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Human Movement Tracking System with Smartphone Sensing and Bluetooth Low Energy in Internet of Things

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Abstract: Real time human movement tracking system is a challenging task in the field of Internet of Things (IoT) in an organization environment.This environment is achieved by the combination of orientation sensor and Bluetooth Low Energy (BLE) technologies in smartphones which belongs to IoT. Orientation sensor senses the day today human activity signals from the user's smartphone and then BLE transmits the sensed signals to monitor using star topology. Received user signals are then manipulated and classified using ten different algorithms. The performance of the proposed method is measured by quantitative measures. Numerical results from the experiment shows superiority of the proposed method.

Key words: Orientation sensor, bluetooth low energy, smartphone, internet of things, numerical results

INTRODUCTION

Internet of things, a fast growing technology is getting popular day-by-day due to increased use of smart mobile devices like smartphones, tablets, notebooks, ultra-books and Personal Digital Assistants (PDA), etc. These devices have become a part of everyone's life in this digital world and can be used for many purposes.

In this study, the goal is to increase the value of smartphone by identifying the position and direction of the user in times of emergences. This information would help to reach the user and help him/her in times of need. A few of our target applications are remote health monitoring and emergency notification systems to help the elderly and physically challenged human activity, Susi *et al*. (2013).

Our research is performed using few of the latest features which are in-built with smartphone orientation sensors and BLE in IoT without the need to attach or mount any external sensors either on the human's torso or on the walls or entrance or ceilings. And also, typical various in-built smartphone sensors are used to identifying the human physical activities for that purpose only and evaluate the performances measures from classified by machine learning algorithms. In this study, the method is implement using star topology (Bisht and Singh, 2015) based human movement tracking system while doing physical activity (running or jogging) in the specific environment if any emergency occurrences takes place in this situation, rehabilitation notification message from remote monitors will be send using star topology with less design complexity and routing delay when compared to mesh (Zachariah *et al*., 2015; Farej *et al*., 2015; Reiter, 2014; Varjonen, 2015).

It is important to note that BLE is suitable for communication within any indoor premises due to its limited range and is the best indoor communication technology because of its low power consumption and low latency and also, it doesn't need any fixed infrastructure (Reiter, 2014; Varjonen, 2015).

In this study, the focus is made on in-pocket recognition and on-body recognition. The subject performs various activities in different directions with the help of a smartphone and the readings are taken using Lab View software in remote monitors and classified performed by different algorithms.

This remaining study is organised as follows: discusses the related work in this area, describes the proposed technique used to tracking user's position and direction of movement, briefs the test and analysis and concludes this research.

Related works: BLE technology is used for sending small chunks of data to interconnected devices. Recently, much research has been focused on BLE for motion sensors (Reiter, 2014; Varjonen, 2015).

The typical proposed analysis of movement, orientation and rotation-based sensing for phone placement recognition from human held smart phone sensors (Incel, 2015). Typical studys use the magnitude of acceleration as motion related information; orientation sensors are utilized to compute the orientation related information. Additionally, pitch and roll values are utilized

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as the rotation related information. Recognition performances can be increased with the use of orientation, rotation and motion related information using only the accelerometer only solution is preferred since, it is one of the least power consuming sensors and it is shown that the accelerometer performs with 76% accuracy for a given dataset. In aforementioned reference, motion and orientation or rotation information alone does not perform well and also the sensors that are used, gyroscope and magnetic field sensors do not perform well. Walking activities makes it easier to identify the positions. It is also shown that an accelerometer sensor can achieve 80% recognition accuracy even with motionless activities where the data is very limited.

In order to identifying physical movement performed by users using Wearable Ambulatory Monitors (WAM) to collect the physical movement dataset and classified the given dataset using the Hidden Markov Models (HMM), K Nearest Neighbours (KNN), Support Vector Machines (SVM), Bayesian Networks (BN), Gaussian Mixture Models (GMM), Logistic Regression (LR), Naive Bayes (NB), Decision Tree Classifiers (DTC) and Artificial Neural Networks (ANN) (Del Rosario *et al*., 2015). The sensing device has three distinct phases namely sensing the information, extraction and physical movement identification.Implemented smartphone applications are one which could estimate the number of steps taken by user when the smartphone is placed in various places on the human body (e.g., belt, armband and wrist strap). The studies of the smartphone sensing components are utilised in the devices which can estimate a variety of physical movements with most potential applications such as healthcare which is designed to collect data about different aspects of an individual's health and wellbeing (e.g., blood pressure, heart rate, weight and location). To improve the algorithms that estimate physical movement by exploiting the individual's personal behaviour, information is extracted by their behaviour and their physiological characteristics (age and current fitness level)as well as their daily routines which may change over time.

Human body orientation detection mechanism using RGB camera-depth sensors fixed in various places. It consists of ten RGB-D video surveillance sequences, captured at three different scenes including meeting room, corridor and entrance with 4000 frames and 11 different persons (Liu *et al*., 2013). In order to imitate the real world scenarios better, a wide diversity of human activities are included in the dataset such as standing, squatting, jumping, walking, running, rotating, waving hands, hugging and so on. As the limitations of the RGB-D sensors, all the people are recorded in the scope of 2.5-10 m. In addition, all the captured scenes which are indoors as RGB-D sensors cannot work in the strong light. There are three stages to capture the human physical activity recognitions. First stage: super pixels extraction for given video frame use RGB-D based human motion segmentation to get each people individual region. Second stage: is static and motion cues extraction. On one hand, features are extracted from each individual and the static classifier is trained to predict the static cues; on the other-hand for the motion cues the super-pixels based scene flow information is estimated by the Particle Filter (PF) algorithm. Third stage: is the fusion stage where static human orientation classification results; SSF information and temporal information are properly embedded to get the final estimation results.

Pyro Electric Infrared (PIR) sensors fixed on opposite walls facing each other to classify the direction of movement and distance between users with the help of PIR sensors. The PIR sensors are placed as two modules; the first module is fixed on the ceiling and second module is fixed on opposite walls facing each other in an entrance. Using the PIR-based modules, they have collected PIR sensor signals when eight different experimental participants were walking through the monitoring field in three different conditions in order to detect the direction and speed of movement and the distance of the body from the PIR sensors. They achieved >94% accuracy in classifying the direction, distance and speed for eight different activities.

The accelerometer and gyroscope sensor data can create privacy breach because accelerometer and gyroscope sensors do not require user permission on operating systems such as android and iOS (Shala and Rodriguez, 2011; Liu *et al*., 2013). Since, the sensors are mostly used for gaming android system does not restrict the access of accelerometer and gyroscope sensors which are used for background services.

Discuss about the inertial Pedestrian Dead Reckoning (PDR) location systems which can be improved with the use of a light sensor to measure the illumination gradients created when a person walks under ceiling with fixed unchanged indoor lights (Jimenez *et al*., 2014). This type of physical movement identification method is not suitable for all types of environment, e.g., day time work on providing location services within a building that has many potential applications including safety, security, resource-efficiency, automatic resource routing by Harle (2013). Focus on the Pedestrian Dead

Reckoning (PDR) based direction finding algorithm by using Magnetic Angular Rate Gravity (MARG) sensors which are equipped in typical smartphone providing accurate, reliable and continuous position tracking services. Discuss a novel solution to the human positioning, based on in plane detection which uses infrared light emitters and sensors placed horizontally on fixed positions along the circumference.

Research on magnetic sensor with smartphone their study aims to recognize human activity based on the smartphone in the user's pocket and automatically identify whether the mobile phone is in the user's pocket before analysis with the help of proximity and light sensors (Tian *et al*., 2014).

In this study, focus is made on in-pocket recognition and on-body recognition. The subject performs various activities in different directions with the help of a different smartphone and the readings are taken using Lab View software and classified using different classification algorithms like rondom forest, random committee, LMT (Logistic Model Tree), rotation forest, bagging, J48, simple cart, BF (Best First) tree, IBK (log and gaussian kernel for K-NN) and REP tree.

In the present research, a detailed study is made on BLE in IOT where in real-time monitoring of information is carried out using Lab View which involves data capture and analysis from a smartphone using sensors for data detection and manipulation and eliminates the usage of traditional methodologies discussed above.

Table 1 gives the methodologies used in different scenarios using different sensors, human physical movement and machine learning algorithms.

Tracking users position and direction of movement: The smartphone carried by a human will be in different locations when being used for different purposes. A few purposes for which a smartphone is used are composing a text message using any smart application, attending a call and placement of different pockets on human torso (Li *et al*., 2016). The human held smartphone orientation based on the rotation matrix. When it returns, the array values is filled with the results; values: azimuth, rotation around the-Z axis, values: pitch, rotation around the-X-axis, Values: roll, rotation around the Y-axis.

Applying these three intrinsic rotations in azimuth, pitch and roll order transforms identity matrix to the rotation matrix given in input R. All three angles above are in radians and positive in the counter-clockwise direction. Range of output is: azimuth from π, to π, pitch from $\pi/2$ to $\pi/2$ and roll from π to π, Azimuth is a rotation ψ of about the Z-axis:

$$R_z(\psi) = \begin{pmatrix} \cos\psi & -\sin\psi & 0 \\ \sin\psi & \cos\psi & 0 \\ 0 & 0 & 1 \end{pmatrix} \quad (1)$$

Pitch is a rotation of θ about the X-axis:

$$R_x(\theta) = \begin{pmatrix} 1 & 0 & 0 \\ 0 & \cos\theta & -\sin\theta \\ 0 & \sin\theta & \cos\theta \end{pmatrix} \quad (2)$$

Roll is a rotation of φ about the Y-axis:

$$R_y(\varphi) = \begin{pmatrix} \text{Cos}\varphi & 0 & \text{Sin}\varphi \\ 0 & 1 & 0 \\ -\text{Sin}\varphi & 0 & \text{Cos}\varphi \end{pmatrix} \quad (3)$$

The $R_{z,x,y}(\psi, \theta, \varphi)$ each rotation can be used to place a 3d smartphone with human in any orientation. A sample for single rotation matrix can be formed by multiplying the Eq. 1-3, the rotation matrix to obtain by as shows:

$$R_{z,x,y}(\psi,\theta,\varphi) = R_z(\psi), R_y(\varphi), R_x(\theta)$$
$$= \begin{pmatrix} c\psi c\theta & c\psi s\theta s\varphi - s\psi c\varphi & c\psi s\theta s\varphi - s\psi c\varphi \\ s\psi c\theta & s\psi s\theta + c\psi c\varphi & s\psi s\theta - c\psi s\varphi \\ -s\theta & c\theta s\varphi & c\theta c\varphi \end{pmatrix} \quad (4)$$

Where:

(θ, φ, ψ) = The three angles (pitch, roll, azimuth), corresponding to rotation around the x, y, z axis

= c() and s() are shorthand for cosine and sine

The given Eq. 4, rotation matrix $R_{z,x,y}(\psi, \theta, \varphi)$ can be compute the user's smartphone angle using pitch, roll, azimuth by equation each element in $R_{z,x,y}(\psi, \theta, \varphi)$ with corresponding in the rotation matrix product $R_z(\psi)$, $R_y(\varphi)$, $R_x\theta$ can be used to find angles of smartphone users. Each time a new rotation matrix is introduced from 3D users smartphone rotation depends on three parameters $R_{z,x,y}(\psi, \theta, \varphi)$ of the smartphone about three perpendicular axis is used to capture the users daily activities of information and communicated to a remote monitor on-demand basis, this process involves communicating information collected by orientation sensors with eight different user's smartphone using BLE in IoT to a monitor which pre-processes, it by calculating the mean (μ) of each Dimension 'D' of 'N' positions using the following Eq. 5:

$$\mu_D = \frac{1}{N}\sum_i^N D_i \quad (5)$$

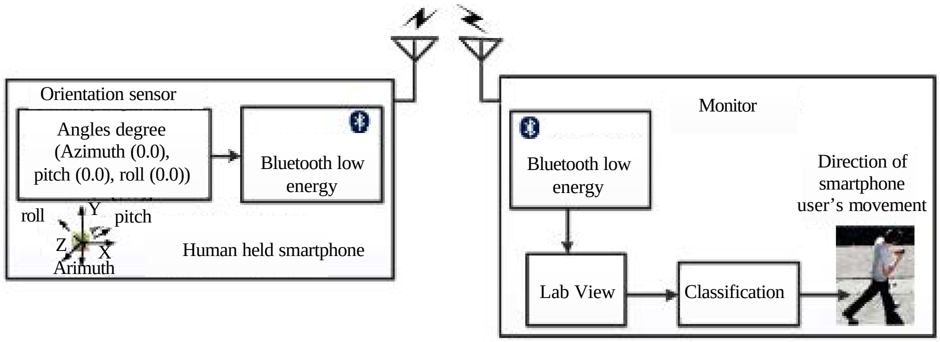

Fig. 1: Overall block diagram of the human movement tracking system

And standard deviation (σ) is calculated using the following Eq. 6:

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(D_i - \mu_D\right)^2} \qquad (6)$$

Are applies a classification algorithm to accurately identify the user's positions and directions.

Communication between user's smartphone and monitor: The only requirement for a monitor is BLE in IoT to obtain human position information from smartphone and efficient processors to perform computation required for the process of human movement tracking system shows in Fig. 1. Placing monitors at the limit of coverage of a monitor's BLE and increasing the number of monitors likewise can increase the area covered for human movement tracking.

The basic information on the position of a human which is collected using the orientation sensor within a smartphone is sent from the smartphone via BLE to a monitor in the range. Usage of this technology makes our research exclusive among the existing indoor human location tracking techniques because BLE in IoT consumes the least power (Reiter, 2014; Varjonen, 2015) and covers the longest range when compared to other indoor wireless technologies like ZigBee, due to its compatibility with most of the mobile devices, a smartphone would suffice to establish communication with the monitor and does not require any other external device for the same.

Motion classification: This model is used to classify the input set of records into the desired classes. For location tracking the movement of the smartphone user, the desired classes are the directions: North, North East, East, South East, South, South West, West and North West. In our technique, the input to such a classification algorithm is the mean and standard deviation previously calculated from orientation sensor.

We have experimented with the following ten different classification algorithms: random forest, random committee, LMT (Logistic Model Tree), rotation forest, bagging, J48, simple cart, BF (Best First) tree, IBK (Log and Gaussian kernel for K-NN) and REP tree.

MATERIALS AND METHODS

Experimental setup: For experimental purposes, we have used eight different environments users with smartphone and a single monitor using star topology in IoT as shown Fig. 2 to identify the position and direction of smartphone users. The dataset is collected with users moving in the eight directions, each person moving a day today activities performed by different time periods captured Fig. 3, shows as sensor data stream from the orientation sensors and BLE within a smartphone to the Monitor via BLE, using following ways of users carrying the smartphone in day today activities, i.e., walking with smartphone carried in back pocket of user, walking with smartphone carried in front pant pocket of user, walking with smartphone carried in jacket pocket of user, walking with smartphone fastened to belt of user, user speaking over the smartphone while walking, user composing a text message in smartphone while walking, user interacting with a smartphone application (involving rotation and shaking) while walking, jogging with smartphone fastened in the armband of user.

Devices and tools used: In-built orientation sensor and BLE in smartphone using IoT in the smartphone and a monitor is used for communicating the captured information to Lab View installed in a machine (Intel Core I 5 configuration) is used as the monitor. The accuracy of the various classification algorithms used to identify the smartphone users position of movement is obtained using the tool Weka 3.6 (Witten *et al*., 2011).

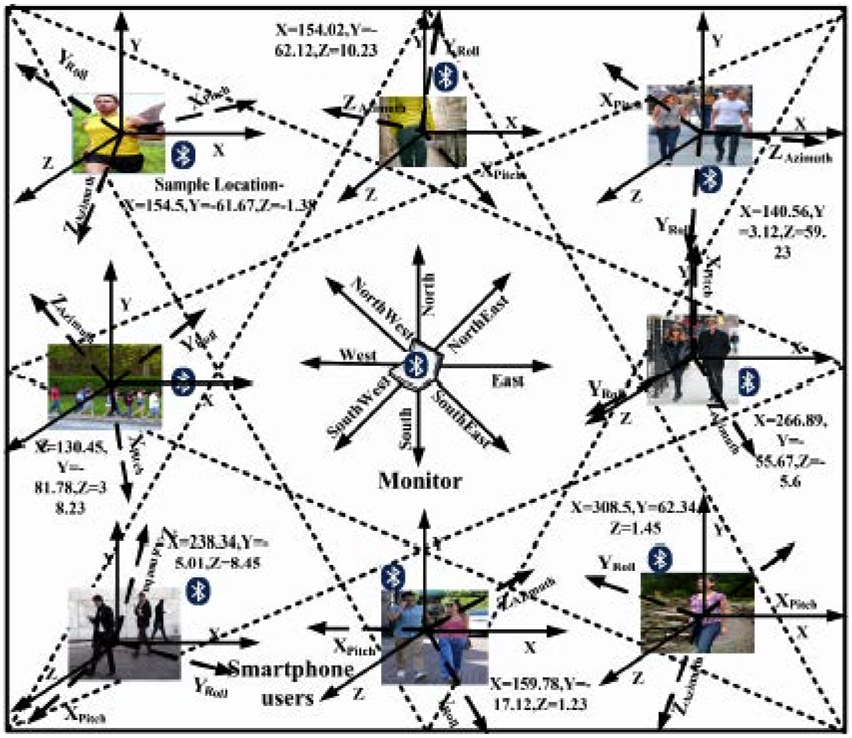

Fig. 2: Results obtained from these environments

Performances measures: In our research, the classification algorithms are used to predict the direction of movement of a smartphone user. To evaluate such a classification algorithm, we have used the following performances measures and numerical prediction by Witten *et al*. (2011).

Precision: The fraction of predicted directions that is relevant:

$$\text{Precision} = \frac{\text{Relevant direction} \cap \text{Predicted direction}}{\text{Predicted direction}} \tag{7}$$

Recall: The fraction of relevant directions that are predicted:

$$\text{Recall} = \frac{\text{Relevant direction} \cap \text{Predicted direction}}{\text{Relevant direction}} \tag{8}$$

F-measure: Measure that combines precision and recall is the harmonic mean of precision and recall:

$$\text{F-measure} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{9}$$

Accuracy: Degree to which the direction prediction is correct:

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}} \tag{10}$$

Error rate: Degree to which the direction prediction is wrong:

$$\text{Error rate} = \frac{\text{Number of wrong predictions}}{\text{Total number of predictions}} \tag{11}$$

Numeric prediction measures: The measures discussed in the study are quoted by Witten *et al.* (2011), the predicated values on the test instances are; the actual values are, it was the probability that a predication was in the class, here, it refers to the numerical values of the prediction for the test instances.

Mean absolute error: The average magnitude of the individual errors without taking into account their sign:

$$\text{MAE} = \frac{|P_1 - A_1| + \ldots + |P_n - A_n|}{n} \tag{12}$$

Root mean squared error: It is the quadratic scoring rule which measures the average magnitude of the error:

$$RMSE = \sqrt{\frac{(P_1 - A_1)^2 + ... + (P_n - A_n)^2}{n}} \quad (13)$$

Relative absolute error: It is the average of the actual values from the training data:

$$RAE = \frac{(P_1 - A_1)^2 + ... + (P_n - A_n)^2}{\left(P_1 - \left(\frac{1}{n}\sum_i A_i\right)\right)^2 + ... + \left(P_n - \left(\frac{1}{n}\sum_i A_i\right)\right)^2} \quad (14)$$

Root relative squared error: is obtained by normalizing the total squared error by the total squared error of the default predictor:

$$RRSE = \sqrt{\frac{(P_1 - A_1)^2 + ... + (P_n - A_n)^2}{(P_1 - A_1)^2 + ... + (P_n - A_n)^2}} \quad (15)$$

RESULTS AND DISCUSSION

The results obtained on evaluating the classification algorithms based on the performances measures and numerical predication measures discussed are tabulated in Table 2-6.

Classification algorithm will produce higher precision, recall values leading to a high F-measure will also be highly accurate and will produce low error rate. Table 2-5 show the results obtained on predicting the direction of smartphone user movement using the classification algorithms based on the evaluation parameters discussed. It is clear from these results that, the average precision, average recall and average F-measure obtained using the tool Weka 3.6 is above 0.86 for all the classification algorithms as in Table 2-4.

Also as shown in Table 5, the average accuracy of direction prediction using all the classification algorithms is >86%. Table 6 gives the evaluation of our research done using the numeric prediction measures discussed earlier.

These results show the effectiveness of our technique where basic position information of smartphone user is collected using orientation sensor and communicated via BLE in IoT.

From Table 2-6, it is clear that random forest algorithm is the best among the ten classification algorithms, since it predicts direction of movement of a smartphone user in the most accurate manner.

Figure 3 shows smartphone user's activities observation from orientation sensors which are taken from eight different activities in eight different directions by eight different persons.

Table 1: Different scenarios using different sensors, human physical movement and machine learning algorithms

References	Application	Sensors used	Placement	Machine learning algorithm used	Movement	Accuracy (%)
Anguita *et al.* (2012)	Physical movement	Inertial measurement unit	Placed in a belt on the waist	Support Vector Machine(SVM)	Standing, walking sitting, lying, staircase ascent and descent	89.0
Khan *et al.* (2013)	Human activity recognition	Accelerometer	Front and back pant pocket and jacket breast pocket	Artificial Neural Networks (ANN)	Standing, walking running, hopping staircase ascent and descent	87.1
Liu *et al.* (2013)	Human body orientation	RGB camera-depth sensor	Hallway and ceiling	Dynamic Bayesian Network	Static and motion	86.9
Bhattacharya *et al.* (2014)	Human activity recognition	Accelerometer and gyroscope	Jacket pocket pant pocket and backpack	Decision tree, nearest Neighbour and SVM	Daily motion except staircase ascent and descent were not studied	86.3
Yun and Lee (2014)	Indoor physical	Pyroelectric				
	movement	Infrared (PIR) sensors	Hallway, ceiling and opposite wall	Bayesian network, Multi-Layer Perceptron (MLP), Naive Bayes (NB) and SVM	Walking (Forward and backward) different speeds (slow, moderate and fast) and Distances (near and far)	94.0
Incel (2015)	Human poisition recognition	Linear acceleration, gravity, gyroscope and magnetic field sensors	Human handheld smartphone devices	K nearest neighbour, MPL and J48	Walking, jogging, running, biking, going up/down stairs and on a bus	85.0
Miao *et al.* (2015)	Physical activity	Proximity and light sensor	Any pocket	J48, NB and Sequential Minimal Optimization (SMO)	Static, walking, running, walking, upstairs and walking downstairs	89.6
Li *et al.* (2016)	Pedestrian navigation	Accelerometer Gyroscope Magnetometer	Ear, dangling with hand, pant pocket	Dynamic Time Warping (DTW)	Walking	80.0

Table 2: Average precision

Algorithms	North	North East	East	South East	South	South West	West	North West	Average precision
Random forest	0.955	0.955	0.977	0.939	0.982	0.897	0.927	0.937	0.94613
Random committee	0.955	0.933	0.954	0.929	0.976	0.897	0.910	0.954	0.93850
LMT	0.944	0.932	0.926	0.939	0.936	0.903	0.879	0.927	0.92325
Rotation forest	0.938	0.941	0.931	0.932	0.927	0.845	0.854	0.896	0.90800
Bagging	0.955	0.933	0.954	0.929	0.976	0.897	0.910	0.954	0.93850
J48	0.916	0.912	0.873	0.924	0.930	0.855	0.826	0.899	0.89188
Simple cart	0.898	0.898	0.919	0.929	0.953	0.818	0.819	0.920	0.89425
BFTree	0.898	0.908	0.920	0.918	0.947	0.813	0.810	0.891	0.88813
IBK	0.904	0.908	0.905	0.916	0.908	0.786	0.791	0.840	0.86975
REPTree	0.882	0.898	0.913	0.885	0.892	0.788	0.833	0.843	0.86675

Table 3: Average recall

Algorithms	North	North East	East	South East	South	South West	West	North West	Average recall
Random forest	0.972	0.966	0.955	0.966	0.949	0.938	0.864	0.960	0.94625
Random committee	0.972	0.955	0.943	0.960	0.938	0.938	0.864	0.938	0.93850
LMT	0.949	0.932	0.926	0.949	0.928	0.900	0.874	0.929	0.92338
Rotation forest	0.943	0.909	0.915	0.932	0.932	0.869	0.830	0.932	0.90775
Bagging	0.972	0.955	0.943	0.960	0.938	0.938	0.864	0.938	0.93850
J48	0.932	0.881	0.898	0.966	0.909	0.835	0.807	0.909	0.89213
Simple cart	0.955	0.898	0.903	0.960	0.932	0.818	0.773	0.892	0.89138
BFTree	0.949	0.898	0.920	0.955	0.915	0.813	0.773	0.886	0.88863
IBK	0.858	0.898	0.869	0.926	0.892	0.835	0.773	0.898	0.86863
REPTree	0.892	0.898	0.892	0.915	0.892	0.824	0.767	0.852	0.86650

Table 4: Average F-measure

Algorithms	North	North East	East	South East	South	South West	West	North West	AverageF-measure
Random forest	0.963	0.960	0.966	0.952	0.965	0.917	0.894	0.949	0.94575
Random committee	0.963	0.944	0.949	0.944	0.957	0.917	0.886	0.946	0.93825
LMT	0.946	0.932	0.926	0.949	0.928	0.900	0.874	0.929	0.92300
Rotation forest	0.941	0.925	0.923	0.932	0.929	0.857	0.841	0.914	0.90775
Bagging	0.917	0.906	0.908	0.927	0.921	0.862	0.827	0.895	0.89537
J48	0.924	0.896	0.885	0.944	0.920	0.845	0.816	0.904	0.89175
Simple cart	0.926	0.898	0.911	0.944	0.943	0.818	0.795	0.892	0.89087
BFTree	0.923	0.903	0.920	0.936	0.931	0.813	0.791	0.889	0.88825
IBK	0.880	0.903	0.887	0.921	0.900	0.810	0.782	0.868	0.86887
REPTree	0.887	0.898	0.902	0.899	0.892	0.806	0.799	0.847	0.86625

Table 5: Accuracy and error rate

Algorithms	Accuracy (%)	Error rate (%)
Random forest	94.6023	5.39770
Random committee	93.8210	6.17900
LMT	92.3295	7.67050
Rotation forest	90.7670	9.23300
Bagging	89.5597	10.44030
J48	89.2045	10.79550
Simple cart	89.1335	10.86650
BFTree	88.8494	11.15060
IBK	86.8608	13.13920
REPTree	86.6477	13.35230

Table 6: Numerical prediction measures

Algorithms	MAE	RMSE (%)	RAE (%)	RRSE
Random Fforest	0.0477	0.1176	21.7887	35.5591
Random committee	0.0348	0.1179	15.9089	35.9089
LMT	0.0230	0.1307	10.4973	39.5313
Rotation forest	0.0722	0.1587	33.0037	47.9740
Bagging	0.0469	0.1402	21.4263	42.3937
J48	0.0312	0.1592	14.2558	48.1352
Simple cart	0.0319	0.1571	14.5885	47.4952
BFTree	0.0325	0.1590	14.8735	48.0723
IBK	0.0340	0.1807	15.5492	54.6326
REPTree	0.0455	0.1677	20.8071	50.7109

Figure 3a shows activities observations which are taken in the north direction by a single person who is performing eight different activities in the same direction during different time periods in a day (Fig. 3b-h), likewise activities observation is taken in another seven different directions by seven different users. Each user in a direction is performing eight different activities.

Figure 3e, shows a user performed eight activities in a South direction in this time periods among the user speaking over the smartphone while walking, in the time graphical view of X-axis (red) while activity of user signal are peak up and down. Certain low time periods, they have abnormal activities.

The monitor identify in user are emergency condition based on the signal up and down increase in the emergency condition, it will give priority for (high, low and medium) based on the signals. Here, Fig. 3g shows in activity for user interacting with a smartphone application (involving rotation and shaking) while walking while the signal are peak up and down is increase for certain time periods compare then Fig. 3e and 2g is high priority for rehabilitation of the user in West direction, in Figure other axis not consider because of value is slightly changes while activities so not predicated any emergency, Y (green) and Z (blue) but X-axis is variations high compare than other axis, in this study, consider X-axis only to identify the users are in emergency condition or not. Figure 3a-h is normal activities performed by smartphone users not consider emergency. Because

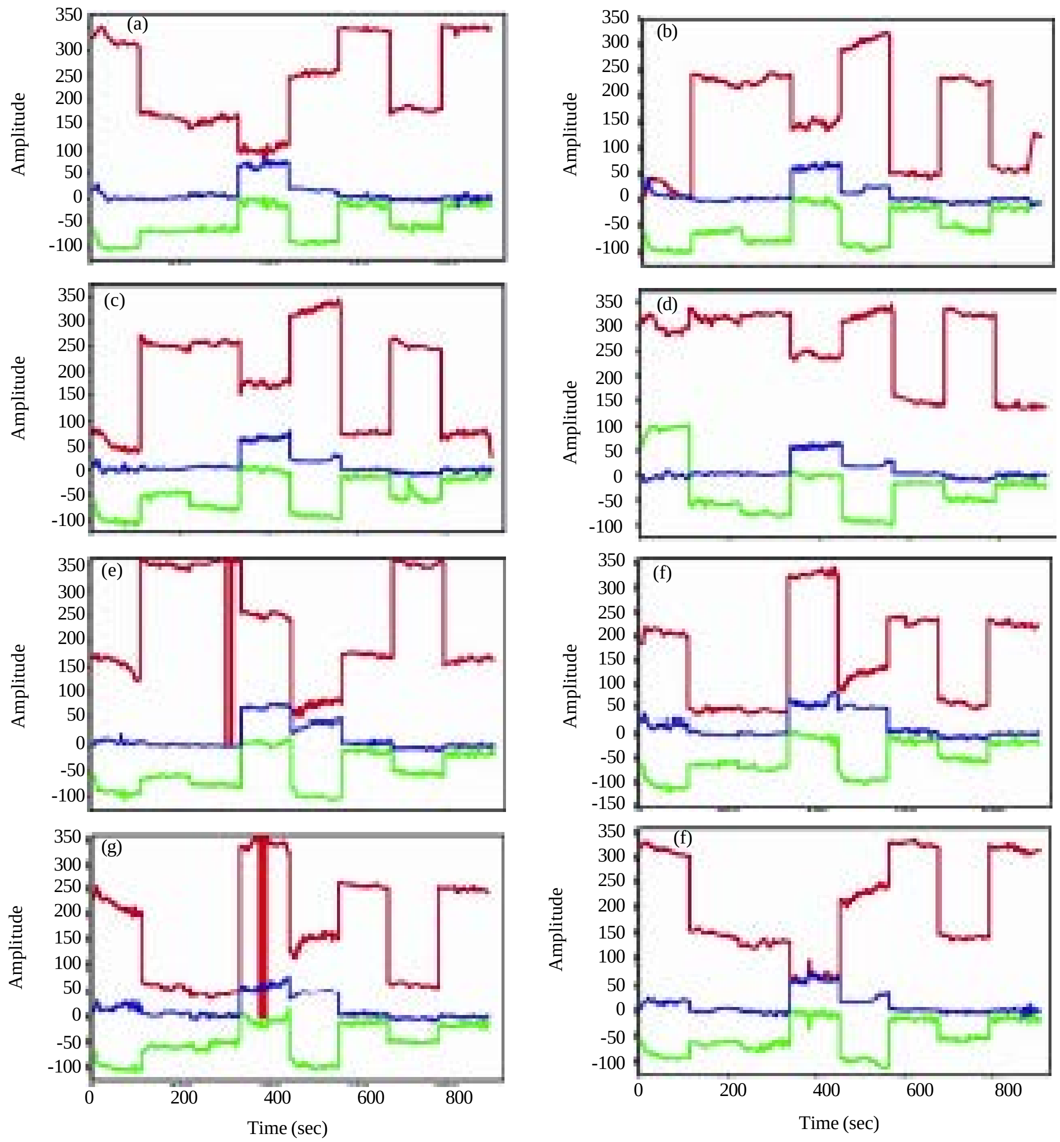

Fig. 3: Sensor data stream from the Orientation sensors within a smartphone to the Monitor via BLE in IoT. The amplitude along three orthogonally mounted axis, X (red), Y (green) and Z (blue) when the smartphone user is moving in the directions; a) North; b) North East; c) East; d) South East; e) South; f) South West; g) West and h) North West

of Fig. 3 is same set of actions is performed for collecting position information in eight directions.

CONCLUSION

In this study, IoT enabled smartphones are used to tacking any user's position and direction of movement provided only an additional device is used to act as a monitor. Orientation sensor in the smartphone senses the position information of its user and BLE transmits this information to the monitor.

The received information is used to identify the relative position of the user. A classification algorithm is then used to identify the user's direction of movement. Thus, unlike existing works which require a lot of infrastructure for indoor human movement tracking, our research is unique, since the task is achieved with the help of human-held smartphones sensor. The proposed research is experimented using ten different classification algorithms. An accuracy of >86% is obtained from all these algorithms. This proves the superiority of the proposed method.

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