless signal patterns through a dummy communication between the wireless nodes and sink. Let us now classify the available activity recognition methods through wireless sensing.

1) *Device Free Methods*

A monitoring system is said to be device-free when the subject does not need to carry any monitoring device. In this case, the measurement is possible through a dense deployment of many wireless sensor nodes creating a mesh of wireless links inside the area of interest. The subject is free to move in this area and his activities are monitored by ambient devices. The coarse-grained movements measured through Wi-Vi [15] or the fine-grained gesture measurement using WiSee [16] and WiTrack [17] uses universal software defined radios (USDR), specialized receivers and other communication hardware to extract carrier wave features respective to the activity performed by the subject. These features are not being reported to the application layer in current WiFi system [18]. These deployments of APs and nodes have an accuracy of several meters. Research works [19] [20] have been able to distinguish some basic activities such as walking, crawling, standing and lying through learning RSS variation patterns through a set of USDR devices. Measurements for daily activities, fine-grained activity measurement and activities involving roaming to other areas are impractical and not accurate enough.

Another device-free, location-oriented activity identification system E-eyes [18] faces problem of identification of multiple persons at multiple locations since this would require a much larger set of activity and location profiles covering different combinations of activities. Also E-eyes was tested without pets or other environmental movements at home. The researchers have assumed null environmental noise, movements and wireless signals [21] [22] [23], which cannot be ignored while making a versatile and round the clock available activity monitoring system like Shimmer platform. In our proposed work we counteract the environmental noise by placing both sender and receiver on the body itself this comes under another category as discussed below.

2) *Device Based Methods*

The wireless sensing is done through wearable radio nodes which communicate with the on body or off-body located sink. The person performs activities in vicinity of these wireless signals. The sink analyzes the received signals parameters to generate activity specific signal profile and use it to classify the signals in real time situation [9]. Use of wireless sensing parameters like Received Signal Strength (RSS) [10], OFDM channel state information (CSI) [11], antenna arrays [12], RFIDtags [13], visible LED lights [14] has been done for localization purpose in abundance. The approaches have shown accuracy ranging from several meters to sub-meter but require subject to carry a wireless emitter. The biggest advantage of device based methods is the subject's movability anywhere wearing the devices. This can be intrusive also and may pose the problem of forgetting to carry such a device especially elderly. Furthermore, they need the support of wireless infrastructure such as multiple access points. The proposed method is this paper also falls under device based sensing category but with single sender and receiver nodes.

The research in this category has mainly concentrated on RSS monitoring among the nodes which is not stable parameter alone [10]. Some have used CSI for activity classification but are not completely device based [21]. They place one sender node on the body which communicates with ambient access point or monitoring point. These systems are semi-device based. We propose to deploy both the sender and receiver on the body itself. Our intuition is that the noise due to air-path and multipath can only be minimized through this deployment and this is also expected that the noise measured now should be due to body movements only.

D. Problems in methods and need to advance

The approaches discussed till now in the domain of activity profiling through wireless sensing, consider only lab based controlled environment which has no known interferences. Channel State Information (CSI) has been proved to be much stable wireless sensing parameter [11] [24]. CSI has not been used for radio sensing to measure gait parameters not even in indoors. The approaches are mainly location, subject and device dependent, so identification of activities is done by comparing them to stored location-subject-activity profiles [21]. The same activity occurring in different locations by different subjects will require more detailed location-activity profiles. The infrastructure based monitoring systems restricts the subject movement space. These methods have majorly indoor activity monitoring as their application domain. Another major problem that we encountered in device-free methods that they allow the subject to move freely in the sensing area but it also increases the chance of activity profiles affected by surrounding noise occurring due to obstacles and multipath signals [9] [24]. On the other side, if the nodes are placed on the body, then the noise added in the transmitted signal is more likely to be because of human motions only and not because of any surrounding noise.

E. Motivation

There are some specific issues that we found essential to address through this work and motivated us to perform this measurement. Wireless sensing reduces the amount of sensor data without changing the basic infrastructure of body area sensor network. The senors on the nodes can be disabled now. Only indoor lab based gait features have been tested using radio sensing, so performance evaluation needs to be done in outdoors in presence of other wireless signals and interferences to build a practical system. If the wireless sensing nodes are placed on the body then they can be closest to the body and the communication should get mostly affected by the body than the environmental factors. So the deployment locations of the wireless sensing nodes should be closest possible to the body. Instead of device free, we have intuition that the on-body deployment monitoring physical layer channel information should be more effective than any other available wireless sensing method.

III. PROPOSED METHOD

802.11n systems use orthogonal frequency division multiplexing (OFDM) which divides the 20/40 MHz channel into multiple subcarriers [25]. The data is transmitted over the subcarriers instead of using complete channel to increase throughput of the system. All the subcarriers use the same modulation and coding scheme. This makes the channel divided into multiple flat fading channels which in turn help to combat with frequency selective fading due to multipath. Obstacles in the wireless range cause wireless signals to reach receiver in multiple out of phase and independently faded copies due to multiple reflections and diffractions [11].

We argue that a subject performing physical activities should act as an obstacle in the wireless sensing range. It should cause activity specific multipath fading to the subcarriers. As the fading of different subcarriers is uncorrelated with each other, the detailed effect of activities on wireless signals can be observed accurately by analyzing these subcarriers. While such effects are often averaged out, when looking at a single average RSS measurement, the individual subcarrier measurements are more likely to change when small movements have altered the multipath environment. This essentially means that our system will not just detect obstructions on the direct path but can also take advantage of the rich web of reflected rays to cover a space.

The received signal can be modeled as $y=Hx+w$, where y is the received signal, x is the transmitted symbol, and w is the white Gaussian noise, all in frequency domain. H is the channel state information (CSI) which is a complex number matrix that indicates the channel frequency response of each individual subcarrier for every spatial stream [10]. Since an activity involves a series of body movements performed over a certain period of time, the distribution of CSI amplitudes is a desirable channel statistic that can capture unique characteristics of activities in both time and frequency domains. CSI values were not available outside the NIC firmware which made it difficult to use it for any other application. Recently, Harperin et. al. [26] developed firmware and driver support for Intel 5300 802.11n NIC that can extract the CSI values in kernel/user space. We use their tool in our work. Note that although 802.11n utilizes 56 subcarriers in a 20 MHz channel, the CSI tool reports 30 values for 30 groups evenly spread over the 56 subcarriers.

Device free wireless sensing uses multiple ambient wireless nodes with multiple links. The deployment of the system is infrastructure based so coverage of the sensing is limited to a specific area only [18-22]. Monitoring of daily life outdoor activities is not feasible with this setup. Moreover, during indoor activity monitoring, effect of non-stationary environmental obstacles will be more on the multipath because of large air-path between sender and receiver as shown in figure 1.

To reduce the chance of distortion we have thought of keeping the communication range very less such that the effect on the subcarriers will be only due to the activities performed. To implement this we have planned to deploy both sender and receiver on the human body itself to minimize the effect of environmental effects on multipath thus on received signal pattern as shown in figure 2.

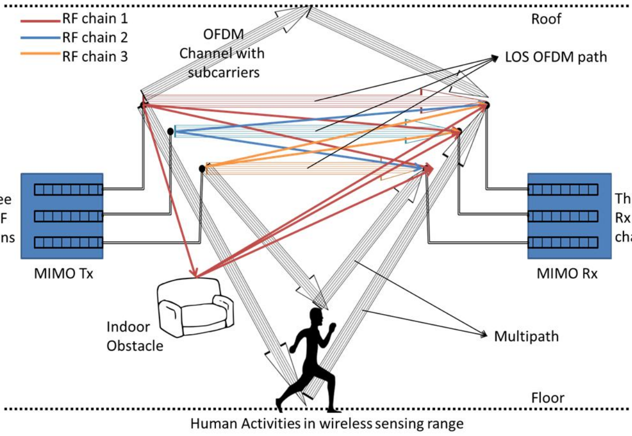


Fig. 1. Scenario of activity monitoring using device-free wireless sensing

The sender and receiver will be set to communicate with each other through dummy ping packets at specific rate. As part of 802.11n packet preamble processing the NIC measures the channel state for each received packet. Through the CSI tool, the channel information available at physical layer and used by firmware can be made available to the kernel driver on the host computer through firmware modifications. The driver makes it available to a custom developed user-space program for processing and analysis.

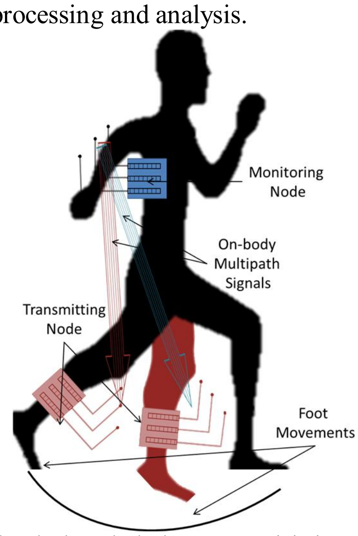


Fig. 2. Proposed on-body node deployment to minimize environmental noise

A. Packet Transfer and Analysis

Dummy packets are transferred between the wireless sensing node and monitoring node placed on the body using echo request (ping) with flooding enabled. This option sends packets with dummy payload to the sensing node with transmission speed of more than 250 packets/second. The sensing node replies with Echo reply packets having copy of the same payload which was received. This reply packet is analyzed for CSI. The physical layer information related to each packet viz. amplitude and phase of each subcarrier is stored. This information can be analyzed for each subcarrier or by averaging the information over all subcarriers.

B. Signal Processing and Feature Extraction

To extract features from the CSI data we analyze it in subcarrier domain, we analyze the data subcarrier-wise for complete time period. The following matrix across time between individual subcarriers is generated.

$$S = [S1, S2, Si, \bullet\bullet\bullet, S30] \quad (1)$$

Where, each Si is vector of length T and includes all the CSI amplitudes for i^{th} subcarrier in this time window. We have taken average of all the subcarriers' values at a particular time instant. This average CSI is used as representative value of CSI. Different walks show different CSI statistical features. The CSI patterns in three walk cases (1 Km/Hr., 3 Km/Hr. and 6 Km/Hr.) are shown in figure 3. The difference in the CSI amplitudes can be visibly seen but it is not completely clear at some time instants. Statistical analysis of the collected samples over time is to be done to estimate the extent of variation in the signals. Human activities create low frequency noise to the wireless signals. The high frequency environmental noise needs to be removed using low pass filter so that the signal now possesses only the effects of human activities.

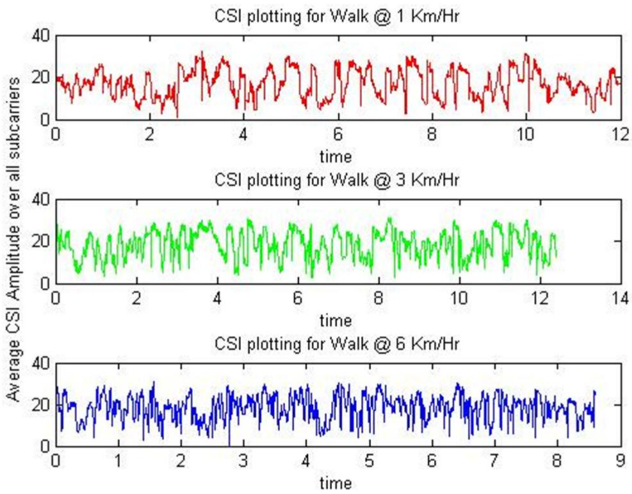


Fig. 3. CSI patterns in three walk cases (1 Km/Hr., 3 Km/Hr. and 6 Km/Hr.)

The filtered CSI signals can be seen in figure 4. All the three signals can be now easily differentiated from each other. The walk at 1 Km/Hr. speed is seen as long cycles while signals due to walk at 6 Km/Hr. change more frequently with comparatively less variations. The signal in green representing the walk at 3 Km/Hr. has its oscillation in-between the other two. After filtering the signals are visibly differentiable up to some extent but to draw a clear boundary between the walk patterns we need statistical analysis of filtered signals.

C. Feature Extraction

Filtered signals seem to be differentiable visually in figure 4 but to actually draw a clear line between the various stride rates we extract statistical features out of them.

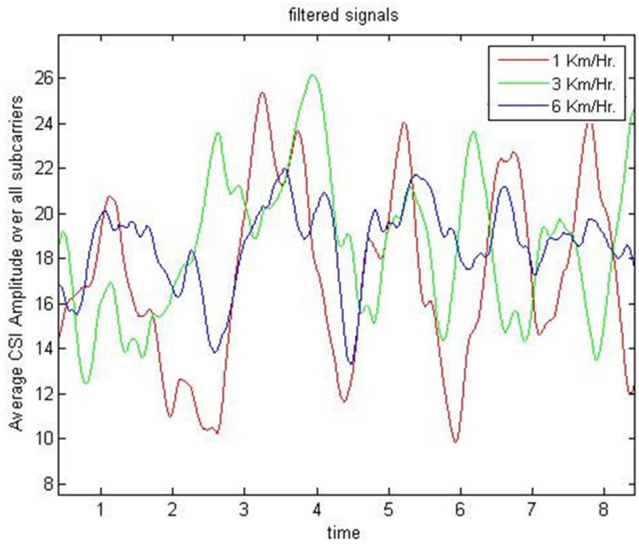


Fig. 4. The filtered CSI signals

1) *Cumulative Moving Standard Deviation(CMSD)*

The first statistical feature extracted from the filtered average CSI over all subcarriers. A window of 500 CSI samples is selected which accounts for approximate 2 seconds of physical activity which is very less in comparison to the previous approaches which is around 5 sec. A moving standard deviation (MSD) of sets of 500 samples over complete data is calculated. The figure 5 below shows a snapshot of MSD over 500 samples to represent visible difference among the walks. A mean of all the MSD's is taken over all the available samples to use this as feature of specific walk.

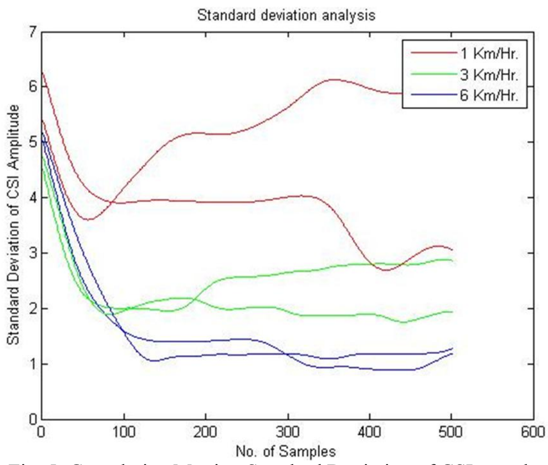


Fig. 5. Cumulative Moving Standard Deviation of CSI samples

2) *Mean Signal Velocity*

It is the rate of change of CSI amplitude over all samples. A running sum of difference between the consecutive CSI samples over complete window is calculated. Then a mean is calculated which is the extracted signal velocity feature of that sample stream as shown in figure 6.

D. *Classification Heuristic to estimate stride rate*

The filtered signals are statistically analyzed to create classification heuristic in the form of a decision tree given in figure 7. Statistical features CMSD (x1) and velocity (x2) are calculated for sample streams each having 500 samples. We generated the tree shown in figure 7 using 10000 such sample streams having one stride rate label (1, 3 or 6) also with them extracted using the video monitoring of the same activity.

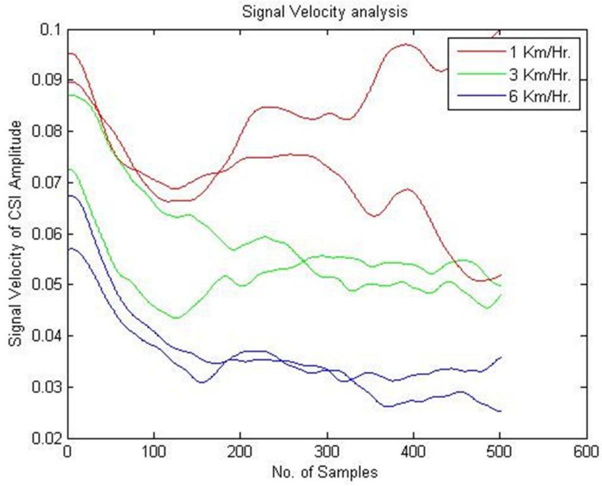


Fig. 6. Mean Signal Velocity

E. *Calculation of steps per second and total number of steps*

Currently we are only able to differentiate among these rate categories. Absolute measurement of the average number of steps per second was 0.8 steps/sec. for 1 Km/Hr., 1.5 steps for 3 Km/Hr. and 2.2 steps for 6 Km/Hr. observed from video recordings. Determination of number of steps can only be done after understanding signal morphology in detail. We currently leave this as our future work. The system also needs to be trained to deduce step length of the subject, as we have planned to train the system for only one subject so the approach needs some modification for this, we will pursue this in next phase of this work.

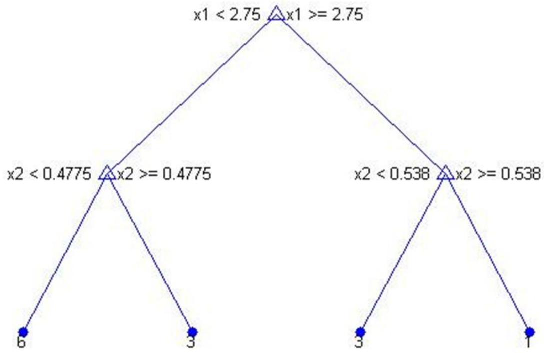


Fig. 7. Decision tree for gait speed classification

IV. EXPERIMENTAL RESULTS

A. *Hardware Setup*

Dell Latitude 4300 Laptop (L1) equipped with Intel 5300 NIC, in a backpack wore on the back and 2 antenna 802.11n wireless router placed at 2 inch above ankle are used as receiver and transmitter respectively. They are worn by the subject as shown in figure 8 and 9. Figure 10 shows the right leg forward position while figure 11 shows the right leg backward position on the treadmill. In figure 12 the subject walking on the tread mill is shown wearing the proposed setup. The person walking on the terrace is shown in figure 13.

B. Tool Setup

1) CSI Tool

CSI Tool [26] has been developed for the channel state measurements using the 802.11 packet traces. It works only with Intel 5300 wireless network interface card (NIC). This tool measures signal strength and phase delays of all the subcarriers since multipath effect is frequency dependent. It returns the CSI in the form of channel matrix for all spatial streams and all subcarriers. This tool has been created by customizing Intel's close-source firmware and open-source iwlwifi wireless driver to unleash the CSI between sender and receiver. We have used this tool to get the CSI information from the ongoing communication between our nodes.

2) MATLAB

MATLAB is utilized to parse the recorded CSI format and to compute the channel's parameters such as number of transmitting and receiving antenna, RSSI values of each NIC's antenna, etc. The analytical module of the proposed system is currently under MATLAB. It has also been used for statistical analysis of the received signals and generate decision tree. The accuracy of the decision tree has also been verified using MATLAB.

C. Subjects

5 Subjects (2 female and 3 males) with average age 36.6 years and no known gait problems has been enrolled for the testing. Each subject performed walk activities and simulated abnormal walk in their own manner.

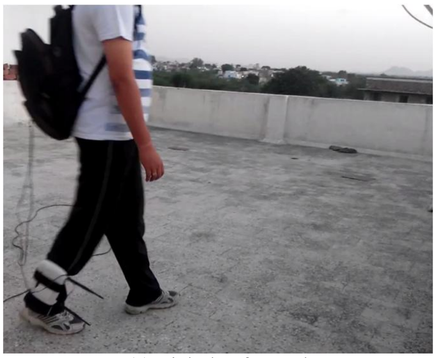
Fig. 8. Weared Measurement Gear

Fig. 9. Monitoring Laptop L1 in backpack

Fig. 10. Wireless router on right in leg forward position

Fig. 11. Wireless router on right in leg back position

Fig. 12. Walking on indorr treadmill



(a) Right leg forward

(b) Left leg forward

Fig. 13. Walking on the terrace

D. Locations

The approach has been tested on two locations. One is indoor hall (L1) of area 15x15 sq. ft. and terrace of the building (L2). The building is in residential area where there are other wireless signals like WIFI, GSM, Satellite Communication were also present. CSI was recorded for all the packets by the CSI Tool while doing activity and video recording is also performed to use as ground truth during verification of the classification result. The hall (L1) has Fan, tube-lights, chairs, floor bed, tread mill as obstacles. It has windows and 2 gates also. The person performs walking on the treadmill by specifying specific speed of the treadmill. Another location chosen is outdoor terrace of the same building with 2 sides neighboring buildings. The subjects perform walking on the terrace equipped with the measurement instrument. The terrace is chosen since it not only has other WIFI signals (2 signals were present most of the time) but also has satellite communication and GSM signals around. So the system has been tested on real life conditions and environmental disturbances. During all the measurements, other than the obstacles present at the locations, one assistant was also present for video recording of the activities, so all the results already have one more subject as an obstacle.

E. Measurement Protocols

The measurements were performed using specific protocols like walking on treadmill at different speeds (1, 3 and 6 Km/Hr.). All the measurements were recorded using the proposed setup and a video camera for verification & sample labeling.

F. Classifier Training and Testing

We built a classification tree using values of the features extracted from various CSI samples' streams recorded for single subject. The number of samples in each stream is kept 500 and stride rate labeling of these streams is done through video recordings done for verification. Testing of the decision tree is done by taking random untrained sample streams of 500 samples in it and finding the stride rate classification using decision tree. This result is matched with already stored label of the same sample which is created using the video made during activity performing. The decision tree made for single subject has been used for verification of stride rate for all others. The system is not required to train for other subjects.

V. ANALYSIS

Now we make an attempt to analyze our current results. Although we are in process of detailed verification of the results for more number of subjects and locations with subcarrier-wise feature extraction, the current results are fascinating.

A. Accuracy of Gait Parameters

The classification tree is able to differentiate among various gait rates with high accuracy because each classified window is not used for decision making alone. We assume that a person will perform gait at a particular rate for at least 5 sec, this is our decision heuristic. Since the sampling rate is more than 250 samples/sec so we collect 1500 classification results in a stack. We keep a track of previous classified results (result from tree) and declared result (decided using decision heuristic). Current window of 500 samples is classified on the basis of 1500 previous classified results (approximate 5 seconds slot) using majority rule. The decision of the gait rate goes with the majority of the classified results in the stack, and is termed as declared result. Declared result is displayed on the terminal. The classified results and declared results may not be same but this method prevents from random fluctuation errors due to noisy readings as the result of the gait rate is declared on the basis of decision heuristic. We also tested system without decision heuristic then the accuracy tends to fall in many cases.

B. Location Independence

The approach can be claimed as location independent as the classifier was trained in indoor hall and it is able to classify the walking rate while the person walked on the terrace. While we tried to differentiate the walk in three given speeds, the accuracy was poor (<60%) since without treadmill the subjects cannot maintain their speed constantly but interestingly, when we classified terrace walk as walking or running then the accuracy is very high (>90%). To get finer resolution of walking speeds we are planning to consider more statistical parameters and training for continuous range of walking speeds instead of currently used discrete speeds.

C. Subject Independence

The approach has been tested on 2 females and 3 males while it was trained for only one subject. Although a more detailed verification of subject independence is required, preliminary results are found to be subject independent as single classifier is able to identify the walking rate for all specially for the walk on treadmill. Subject independence is not accurate yet while walking on the terrace.

D. Presence of Obstacles and Other Signals

The approaches mentioned in literature uses a calm environment having no other noise sources, so that the signals are maximally affected by human activities only but this restricts them up to labs only. We have performed experiments on the terrace, indoor hall with 2 other Wi-Fi signals available, another person was also allowed to do some physical movements (video recording) in 3 meters periphery of the subject. Even in this condition we are able to identify the walking rate accurately, this proves that placing the sender and receiver both on the body minimizes the effect of surrounding noises.

E. Comparison with recent works for the parameters

As per our knowledge this is the first ever attempt to monitor walking activities outdoors without inertial sensors placed on various body parts with only one sender and one receiver are required. The classifier was trained and tested in noisy environment where several moving surrounding obstacles and other ambient wireless signals exist, but the classifier is able to detect stride rate accurately. In contrast, approaches in the literature have kept the surroundings calm as much as possible [18-23] which reduces their practicability for real-life deployments outside labs [1-3]. The proposed system bounds the subject to wear both the sender and monitoring nodes. This may be inconvenient for the subject in comparison to the ambient nodes' scheme, but this has certainly increased the accuracy and practicability of the wireless sensing without inertial sensors. Now the subject is free to move without any wireless range consideration and also the noise incorporated in the communication is mainly due to physical activities performed by the subject. This makes the proposed method a landmark in physical activity monitoring through wireless sensing domain to make it ubiquitous.

VI. Conclusion and Future Work

The preliminary results are found satisfactory to distinguish walk from standing straight with high accuracy above 90% for all subjects (more accuracy details will be provided in subsequent publication due to space constraints). Various walking speeds can be classified to identify slow or normal walk on the basis of step count per second independently of subjects and experiment locations. Stride rate and stride length are roughly calibrated per person. The main advantage of the proposed work is that there is no requirement to train the system for specific subject to measure steps count and stride rate. A common measurement protocol is followed for all subjects using a common low pass filter and specific statistical bounds. In future we plan to apply the protocol for clinical tests instead of normal subjects. Distinction between walking on floor and upstairs-downstairs is to be done as part of next phase. More robust statistical features are to be extracted from the received CSI traces for all the subcarriers for in-depth understanding of effect of gait parameters on the wireless signals. Fine-grained gait abnormalities like leg shivering are still not detectable with this method. Currently as CSI is available in a laptop only with specified customizations so the backpack is compulsory to wear.

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