CORREDOR, A mobile Human-Centric Sensing System for Activity Recognition

Luis G. Jaimes* and Idalides J. Vergara-Laurens†
* College of Science, Engineering, and Mathematics, Bethune-Cookman University, Daytona-Beach, FL, 32114
Email: jaimesl@cookman.edu
† Department of Electrical and Computer Engineering - Universidad del Turabo, Gurabo, Puerto Rico, 00778
Email: ivergara@suagm.edu

***Abstract*— This paper presents Corredor, a human-centric-sensing system that encourage people's physical activity. The main objective of Corredor is to help people, that suffer obesity, during their workout as part of their treatment. Corredor uses phone's embedded sensors along with machine learning algorithms to recognize human activities such as running, walking and standing. Corrredor runs enterally in the user's phone and does not require any external server processing. In addition, Corredor displays on the screen the followed route by the user, indicating the segments where the user was running, walking or standing. The system computes a set of 64 features from real-time accelerometer data using a 5 seconds sliding window with 50% of overlapping. The computed features are used to train a C4.5 decision tree which in turns is used to recognize workout activities. After system evaluation, our results show that Corredor achieves up to 93.7% overall accuracy. Finally, the application saves the historical data and is able to show them using Google Maps.**

I. Introduction

Advancements in pervasive computing are rapidly changing preventative healthcare. Under the status quo, the average healthy individual visits the doctor rarely, perhaps just once a year. The doctor assesses the patient and then may prescribe medications and recommend behavior changes (reduce fat consumption, exercise more, etc.). One year later, the patient returns and this process is repeated. In the emerging new model of health care, the patient carries sensors that monitor health in real-time, as the patient goes about normal daily life [7], [8], [10], [15], [18], [20]. A smart phone and cloud-based services assess monitored data at a much higher frequency (on the order of minutes or seconds, if needed). Here patients play a more significant role in the management of their health. The idea is to build *Personal health systems* which are designed for use by the patient rather than the doctor, and ubiquitous, meaning anywhere-anytime interaction with ones health via mobile devices.

Physical activity is considered a preventive mechanism to avoid and control problems such as obesity and psychological stress. Both are well know issues in public health. Obesity is a leading cause of death worldwide, with increasing prevalence in adults and children. Obesity-related conditions include heart disease, stroke, type 2 diabetes and certain types of cancer. Medical costs associated with obesity were estimated at $147 billion; the medical costs for people who are obese were $1,429 higher than those of normal weight [11]–[14], [21].

Taking these facts into consideration, in this paper, we present Corredor, human-centric sensing system for activity tracking and recognition with application in preventive health. Physical activity is considered a preventive mechanism to avoid and control problems such as obesity and psychological stress. Both are well know issues in public health. The main idea is to employ persuasive and behavioral techniques to keep the patient engaged and motivated to meet health goals.

Corredor is a mechanism that allows people to track their workout progress using smart phones which has potential application in *mHealth*. Given the fact that people use their phones on a daily basis and carry them almost every place, this is an illustrious technology that could potentially help solve this health epidemic. However, the sensor raw data are not sufficient in order to identify people's behavior. One of the key challenges in creating useful and robust ubiquitous applications is context detection from noisy and often ambiguous sensor data [5]. Thus, the proposed mechanism has two stages: the training, and the testing. The first allows the application learn the relation between sensor data and person's activities since different people run and walk in different way generating different acceleration signals [16]. The testing stage identifies person's activities using a feature extraction algorithm in the frequency and the time domains.

Our application allows users to track their running, walking, or standing activities. The system has two modules, the activity recognition module, and the visualization module. The first recognizes, and reports to the user the performed activities and their time duration; while the second module uses the phones GPS and Wifi sensor to collect outdoor and indoor location data, and allows users to track the followed route during her workout showing the segments running, walking and standing. This feature allows users to plan their route in terms of goals during their workout.

The rest of the paper presents the related work to this project followed by the system description, the experimental settings and results. Finally, the conclusions are presented along with some considerations for future research in this area.

II. Related work

The rapid development of mobile devices equipped with very accurate sensors (e.g., accelerometers, cameras, GPS, etc.) has facilitated the process of taking data about individuals and their surroundings. In addition, there are available external sensors equipped with communication capabilities which allow their integration with other mobile devices within Personal Area Networks (PANs) or Body Area Networks (BANs) [16]. For instance, *Scosche Rhythm Bluetooth Armband Pulse Monitor* is a device that measure the heartbeat and transmits it to an Android application; this application monitors the burned calories while the person's workout [9].

On the other hand, human activity recognition has became a useful tool for military, security, and, especially, for medical applications [17]. In this last subject, for example, people suffering of diabetes, obesity, or heart disease often require to be monitored during their treatment.

Although several applications have been proposed for human activity recognition using smart phone, many of them require additional devices such as external straps that the patient must wear in order to sense data. This is the case of *Centinela* which requires the $BioHarness^{TM}$ BT chest sensor strap manufactured by Zephyr [4]. On the other hand, there exist several options in the android market that track a users exercise and running routine. A few of the most well known products are Nike+ [2], Runkeeper [3], and Ghost Race Pro [1]. However, within these applications, the user is required to manually activate and specify the insensitive level of activity. Our proposal is different because it introduces online activity recognition. This recognition technology is unique in the fact that is activates automatically. The commercial devices available today are required to be manually turned on. Some advantages of this approach include convince, accuracy and privacy.

III. System description

We design an android application that allows the users to track their running, walking, or standing activities. Users can chose whether to manually input data or to use automatic recognition module. These tasks can be used all day long automatically or manually activated, see Figure 1.

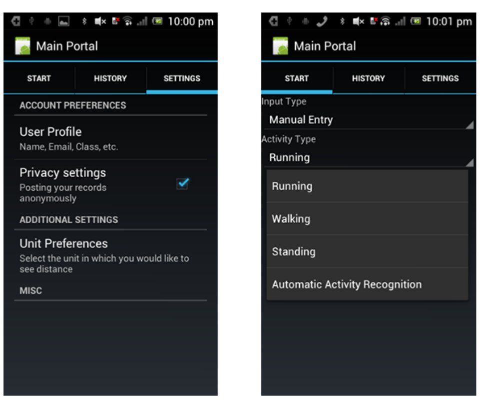

Fig. 1. Main Portal

The system is organized in two main modules, the activity recognition module, and the visualization module. The Corredor's activity recognition module is in turns subdivided in the three two modules: collector module and the classification module. The collector application collect ground true data, which is used by the tester module to build the classier that will be used later for activity recognition. The visualization module uses the phone's GPS and Wifi sensor to collect outdoor and indoor location data. This data is stored in the phone's database and presented to the user using the Google Maps API. Figure 2 shows the Corredor's main modules and and their interrelationships. The following are the main elements of the Corredor.

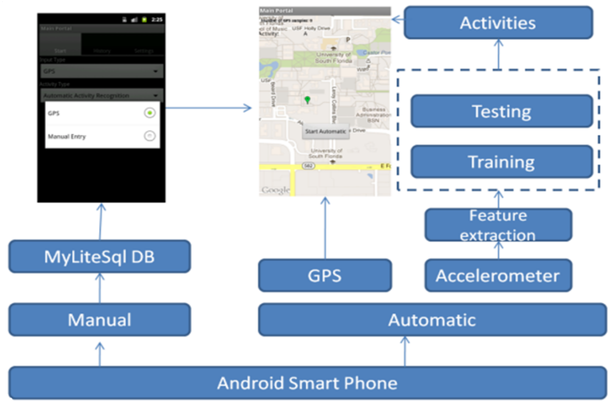

Fig. 2. System architecture

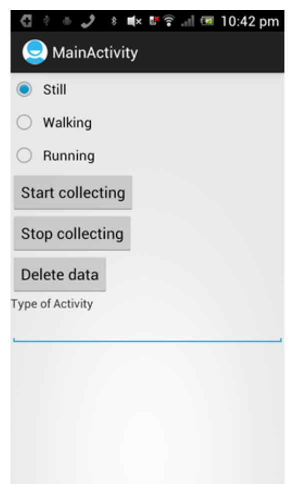

Fig. 3. Collector application

A. Data collection

We created an Android application for data collection, the application uses the phone's accelerometer sensor for activity recognition, and GPS for visualization. We collect the three values associated with accelerometer data, namely the axes x,y, and z at a sampling rate of 50Hz. On average, sensor values were received every 5-10 ms. The data ground true collection was performed by a single individual for running, walking, and still. For running and walking, the phone was held in the hand in various positions to simulate possible real-life scenarios. For sitting still, the phone was in the pocket and recorded data during normal desk work. Figure 3

B. Feature extraction

We compute a set of 64 features, 63 in the frequency domain, and one in the time domain. Every time that we obtain a new (x, y, z) acceleration sample we compute its magnitude m using Equation1

$$m = \sqrt{x^2 + y^2 + z^2} \tag{1}$$

We buffer up 64 consecutive magnitudes, namely, $\{m_0, \ldots, m_{64}\}$ and compute the Fast Fourier Transform,(FFT) of each element in order to form a new frequency vector with elements $\{f_0, \ldots, f_{63}\}$. Finally, the last feature corresponds to $max_a = max\{m_0, \ldots, m_64\}$, forming the feature vector $\{f_0, \ldots, f_{63}, max_a\}$.

The data was divided into five-second time windows. We implemented the concept of sliding time windows, which overlapped by 50% as shown in Figure 4. Sliding time windows are widely known to reduce classification error during activity transition.

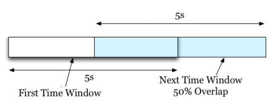

Fig. 4. Overlapping time window

C. Classification

Using the collection mechanism described ins section III-A we build a ground true with label features of three activities as show Figure 5.

```
@attribute fft_coef_0061 numeric
@attribute fft_coef_0062 numeric
@attribute fft_coef_0063 numeric
@attribute max numeric
@attribute label {still,walking,running}

@data
305.271594,43.009646,41.29862,67.64922,82.050948,38.169677,27.971887,10.556445,8.118206,12
.918979,14.185654,13.985737,8.428477,1.820288,3.526609,4.09562,1.477731,1.343103,4.633665,
5.550255,2.387557,2.363167,2.776934,2.826126,2.893059,2.264975,1.591975,2.409471,2.315285,
1.991414,1.821754,2.172002,2.666548,2.172002,1.821754,1.991414,2.315285,2.409471,1.591975,
2.264975,2.893059,2.826126,2.776934,2.363167,2.387557,5.550255,4.633665,1.343103,1.477731,
4.09562,3.526609,1.820288,8.428477,13.985737,14.185654,12.918979,8.118206,10.556445,27.971
887,38.169677,82.050948,67.64922,41.29862,43.009646,13.047676,running
281.934083,5.04772,70.214441,38.493674,23.801889,18.404915,13.740349,5.707672,0.312827,8.0
35266,3.331559,4.18146,1.100968,2.35945,2.793879,0.947144,0.378641,0.699983,1.255413,0.940
252,0.467618,0.290354,0.848083,0.454801,0.550048,0.79154,0.331874,0.650464,0.475031,0.8165
```

Fig. 5. Ground True file

We download the ground true data from the phone and use Weka to build a used the ground true to generate a J48 prune decision three as shown in Figure6

The resulting classifier, namely the jar file is include as a subroutine of the phone application and used along with the FFT subroutine for classification in the production stage as showed in Figure 7.

```
=== Classifier model (full training set) ===

J48 pruned tree
------------------

fft_coef_0000 <= 6.313117: still (249.0)
fft_coef_0000 > 6.313117
|   fft_coef_0000 <= 328.310808
|   |   fft_coef_0017 <= 1.694994
|   |   |   fft_coef_0014 <= 4.16974
|   |   |   |   fft_coef_0002 <= 11.427422
|   |   |   |   |   fft_coef_0016 <= 0.681036
|   |   |   |   |   |   fft_coef_0002 <= 2.110654: walking (2.0/1.0)
|   |   |   |   |   |   fft_coef_0002 > 2.110654: still (3.0)
|   |   |   |   |   fft_coef_0016 > 0.681036
|   |   |   |   |   |   fft_coef_0032 <= 0.137459: walking (3.0)
|   |   |   |   |   |   fft_coef_0032 > 0.137459
|   |   |   |   |   |   |   fft_coef_0008 <= 3.362622
|   |   |   |   |   |   |   |   fft_coef_0000 <= 76.23935: running (3.0/1.0)
|   |   |   |   |   |   |   |   fft_coef_0000 > 76.23935: walking (2.0)
|   |   |   |   |   |   |   fft_coef_0008 > 3.362622: running (8.0)
|   |   |   |   fft_coef_0002 > 11.427422: running (19.0)
|   |   |   fft_coef_0014 > 4.16974: walking (12.0/1.0)
|   |   fft_coef_0017 > 1.694994
|   |   |   fft_coef_0004 <= 46.068704
|   |   |   |   fft_coef_0001 <= 53.625831
|   |   |   |   |   fft_coef_0000 <= 219.717641
|   |   |   |   |   |   fft_coef_0009 <= 4.139647: walking (30.0)
|   |   |   |   |   |   fft_coef_0009 > 4.139647
|   |   |   |   |   |   |   fft_coef_0013 <= 2.472347
|   |   |   |   |   |   |   |   fft_coef_0003 <= 9.283525: walking (3.0)
|   |   |   |   |   |   |   |   fft_coef_0003 > 9.283525: running (6.0)
|   |   |   |   |   |   |   fft_coef_0013 > 2.472347: walking (64.0/8.0)
|   |   |   |   |   fft_coef_0000 > 219.717641: running (10.0)
|   |   |   |   fft_coef_0001 > 53.625831: walking (146.0/2.0)
|   |   |   fft_coef_0004 > 46.068704: running (12.0/1.0)
|   fft_coef_0000 > 328.310808: running (184.0)

Number of Leaves  :     17

Size of the tree :      33
```

Fig. 6. J48 classifier

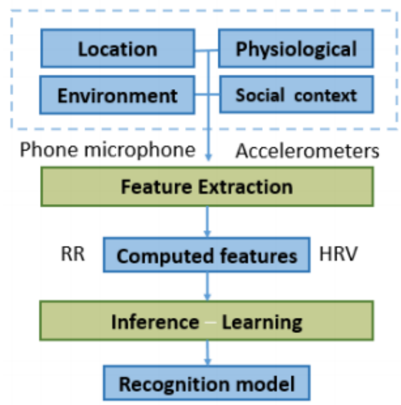

Fig. 7. Activity recognition process flow

D. Visualization

We used the GPS for outdoors and WiFi/Antena Triangulation for indoors. We then broadcasted the inference activities to the MAP application and mapped the GPS signals to the activities. As result we obtained the following function:

The visualization module retrieve the inferred activities store in the phone database as well as location coordates a this time to generate a route map as show in Figure 8.

IV. Evaluation

The accuracy of the classifier was evaluated using a customized form of stratified ten-fold cross validation. Ten-fold cross validation randomly splits the testing set into ten equally sized subsets. The folds are stratified, which means each fold contains a proportional amount of each class. For each fold, we train on the other nine folds and test on the current fold, and average together each folds classification accuracy for a

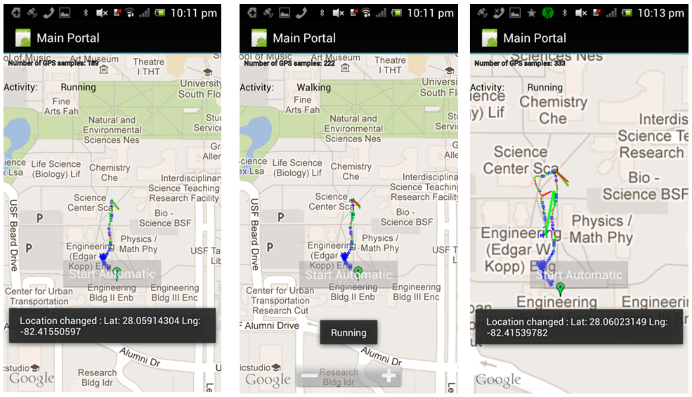

Fig. 8. Corredor's visualization interface

TABLE I
CONFUSION MATRIX

Class	Still	Walking	Running
Still	248	1	3
Walking	1	232	19
Running	5	22	225

total predicted accuracy. Table I presents the confusion matrix, here the elements of main diagonal are significatively bigger than the elements out of diagonal showing a low level of false positives and true negatives. Table II shows the detail accuracy per class, and its last line presents the weight average over the three activist. Finally, Table III presents a shows the number of correctly and incorrectly classified instances as well as the mean and absolute classification errors. of the computed statistical error estimation.

TABLE II
DETAIL ACCURACY BY CLASS

Class	Tp Rate	FP Rate	Precision	Recall	F-Measure	Roc Are
Still	0.984	0.012	0.976	0.984	0.98	0.986
Walking	0.921	0.046	0.91	0.921	0.915	0.95
Running	0.893	0.044	0.911	0.893	0.902	0.935
Weighted avg	0.933	0.034	0.932	0.933	0.932	0.957

TABLE III
SUMMARY OF STATISTICAL ESTIMATORS

Correctly classified instances	705
Incorrectly classified instances	51
Kappa statistic	0.8988
Mean absolute error	0.051
Root mean squared error	0.2055
Relative absolute error	11.4796%

V. FUTURE WORK

In this work, we explore a preliminary approach to save energy based on a modification of the popular C4.5 algorithm. The main idea behind this modification is to take into account not only information gain as a criteria for branch partition but also energy consumption. The following section sketch the main components of our approach.

A. The Power-Aware Decision Tree Algorithm

The Power-Aware Decision Tree algorithm (PAT) considers the sensors' power consumption along with feature's information gain in order to increase the accuracy of the activity recognition process as well as the power efficiency. PAT is based on the popular C4.5 algorithm developed by Ross Quinlan, which greedily chooses splits on attributes to build a decision tree by maximizing information gain [19].

B. PAT training stage

C4.5 uses the concept of information entropy to calculate the level of uncertainty of an attribute split and compare it with the information entropy without the split. The Kullback-Leibler (KL) divergence (also known as information gain) is the difference between those two information measures, and is used as the criterion to generate the splits while the decision tree is being built. The KL divergence is a way of comparing two probability distributions, and is defined as follows [6].

Definition 1 (Kullback-Leibler Divergence): For two distributions $q(x)$ and $p(x)$:

$$\mathrm{KL}_{q|p} \equiv \langle log\, q(x) - log\, p(x) \rangle_{q(x)} \geq 0$$

We introduce a new criterion for split selection that takes into account not only the KL divergence, but also the knowledge of sensor power efficiencies. The main idea is to create a tree that favors a combination of the most power efficient *and* the most informative attributes. Table IV shows the weights assigned to each of the sensors that were used, with 1 being the least power efficient and 10 being the most power efficient. In actual applications, these weights would correspond to the relative power efficiencies of the sensors.

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TABLE IV
WEIGHTS. IT MEANS LEAST POWER EFFICIENT AND 10 MEANS MOST POWER EFFICIENT.

Accelerometer	Gyro	Gravity	Linear Acceleration	Rotation Vector
2	1	10	4	8

Like C4.5, PAT chooses splits by finding the attribute that will maximize the split criteria. The split criteria is a linear combination of the Kullback-Leibler divergence and the power efficiency of the attribute's associate sensor. We control the relative weights of the KL divergence and the power efficiency with a parameter θ. This new split criteria S is defined as follows:

VI. Conclusions

This paper presents Corredor, a human-centric sensing platform for human activity recognition based upon human acceleration data. An extensive evaluation was performed for a set of 64 features, a J48 decision tree, eight classification, and 5 seconds sliding window with a 50% of overlap . Overall, the mean accuracy achieved was 93.2%. This result supports the hypothesis that a energy efficient system based on only acceleration data are enough to reach high labels of activity recognition accuracy.

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