Human Activity Recognition using Embedded Smartphone Sensors

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Abstract – *Nowadays, everyone has smartphones and everyone is becoming health conscious. Smartphones have embedded sensors. One such sensor, the accelerometer, gives values in all 3 dimensions and these values can be used to recognize the activity being performed. We are applying machine learning to a dataset of acceleration values and training a classifier to recognize activities in android smartphone. We are using KNN algorithm for classification which gives 94% accuracy on the test set We are using this activity recognized to calculate calorie count. We have designed a real-time, offline activity recognition system for Android.*

Key Words: Accelerometer, Android Application, Embedded Sensors, Human Activity Recognition, KNN, Smartphone,

1.INTRODUCTION

Smartphones have become ubiquitous. They have various sensors embedded in them like accelerometer, gyroscope, light sensors, proximity sensors and so on. The values from the accelerometer can be used to detect activity being performed by the user. The accelerometer values for different activities exhibit a specific pattern. We have trained a classifier to recognize these patterns. We have used KNN (K-Nearest Neighbours) Algorithm using three nearest neighbours. We are currently detecting sitting, standing, walking, sleeping and jumping with an accuracy of 94%. We can train the model to recognize more activities. HAR has applications in healthcare, monitoring, and user identification. We are developing the application for healthcare where we are calculating calories burnt based on the activity recognized.

2. LITERATURE REVIEW

Paper 1: [1] An unconstrained activity recognition method using smartphones.

This paper provides human activity recognition performance rates, using accelerometer and gyroscope signals acquired using smartphones. Covering seven basic actions which are walking, running, jumping, standing, ascending stairs, descending stairs, and standing up and sitting down as one action and a complex action getting in and out of a car, with more than 100 subjects in a database collected in different environments. K-star algorithm is used with 6 classifiers which give 98% accuracy for the activity recognition.

Paper 2: [2] Basic Human Activity Recognition Based on Sensor Fusion in Smartphones.

The paper suggests that recognition performance of accelerometer, gyroscope, and magnetometer when used separately and simultaneously on a feature-level sensor fusion is examined to gain valuable knowledge that can be used in dynamic sensing and data collection. Six ambulatory activities, namely, walking, running, sitting, standing, walking upstairs and walking downstairs, are inferred from low-sensor data collected from the right trousers pocket of the subjects and feature selection is performed to further optimize resource use.

Relief f algorithm is used for feature extraction. Decision tree and k nearest neighbor algorithms are used for classifications. The paper shows that k nearest neighbor algorithm is giving best result when compared with decision tree.

Paper 3: [3] MobiRAR: Real-Time Human Activity Recognition Using Mobile Devices.

This paper shows MobiRAR, a real-time human activity recognition system using mobile devices. The system utilizes the acceleration sensing data from the accelerometer commonly instrumented in mobile devices such as smartphones or smart watches. Activity recognition system includes four steps data processing, segmentation, feature extraction, and classification. In this paper 10 everyday activities including unknown activities collected from 17 users. Two classifications algorithms-HMM (Hidden Markov models) and Decision tree algorithm are used for activity recognition.

3.SYSTEM OVERVIEW

Our system is an android application which continuously recognizes current activity being performed and calculates metrics such as calorie count and step count and sets phone modes accordingly. The classifier model file is imported and current values taken by the embedded accelerometer in the smartphone are classified. The calorie count and step count are calculated and calorie count is synced to the server once every day for report generation and history maintenance.

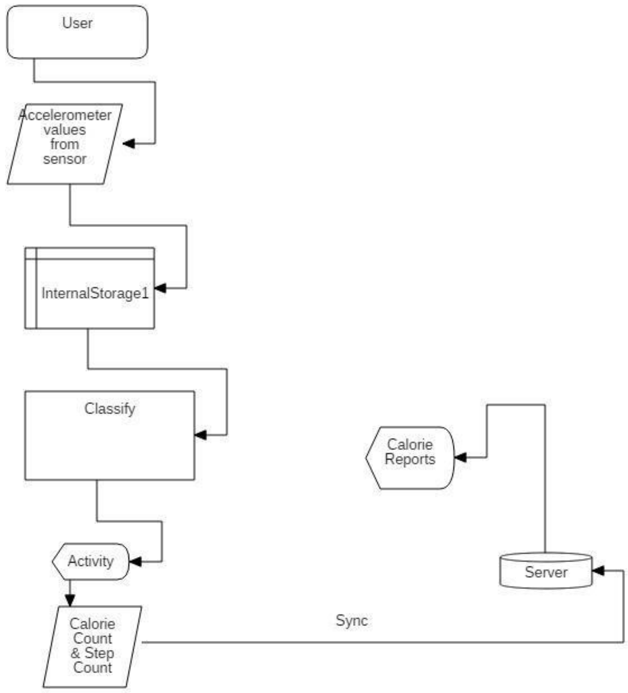

Fig -1: System Flow

4. DATA ACQUISITION

The dataset is created by 4 users (2 male, 2 female) each recording every activity for 30 seconds. Our dataset consists of 8000 instances and 5 attributes. The data is taken when keeping the phone in the front right pocket of pants. The dataset records triaxial accelerometer values (values of x, y, and z-axes), one feature and label. We are generating magnitude feature which is:

$M=\sqrt{a*a+b*b+c*c}$

Where:

M=Magnitude (feature)

a= x-axis value of accelerometer

b= y-axis value of the accelerometer c= z-axis value of accelerometer

5. METHODOLOGY

5.1 Training the classifier

The classifier is trained using the generated dataset. The algorithm used is KNN with three nearest neighbors. The classifier is trained using weka java API (version 3.6). Ibk () classifier function in weka is used for KNN classifier. The classifier is tested on a test dataset of 376 instances and gives 94% accuracy. This classifier is exported using weka Serializationhelper and a ". model" file is generated.

5.2 Getting Sensor Values

Sensors in android can be accessed by using Sensor Event Listener Interface in android. The current values are taken and magnitude is generated and this data is written to a file "accelerometer.csv" stored in the phone's internal storage.

5.3 Recognizing Current Activity

The model file is stored in the assets folder in the android project directory. It is imported using Asset Manager class in Android. The model file is imported and the data from "accelerometer.csv" is read and converted into an instance. This instance is given to imported classifier and appropriate activity is displayed.

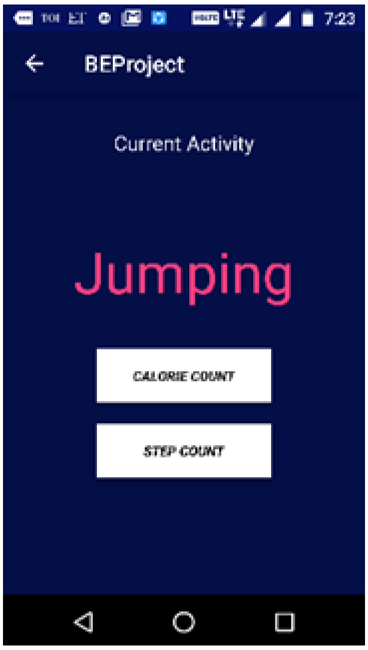

Fig -2: Output Screenshot

5.4 Calorie Count

Every activity has a MET (Metabolic Equivalent) value[4]. This value, along with a person's weight can give the value of calories burnt during an activity.

Cal=MET*wt

Where:

Cal=calories burnt per hour MET=metabolic equivalent wt=weight of user

We are accessing sensor 5 times each second. So, calories burnt for each activity recognized can be given by.

Cal= MET*wt/5*60*60

The MET value is 1 for sitting, 0.9 for sleeping, 12 for jumping.

Fig -3: Calorie Count Output

5.5 Step Count

StepCounter sensor is present in the smartphone which counts the steps taken by the user. For continuous tracking steps of the user, do not unregister it. So, it continuously keeps counting steps in the background even when the app is suspended.

Fig -4: Step Count

CONSTRAINTS

The phone should be in the right pocket. The user should have an Android smartphone.

6. RESULTS

The current activity is being correctly recognized and displayed. Calorie count and step count is being correctly displayed. The accuracy for classification is 94% and step count and calorie count are also fairly accurate. The application fulfills all its objectives

```
Correctly Classified Instances         356               94.6809 %
Incorrectly Classified Instances        20                5.3191 %
Kappa statistic                          0.9232
Mean absolute error                      0.0228
Root mean squared error                  0.13
Relative absolute error                  8.2041 %
Root relative squared error             34.9431 %
Total Number of Instances              376

=== Detailed Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall   F-Measure   ROC Area
Class
                 0.71      0          1          0.71     0.83        0.857
sit
                 1         0.033      0.942      1        0.97        0.992
stand
                 0.935     0.013      0.979      0.935    0.957       0.986
walk
                 1         0.006      0.917      1        0.957       0.999
sleep
                 0.974     0.021      0.844      0.974    0.905       0.996
jump
Weighted Avg.    0.947     0.019      0.951      0.947    0.946       0.979

=== Confusion Matrix ===

   a   b   c   d   e   <-- classified as
  22   3   2   2   2 |   a = sit
   0 131   0   0   0 |   b = stand
   0   5 143   0   5 |   c = walk
   0   0   0  22   0 |   d = sleep
   0   0   1   0  38 |   e = jump
```

Fig -5: Accuracy

7. CONCLUSION

Our application recognizes the activity in real time without requiring a client-server connection. The activity is recognized and displayed on the phone itself. Hence, we have designed a real-time, offline activity recognition system. The accuracy we are getting is acceptable and real-time activity is being displayed. Thus, we have used KNN algorithm to perform machine learning on our dataset and we have designed a cost-effective and real-time system.

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