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AN INVESTIGATION OF HUMAN ACTIVITY RECOGNITION USING SENSORS IN SMARTPHONES

Durgaprasad Gangodkar[1], Devesh Pratap Singh[2], Dibyahash Bordoloi[3]

[1]Department of Computer Science & Engineering,Graphic Era Deemed to be University, Dehradun, Uttarakhand India
[2]Department of Computer Science & Engineering,Graphic Era Deemed to be University, Dehradun, Uttarakhand India
[3]Head of the Department, Department of Computer Science & Engineering,Graphic Era Hill University, Dehradun, Uttarakhand India

ABSTRACT

Mobile devices can be used for data mining applications since they are user-friendly and integrate many potent sensors. As computer technology is developing quickly, this connection between humans and computers is becoming a research area. These sensors include acceleration sensors as well as vision, audio, light, temperature, direction, and GPS sensors. In this work, we discuss the use of accelerometers in Android mobile devices and computers for handwritten digit gesture identification, as well as an overview of current hand gesture recognition systems. Challenges of the gesture system are addressed together with key difficulties of the hand gesture recognition system. Additionally, review techniques for current gesture recognition systems are provided.

Keywords: Hand Gesture, GPS, Human Computer Interaction (HCI).

INTRODUCTION

The creation of a human-computer interface using gestures that may be utilised to convey meaningful information is the main objective of hand gesture recognition system development. The percentage of disabled people in India is rising daily in both urban and rural areas. Writing is a difficult activity for those who are physically disabled, elderly, or paralysed. Therefore, our product functions as a gadget that can read handwritten digits written in gestures, enabling disabled, elderly, and paralysed people to communicate meaningful messages just by making a few gestures. For gathering the data required by a gesture recognition system, various approaches have been suggested.

To extract gesture features, other techniques required additional hardware such as MEMS accelerometer sensors, RF transmitter receivers, microcontrollers, data glove devices, and colour markers. There are further techniques that segment the hand and extract the required elements based on the appearance of the hand and the skin tone. Comparing our methods to the ones above, they are thought to be simpler and less expensive. In other reviews, the applications of gesture recognition systems were discussed, including how important they are to human computer interaction (HCI), robot control, games, and surveillance. In this work, we show the development of gesture

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recognition systems through a discussion of the various steps needed to construct a whole system with high accuracy and low cost utilising various algorithms. The literature review describes a number of survey works on gesture recognition that use various methods. We intend to describe current developments in gesture detection using mobile sensors in this study. The five primary phases of the suggested gesture recognition algorithms are signal capture, signal pre-processing, feature extraction, feature selection, and recognition with a final conclusion.

The topic of gesture recognition has undergone substantial research in the past, which is briefly discussed in this chapter. Recent research has concentrated on the creation of digital pens with accelerometers enabling handwritten digit gesture identification. Time-series acceleration signals can be converted by the technique into significant feature vectors.

[2] explains and assesses a system that identifies a user's physical activity by using the accelerometers in phones to carry out activity recognition. An accelerometer-based pen gadget is presented in [3] for use with online handwriting recognition applications. The tri-axial accelerometer, microprocessor, and RF wireless transmission module make up the accelerometer-based pen device. With no spatial restrictions, users can write digits in the air while holding the pen instrument. The accelerometer built inside the pen gadget produces the accelerations caused by hand motions, which are then wirelessly transferred to a personal computer for additional signal processing. Then, in the training stage, a dynamic temporal warping (DTW) technique is used to align the accelerations and seek class templates for every digit. Finally, the alignment with the class templates during testing can be used to identify accelerations.

[6] discusses a research in which a very accurate SVM classifier is developed utilising just one training example per class. This approach improved accuracy on 1 training example per class by 14% during preprocessing, and the addition of axis-wise Simple Fourier On one training sample per class, transform coefficient features increased accuracy by 5%. Our classifier achieves 96% accuracy using 5 gesture classes, 1 training sample for each class, and 30 test instances for each class. The classifier achieves 98% accuracy with 5 training examples for each class, which is higher than the accuracy of earlier HMM-based efforts with 10 examples. As a result, it is possible to execute accelerometer-based gesture detection in real-time and identify user-defend movements with high accuracy while requiring little user training.

[7] suggested a method for activity recognition that consists of five key components. Data gathering, segmentation, feature extraction, and classification are all done while an Android application is being created. Users construct and develop their own applications in order to create an application. The raw data for walking, running, and standing still are taken independently during data collection by turning on the app on the phone and placing it in a shirt pocket or a trouser pocket. Every 20 second period, raw data is obtained. A buffer register is initialised to store the data gathered during feature extraction. The x, Y, and Z axes of the buffer will first be initialised with zero data. Arrays are used to store the data. It may be possible to extract features for the data collection. The mean, standard deviation, maximum value, and minimum value are among the temporal domain characteristics. The FFT analysis of the data can be used to compute frequency domain features. In order to classify activities like standing, moving around, and running, it is necessary to repeatedly observe each action while setting a threshold frequency value that corresponds to the activity's

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maximum amplitude level. In the training step, the activity is fixed by comparing the frequency point corresponding to the maximum amplitude with the threshold value. The activity will be appropriately categorised during testing.

PROPOSED WORK

As per discussed above methods of gesture recognition, to capture acceleration signals generated by hand motion of different gestures, requires various different hardware like MEMS accelerometer based digital PEN or hand gloves. Acquisition of signals required RF transmitter and receiver module which increases the cost of project. Our paper represent a technique with zero cost by simply using android mobile which is capable of both sensing and transmitting the signal. Further processing is as follows.

A. Hardware and Software Platform

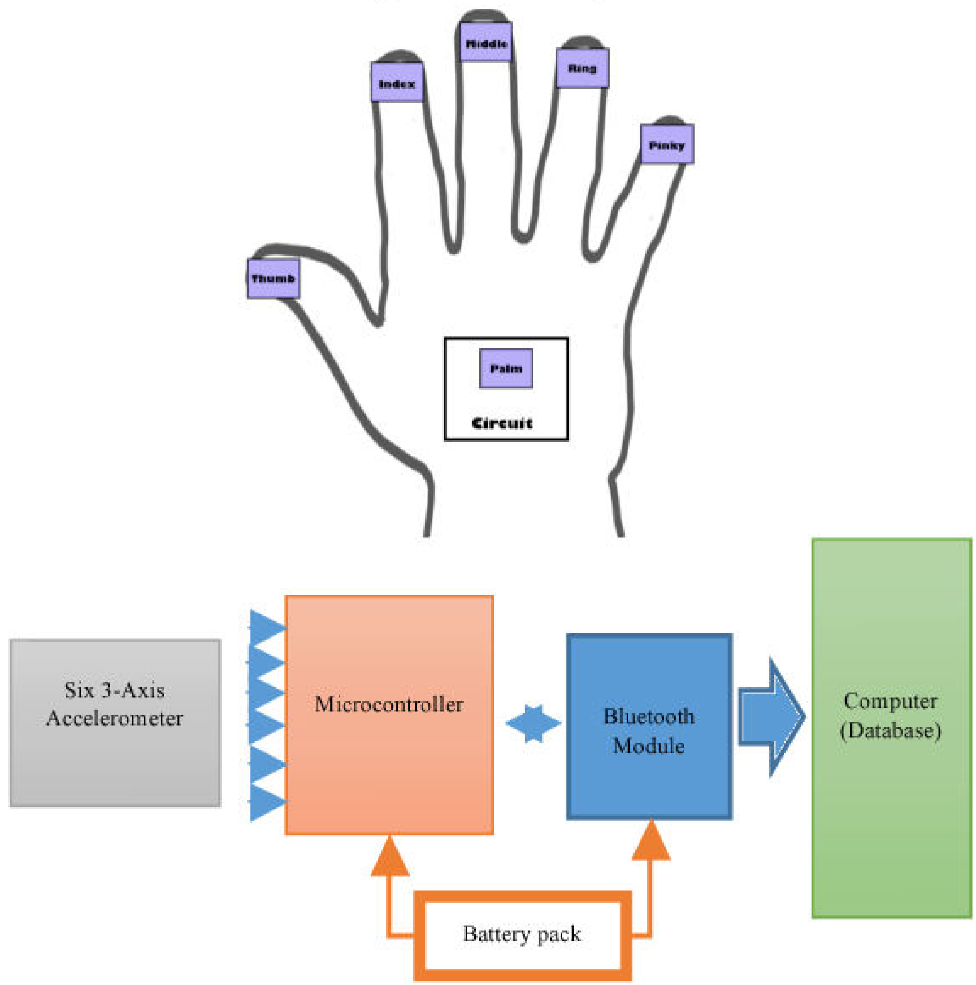

Fig. 1. System overview

Figure 1: proposed system for gesture recognition

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Acquisition of Input Signal

Mobile phone MEMS accelerometers are able to determine the device's orientation, which can be useful information for trajectory recognition. It has been suggested to use sensors to detect or record the acceleration signals produced when writing trajectories. Mobile phone-generated acceleration signals are communicated to computers via the appropriate interface.

Signal Preprocessing

The fact that our palm always trembles a little bit when moving introduces noise into the raw acceleration signals. In order to extract the accelerations induced by hand motions, the calibrated acceleration signal is first subjected to a high-pass filter in order to remove the gravitational acceleration. This is done in the second step of the signal preprocessing.

Feature Extraction

In the method for activity recognition, we take features out of the acceleration signal produced by hand movements. Both the frequency and temporal domains are used to extract characteristics. Both time-domain and frequency-domain features can be used to describe something.

Time-domain attributes

1. Mean: Each segment's value for each dimension is represented by the mean feature.

2. Max, Min: Each segment's value for each dimension is represented by the maximum and minimum features.

3. Variance/(STD)Standard deviation measures the degree of dispersion of a data set.

4. Correlation: The acceleration values are correlated between each pair of axes.

Frequency-domain characteristics

The periodicity of the signal is described by frequency-domain characteristics, which are commonly computed using the FFT.

1. Power

The sum of the discrete FFT component magnitudes squared is used to calculate the energy feature.

Classifier

The gesture is recognised using the gesture classification approach. The right choice of feature parameters and a good classification method have an impact on the recognition process. The testing signals' feature values and feature data base values are classified by a classifier, which then produces an output. Unsupervised learning and supervised learning were generally the two primary learning methods used in classifiers. In supervised learning, classifiers only train on labelled data; however, training on unlabeled data is challenging, costly, and time-consuming since it requires human expertise. On the other hand, there is no supervisor in unsupervised learning to teach classifiers to label the data. In this approach, the classifier only uses unlabeled input to categorise the data based on some shared characteristics. The classification process is carried out in two steps during self-training. In order to predict the labels of unlabeled data, the classifier must first be trained on known data. The training set with estimated labels is supplemented with the unlabeled data with high confidence scores, and this cycle is repeated until convergence.

In this study, we provide Probabilistic Neural Networks, another iteration of the Help-Training technique. Following classification using a PNN classifier, the signal is compared to the gesture's stored feature data, and if a match is discovered, the corresponding digit is shown.

CONCLUSION

Gesture recognition is useful for both sign language recognition, a modern application that is in high demand, and human-computer interaction. As these techniques suffer from a number of conditions like additional hardware which includes transmitter, receiver hand glove like devices which makes it expensive, various methods for gesture recognition are discussed in this paper by multiple writers. These techniques include accelerometer based digital pen like device and hand glove based gesture recognition technique. Since our solution is more affordable than the alternatives, To improve gesture recognition accuracy, we utilise a suitable classifier. Issues with gesture recognition are explained, and recent recognition systems are thoroughly discussed.

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