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Human Demeanor Assimilation Using Deep Learning

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ABSTRACT : This paper involves in predicting the movement of a person based on sensor data and traditionally involves deep domain expertise and methods from signal processing to correctly engineer characteristic from the raw data in order to fit machine learning model. Recently deep learning methods such as convolutional neural networks and recurrent neural networks have shown capable and even achieve state-of-the-art results by automatically learning feature from the raw Sensor data .In this paper,you will discover the problem of human demeanor assimilation and the deep learning methods that's are achieving state-of-the-art performance on this problem.

KEYWORDS: Deep learning ,Machine learning ,Sensor data, Neural network ,Signal processing.

I. INTRODUCTION

Human Activity Recognition and Analysis deals with the recognition of certain human activities and certainly manipulating the recorded data to check the fitness. Activities such as walking, running, jogging are some of the physical activities that a person performs in his day to day lives. Our Hardware is able to record the data for such activities. Later the recorded data is manipulated for certain purposes that we have described in our complete project work. The synergy of communication, computation and sensing capabilities in mobile systems-on-chip devices such as smartphones has made possible the development of wearable smart sensor systems for user activity monitoring and recognition. A human activity hierarchical recognition system without using the smartphone to be constrained to a single fixed position is presented. It is worked based on neural system. Experimental results on Android-capable smartphones on four on-body locations show that the recognition system achieves high classification rates, above 92%, for five activities including slow walking, fast walking, jogging, and up-down stairs walking, which outperforms other proposals.

II. SYSTEM DESIGN

In this section it is used to describe the step by step process of how to discriminate between different activities using the acceleration data collected from a smartphone. First, we need to collect the data. Then we analyze the data to extract informative features. Finally, we use these data for training to build a model based on the selected features and validate it.

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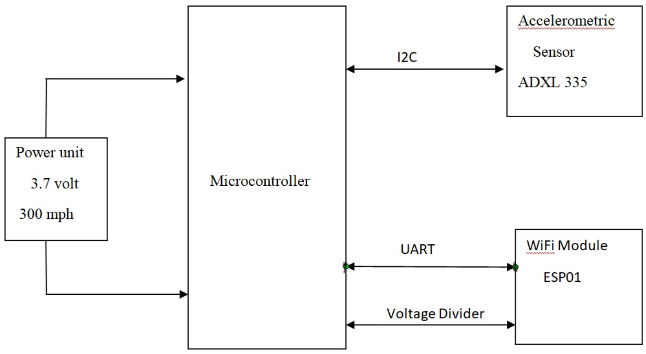

Fig -1: Block Diagram

2.1 ARCHITECTURE DIAGRAM:

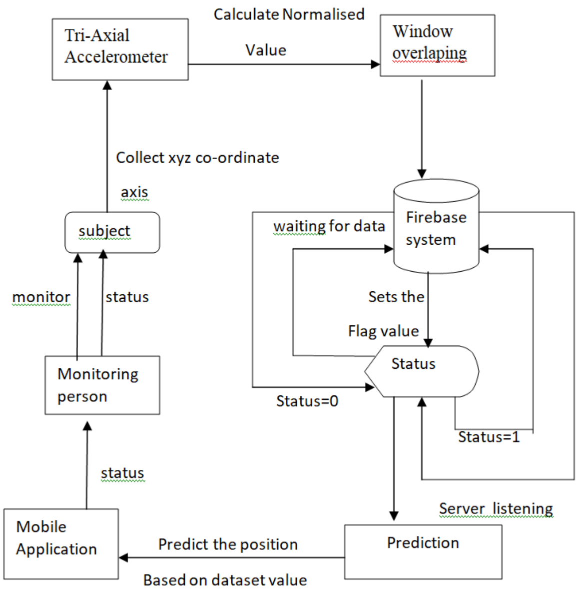

Fig -2: Architecture diagram

III. MODULE DESCRIPTION

3.1. Data Collection

Tri axial accelerometer is used to collect data in the Android phone to measure acceleration. Data from this accelerometer includes the acceleration along the x-axis, y-axis and z-axis. These axes capture the horizontal/sideway movement of the user (x-axis), upward/downward movement (y-axis), and forward/backward movement (z-axis). Figure 1(a) demonstrates these axes relative to a user.

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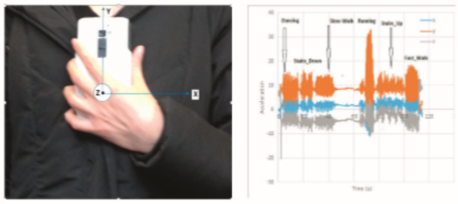


(a) (b)

Figure 3.1.(a) Android smartphone with a built-in accelerometer and its axis directions. Figure 4.1(b) A subject's tri axial accelerometer data over time in different activities

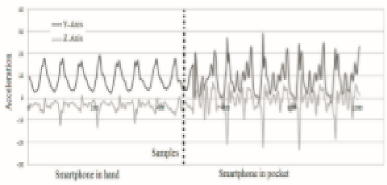


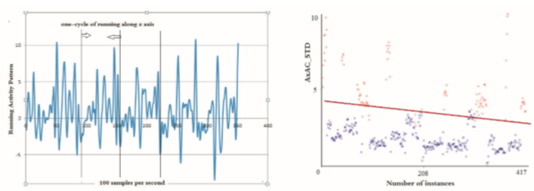
Figure 3.2 Sample acceleration signals for walking (performed by an identical subject) with the smartphone in two different position. our subjects, two male and two female between 29 to 33 years of age, volunteered to participate in this research study.

These subjects, each carrying a cell phone, performed all the six activities:

- Running: The user is running,
- Slow-Walk: The user is walking with slow pace,
- Fast-Walk: The user is walking with fast pace,
- Aerobic Dancing: The user is moving rhythmically,
- Stairs-Up: The user is going up a staircase, and Stairs-Down: The user is going down a staircase

3.2 Feature Extraction

To extract descriptive features for the four time series obtained in the previous section, we apply a technique of window overlapping .The accelerometer data along the z-axis for each of the six activities. All activities exhibit periodic behaviors but with distinctive patterns. We can take advantage of their periodicity to calculate features from consecutive windows with certain size.



(a) (b)

Fig. 5. (left): A few cycles of acceleration data along z-axis (forward) for Running; (right): AxAC.STD is the standard deviation of the AC component of acceleration along x-axis. This feature can distinguish the two clusters.

3.3. Feature Evaluation

Feature creation is a critical step in the development of any classifier. this system need not solve the classification task on raw acceleration data. Generally after an informative data representation is created in terms of feature vectors,it performs the classification. In our work, the accelerometer generates three time series along x-axis, y-axis and z-axis, denoted by AX, AY and AZ ,respectively. Each time series combines the linear acceleration due to body motion and due to gravity. We propose a digital low pass filter in order to separate the AC component from the DC component in each time series. The high frequency component, the AC component, is mostly related to the dynamic motion the subject is performing such as walking or running. On the other hand , the low-frequency component of the acceleration signal, the DC component, is

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mainly tied to the influence of gravity. Setting the cut-off frequency to 0.25Hz, our low pass filter is calculated as follows: ADC[n] = a1A[n]+b1ADC[n−1],where ADC is the filtered output data and A is the raw input data(AX, AY, AZ). The filter coefficients a1 and b1 are constants that are computed using sampling rate and cut off frequency. The optimal cut off frequency in order to exclude gravity component alone would range from 0.1 to 0.5 HZ12.

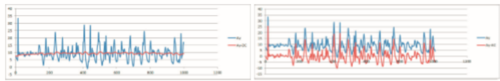

Fig. 3. Low pass filter (top figure) results in a signal containing only the gravitational acceleration, high pass filter (bottom figure) results in a signal containing only the body acceleration.

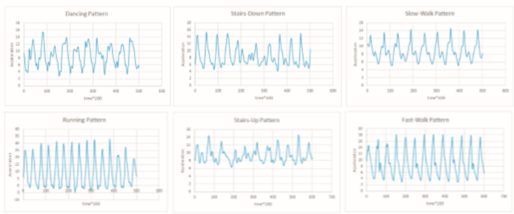

Fig. 4. Acceleration plots for the six activities along the z-axis that captures the forward movements. All six activities exhibit periodic behavior but have distinctive pattern. Running and Fast-Walking exhibit similar patterns.

3.4 Interfacing microcontroller with accelerometric sensor

In I2C for each byte, the receiver has to send the acknowledgment , which is a proof that data is properly received by the receiver to continue the communication. The communication has to be started by the master to assert a start condition on the bus. After transmission of the condition,the master send a 7-bit address with associated a read or write bits. Then master release the data lines to put the data line (SDA) in high impedance state, which permit the receiver to give the acknowledgment. If this transmitted addresses have matched with any receiver which is connected then it pulls down the SDA lines low for the acknowledgment and after the acknowledgment, it releases the data lines. The master produces a clock pulse to read this acknowledgment bit and continue the read or write operation. If this transmitted address is not matched with any receiver then nobody can pull down the data lines low, automically master understands it is a NACK and in that situation, master establish a stop bit or repeated start bit for further communication.

Figure 3.4 Serial clock diagram of I2C protocol

3.5 Client Server Interaction

It uses the Hand Shaking algorithm to transfer data from device to server. Embedded system sends a weight signal which indicates the status flag of the human posture to the server.

3.6 Mobile Application

The current status of the person to be monitored is viewed by mobile application. As it is connected through the internet, it can be used by anyone irrespective of the distance.

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IV. CONCLUSIONS

- We have successfully collected the data through hardware.
- Implemented appropriate visualisation of the collected data.
- Filter chosen correctly filters out the noise in the channel and noise due to gravitational acceleration.
- The used time-window correctly compares the data.
- Expected feature analysis has been successfully implemented.(peak detection)
- Expected performance outcome has been achieved.
- An easy access GUI has been created.
- The developed system can classify the activities like sitting, jogging and walking.
- An informative message with percentage about the overall fitness can be made.
- We have ultimately reached our basic aim of the project to classify and analyse the different human
- activities and to produce performance result using the GUI.

V. FUTURE ENHANCEMENTS

Since we are maintaining separate firebase for storage purpose, the processing speed exceeds. We are planning to enhance it further by storing all the collected data in microcontroller itself.

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