Automatic Phone Slip Detection System

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Abstract Mobile phones are becoming increasingly advanced and the latest ones are equipped with many diverse and powerful sensors. These sensors can be used to study different positions and orientations of the phone which can help smartphone manufacturers to track the handling of their customer's phones from the recorded log. The inbuilt sensors such as the accelerometer and gyroscope present in our phones are used to obtain data for acceleration and orientation of the phone in the three axes for different phone vulnerable position. From the data obtained appropriate features are extracted using various feature extraction techniques which are given to classifiers such as the neural network to classify them and decide whether the phone is in a vulnerable position to fall or it is in a safe position.

Keywords Variance · Zero crossing rate · Fast fourier transform Pattern net neural network · Fit net neural network · Cascade neural network

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1 Introduction

Human activity recognition system using devices like cameras or microphones have become an active field of research. It has the potential to be applied in different applications such as ambient-assisted living. So human activity recognition system has become a part of our daily lives. Smartphones incorporate many diverse and powerful sensors, which can be used for human activity recognition such as GPS sensors, audio sensors (microphone), vision sensors (cameras), temperature sensors, acceleration sensors (accelerometers), light sensors and direction sensors (magnetic compasses). The data from these sensors can be transferred using wireless communication such as Wi-Fi, 4G, and Bluetooth [1]. We have seen that accelerometers and gyroscopes have the most applications as they are the most accurate ones [2].

Studies have shown that activity recognition system using mobile phones are the most extensively used topic in the research domain. Motion-based and location-based activity recognition using inbuilt sensor and wireless transceivers are the dominating types of activity recognition on mobile phones [3]. Under motion-based activity recognition systems, three-axis accelerometers are the most used sensors available on phones. Most of the studies focus on detecting the locomotion activities, such as standing, walking [4]. Study on various phone positions and orientations and how these positions change different parameters of inbuilt gyroscope and accelerometer has been limited [5, 6]. When a phone is kept at a particular orientation or position there many parameters associated with it. The location of the phone decides a lot about its future [7].

Good results have been obtained using Ameva discretization algorithm and a new Ameva-based classification system to classify physical activity recognition on Smartphones [8]. On comparing the accuracy of human activity recognition, it was found that using only a basic accelerometer gave an accuracy of 77.34%. However, this ratio increased to 85% when basic features are combined with angular features calculated from the orientation of the phone [9]. Human activity recognition using accelerometer was done for some common positions and accuracy was around 91% [10]. Hence an accelerometer alone cannot give very accurate results. But activity recognition significantly increases the efficiency. In contradiction, [11] suggests that this technique still needs a lot of research before it can be used for the general masses. Using few preprocessing techniques, efficiency can be increased too but with many limitations [12].

In this paper, we have focused on different phone positions which are considered to be risky and harmful. Based on these risky positions various parameters such as the roll, pitch, and azimuth changes. Whether the phone is at a slipping point or kept on a table or kept on a book. All these factors would decide if the phone will be safe after a certain movement or jerk is applied. And if the jerk moves the phone by a certain distance, will the phone be still safe or there would be a wide change in orientation of the phone which may result in the fall of it. To know all these things beforehand, we have come up with an idea which will tell the user by the change in orientation of the phone that whether the phone is safe or it is in a risky position. The most basic sensors that can be used for these cases are accelerometer and gyroscope. So here we selected some cases which include normal touch, accident keep, complete slip, slip till tipping point, flip and fall. For all these six positions, 20 samples each are taken. The acceleration and orientation values for each sample are stored.

The data obtained was plotted which was then filtered and the appropriate features were extracted [13]. Based on the features extracted, classification algorithm can be implemented using machine learning so that the system can automatically classify different positions. From [14], we got to know that people do consider many aspects before placing a phone somewhere. So, based on those aspects, we selected the various positions of the phone.

In Sect. 2, the methodology of how data was collected for various samples of different phone slipcases and also procedure to generate the required database is discussed. In Sect. 3, the procedure followed to extract features from the created database is discussed. In Sect. 4, the method used to create a database from the extracted features is mentioned. In Sect. 5, various machine learning classification algorithms are discussed and also how these algorithms are used to classify various phone slipcases is discussed with the observations obtained after implementing the various classification algorithms is discussed and tabulated. In Sect. 6, the final conclusion is drawn depending upon the results obtained.

2 Creation of Database

In our study, we considered six phone slipping cases: normal touch keep case, accidental keep case, complete slipping case, slip till tipping point case, flipping case and falling case. The following phone slipping case was chosen as these are the most common ways by which a phone is vulnerable to fall or slip. The first case which is the normal touch keep case is the reference case where the phone is just kept on the table by the user and the observations are recorded while performing this act. The second case is the accidental keep where the phone is thrown on a table or chair in a violent way. The next case is the complete slipcase where the phone is made to slip completely down a slope. The next case is slip till tipping point case where the phone is placed on a slope and the reading are recorded until the point the phone starts slipping. In the flipping case, the phone was flipped and thrown from one point to another. The last case is the falling case where the phone was subjected to a controlled fall from different heights. Phone position cases is shown in Fig. 1.

In order to create the required database, 20 samples were taken for each of the phone slipping cases. As there were six cases, totally 120 samples. To collect the samples for each case, MATLAB mobile application was used. For each of the samples of the different cases, data was collected for the acceleration along the x, y, and z-axes and also on the orientation- azimuth, pitch, and roll using the device built-in sensors-accelerometer and gyroscope [1]. Angular projection of phone [15] is shown in Fig. 2.

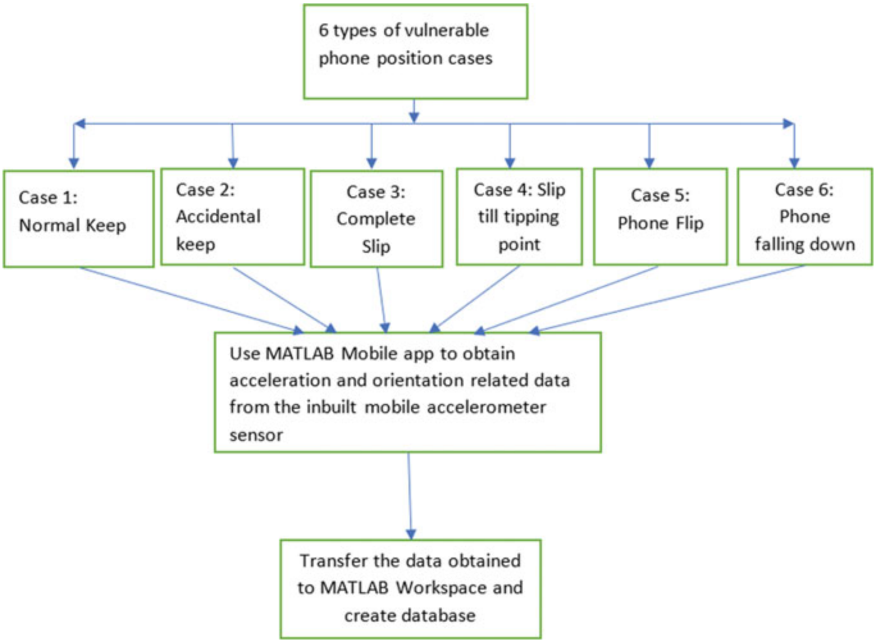

Fig. 1 Phone position cases

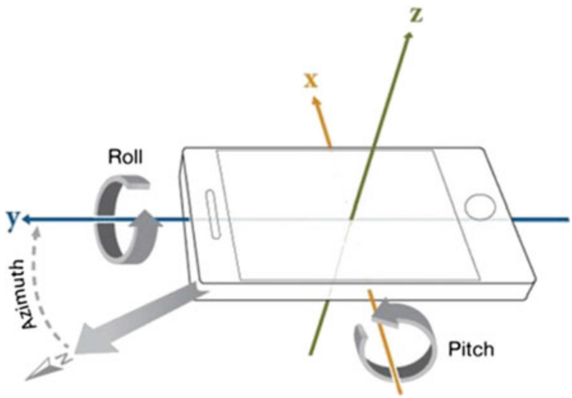

Fig. 2 Angular projection of phone

Figures 3 and 4 show a sample of accelerometer readings versus time and gyroscope readings versus time for the first case—Normal touch along the three axes. The same procedure for the following five cases.

The data obtained from the phone was made into a database for further use. This database was subjected to various feature extraction procedures. As a result of which, necessary and important features were obtained.

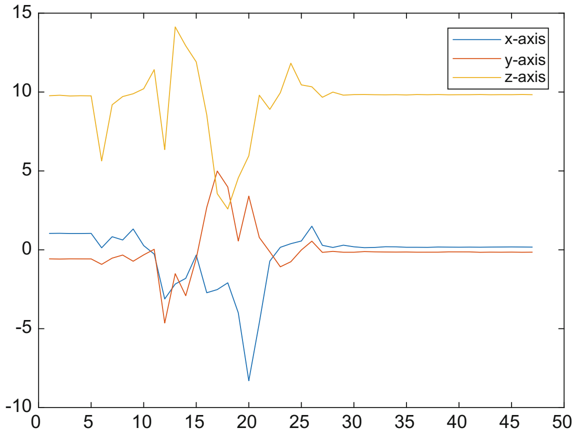

Fig. 3 Normal touch keep-accelerometer reading

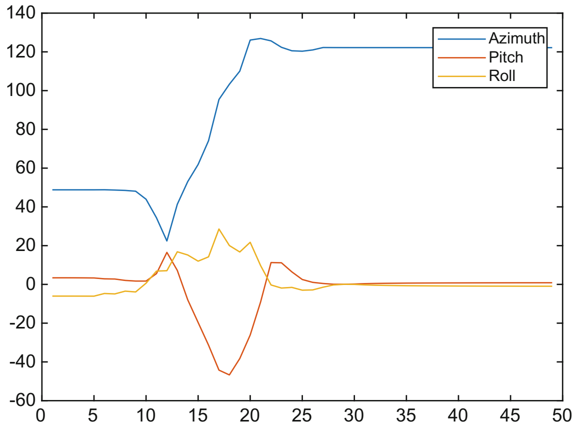

Fig. 4 Normal touch keep-gyroscope reading

3 Feature Extraction

One of the main objectives is the extraction of various features from the created database of different phone slipcases. From the samples, the required features and parameters are extracted for further classification purposes. The vast database was transformed into a set of reduced set of features. The various feature extraction used are as follows

- Mean—the average value of the magnitude of the various acceleration values and orientation values for each sample of various cases was taken for the different three axes.
- Variance—the average of the squared difference of the sample values from the mean value which is taken independently for each of the three axes.

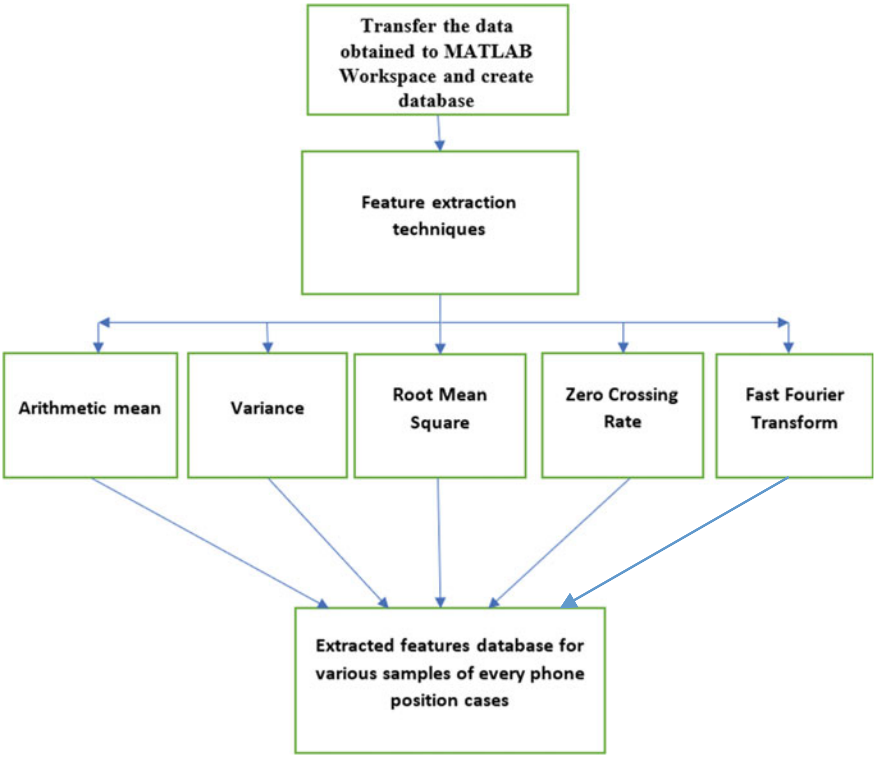

Fig. 5 Feature extraction process

- Root Mean Square (RMS)—the square root of the sum of different sample values was taken independently for each of the three axes.
- Zero crossing rate (ZCR)—the number of times acceleration samples change from positive to negative and back is calculated.
- Fast Fourier transform (FFT)—the first five of the fast Fourier transform coefficients of the various acceleration samples for the three axes are taken.

From the database created, the total number of acceleration related features and the orientation related features extracted from a sample of each case along all the three axes combined was 54. Figure 5 shows the feature extraction process [16].

4 Creation of Extracted Feature Database

After extracting the necessary features from the various samples, the features were arranged based on the samples values for different phone slipcases [17]. The features were also arranged in a manner where all the features for all samples for one particular case were put together. To check the validity of the feature database created, the concept of correlation was used. It was checked if the correlated value tended to 1 or 0 when different samples of same phone slipcase were considered. This was done to check that all the sample value for each case were similar to each other or not and to check if the samples value for different cases were not similar to each other.

5 Results and Discussions

In our paper, six phone slip cases were considered, namely normal touch keep (A), accidental keep (B), complete slip (C), slip till tipping point (D), flip (E), and fall (F). The extracted feature database was created and it was subjected to various classification algorithms were used to classify these cases. The number of training and testing feature has been presented in Table 1.

We used four major neural network classifiers to observe the results, they are Feedforward [18], Pattern NET, Fit NET, and Cascade NET. Pattern Recognition network uses the basic neural network for grouping or classifying the patterns present in the dataset. In this paper we used pattern recognition for classifying the pattern among different slipcase and training has been done by proving predefined targets in a supervised way. Fitness network is basic feedforward network which uses a genetic algorithm to tune the learning parameter, this network can be used for solving both regressions as well as for classification. Here it is used for classification purpose by providing 70% data for training and the rest 30% for testing. In Cascaded Neural Network, each layer neurons are interconnected with its preceding, succeeding, and input layer neurons which produces confined outputs since the network has number of weights due to more interconnection neurons, the memory and time required for training are comparatively higher than other networks.

The total features extracted from all the samples in every case is 6480. The total testing and training features are 1944 and 4536 respectively as shown in Table 1. The results obtained after implementing these neural networks on the extracted features are summarized in classification performance table (Table 2). In Table 2, the various neural network was implemented on pairs of the phone slipcases and the classification accuracy in percentage was observed. Then, for the particular neural network, the average of classification percentages was calculated to indicate which of the neural network can classify various phone slipcases. Also, the average of the classification

Table 1 Feature split up table

Total case	6
Total features	6480
Training features	4536
Testing features	1944
Samples/case	20

Table 2 Classification performance

Cases	Pattern Net (%)	Feedforward (%)	Fit Net (%)	Cascade (%)	Average on cases (%)
AB	66.67	58.33	41.66	58.33	56.247
AC	66.67	66.66	50	58.33	60.415
AD	91.66	50	50	75	66.665
AE	83.33	50	50	58.33	60.415
AF	100	50	58.33	50	64.582
BC	66.66	50	41.66	41.66	49.995
BD	75	58.33	41.66	58.33	58.330
BE	58.33	58.33	50	66.66	58.330
BF	58.33	50	50	58.33	54.165
CD	73	41.66	50	41.66	52.080
CE	83.33	41.66	50	50	56.247
CF	58.33	50	50	41.66	49.997
DE	50	50	41.66	58.33	49.997
DF	58.33	41.66	41.66	66.66	52.077
EF	58.33	58.33	50	50	54.165
Average	69.998	51.664	47.775	55.552	56.247

percentage for each sample after implementing in the various neural networks were calculated to identify which phone slipcase can be easily classified. From Table 2, it can be inferred that the classification accuracies in percentages among various pairs of the phone slipcases is maximum when pattern net neural network is employed because the classification percentages for a particular pair after employing every neural network is maximum in Pattern Net and the average of the classification percentages for various cases is maximum in Pattern Net. Moreover, the recognition on AD shows more than average results when compared to other cases due to high accuracy rate in Pattern Net. The highest 100% accuracy can be found in Pattern Net on AF samples since cascaded Net show 25% lesser than AD the average on cases reduces by 2.083 units. In some case like DF, BE, and DE, Cascade Net performs better than the other networks with accuracies of 66.66%, 66.66%, and 58.33% respectively. Finally, the overall ranking of four networks has been given as 1-Pattern Net, 2-Cascade Net, 3-Feedforward Net, and 4-FitNet. Since Fit Net has learning factor in both neural net and GA, therefore, the accuracy of the Fit net can be increased by increasing the training samples.

6 Conclusion

From the results obtained, we can conclude that after employing the Pattern Net on the extracted features, the classification accuracies for different pairs of the phone slipcase is maximum and also, on the whole, the average classification accuracies for pattern Net for all the cases is maximum (69.998%). Therefore, it can be concluded that out of the four used neural networks, the Pattern net can more efficiently classify various phone slipcases so say if a particular phone slip position is vulnerable or safe.

In future, we plan to improve our phone slip recognition system in several ways. First, the efficiency of the project can be improved if it can classify various complex phone positions. Second, various additional and more sophisticated features can be extracted from various samples of different chosen cases to improve the classification accuracy. The work presented in this paper is a part of a larger effort to classify various phone positions into vulnerable and safe positions. Mobile phones are becoming increasingly advanced and the inbuilt sensors present in them can be configured in a way to identify if the phone is in a vulnerable position to fall or it is in a safe position.

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