A MOBILE FRAMEWORK FOR PERSONALIZED HEALTH ASSESSMENT

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Abstract: ***On a growing scale of smart phone technology and onboard sensors has enabled non-invasive physiological measurements, which can simplify self and remote assessments. The main objective of the project is to develop an android application to extract the heart rate (HR) and breathing rate (BR) using a cell phone camera in a non-invasive way and to track the user physical activity and estimate his energy expenditure using 3axis accelerometer and GPS in a smart phone, without the need of external sensors. The heart rate measure method works by placing the index finger over the cell phone camera and computing the amount of light absorbed by the finger tissue. The phone thus acquires the Photoplethysmographic (PPG) signal through which the HR is estimated by using a peak detection algorithm. We then computed BR from the fast Fourier transform (FFT) of the estimated HR signal. The FFT plots showed a clear harmonic peak at the frequencies forms respective breathing to which it corresponds. To estimate the energy expenditure the accelerometer data, feature extraction, activity recognition and calorie estimation data are collected. Here the users performs various activities such as running, cycling, walking also by keeping the phone in the pants pocket and then are classified user activities on the basis of frequency component present in the acceleration data.***

Keywords: An*droid, Breath Rate Heart Rate, Sensor, GPS, Step Meter, Health Care, Metabolic Equivalent.*

1. Introduction

With the advancement in technology, mobile phones or smart phones are rapidly becoming the central computer and communication device in people's lives. Smart phones include many sensors such as cameras, microphones, light sensors, temperature sensors, acceleration sensors, GPS, orientation sensors, magnetic field sensors, pressure sensors, proximity sensors.

The availability of these sensors will revolutionize many sectors of our economy including healthcare, social networks, environmental monitoring and transportation.

This project explores the use of two sensors namely light sensor and acceleration sensors. Light sensor that allow to measure person's heart rate using the phone's camera. The user starts the application, places one's finger over camera lens and presses a button. After that application turns on camera flash and starts the measurement. The measurement is about the amount of light absorbed by the finger tissue. During the measurement application captures frames from the camera, analyzes them and then, after measurement done, shows the measured user's heart rate on the screen. Usually measurement takes 10 seconds.

This is based on the effects of respiratory sinus arrhythmia (RSA). That refers to the variation in heart rate when breathing. During inspiration the HR accelerates and during expiration the HR slows down.

Figure 1 illustrates the effects of RSA using the PPG signal (not filtered) collected from a cell phone's camera recordings. The peaks under the red line correspond to the heartbeats, and the peaks shaped by the red line are the respiration rate traced by the heart rate over time. The HR is extracted from the PPG signal obtained from the video recordings. Respectively, BR is computed by applying the FFT to the HR data.

Acceleration sensor that is 3 axis accelerometer and GPS in the smart phones to detect the user physical activity such as walking, running and many more thus estimate the energy expenditure.

BR measurement is important because it could help subjects to achieve a calm state and to detect and prevent abnormal respiratory rates that may lead to cardiac arrest, stroke and chronic obstructive pulmonary diseases.

To implement this system, we collected the accelerometer data from different users as they performed activities like walking and running by wearing the phone in the pants pocket and then classified the user activities on the basics of frequency component present in the acceleration data. Here the user activity is recognized using FFT algorithm, ie, on the basis of frequency component present in the acceleration data. Based on the recognized activity, we can find the Metabolic Equivalent (METS) value and thus estimate calorie consumption based on the METS conversion method. Heart rate monitoring during physical exercises allows to avoid health hazards and to estimate the extent of one's physical training.

The need of this project is increasing now a days because today's way of life involves less physically activity. People travel on car and bus, rather than walking, and many people work in offices, where they are sitting still for most of the day. This means that the calories they eat are not getting burnt off as energy and instead, the extra calories are stored as fat, which is not good for health. Moreover, eating excess calories leads to weight gain Therefore by monitoring their daily energy expenditure; they can balance their weight against food intake.

2. System Modules

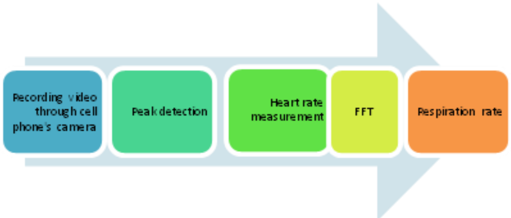


Figure 1 *Block Diagram-Module 1*

2.1Heart Rate Detection

The heart rate is being obtained as follows; During the cardiac cycle, when the heartbeats, it creates a wave of blood that reaches the capillarity at the tip of the finger, when the capillarity is full of blood, it will block the amount of light that can pass through. When the blood retracts, more light can pass through the tissue. If these changes are recorded over time, a waveform is going to be created that correspond to the pulsatile changes in the arterial blood in that tissue. From the recorded video, the green values from every frame were extracted in order to acquire the PPG signal (figure 1). The green intensity average in the PPG signal formed peaks that correspond to cardiac pulse.

A peak detection algorithm was used in order to find all the cardiac peaks in the signal. Once a peak was found, the time difference between consecutive peaks was computed. This time difference is known as R-R interval (RRI). From the RRI values the HR was estimated using the formula given below.

$$\mathbf{HR} = \frac{60}{RR}$$

Equation 1. Heart rate equation

2.2Respiration Rate Detection:

After acquiring HR from the PPG signal, the next step was extracting BR from the HR in the spectrum domain. This is possible because respiration rate modulates amplitude and frequency of a signal. Before spectral analysis, the HR signal was interpolated in order to address the issue of irregular sampling from the cellphone and because R-wave are not equidistantly timed events. After this, the fast Fourier transform (FFT) of the HR was computed. We observed that the FFT plots showed a clear harmonic peak at the frequencies, which corresponded to the respective breathing rate. Figure 5 shows the FFT of the HR signal.

2.3HR & BR Estimate App Prototypes

A peak detection algorithm is implemented in order to detect every cardiac pulse peak from the PPG signal. A peak is defined as the highest average of green values in a fixed window size. We empirically chose a window size of 0.7 seconds because it led to least number of false peaks. Once a peak is found, its timestamp is used in order to find the time difference between adjacent peaks, which gives us the RRI. We compute the HR from RRI using the formula presented above (equation 1). After the HR is acquired from the application, the HR is interpolated following which the FFT will be applied in order to find the breathing frequency of the subject.

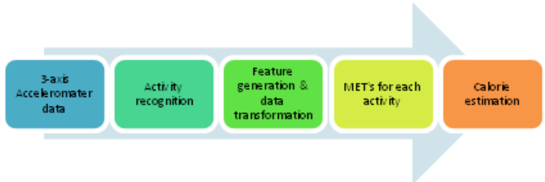


Figure 2 *Block Diagram-Module 2*

2.4Accelerometer Data and Activity Recognization:

We describe our protocol for collecting the raw accelerometer data. In order to collect data for our supervised learning task, it was necessary to have a large number of users carry a smart phone while performing certain every day. These subjects carried the phone in their front pants leg pocket and were asked to walk, jog, ascend stairs, descend stairs, sit, and stand for specific periods of time. The data collection was controlled by an application we created that executed on the phone. This application, through a simple graphical user interface, permitted us to record the user's name, start and stop the data collection, and label the activity being performed. We collected the accelerometer data every 50ms, so we had 20 samples per second. The data collection was supervised to ensure the quality of the data.

2.5Feature Generation & Data Transformation:

Standard classification algorithms cannot be directly applied to raw time-series accelerometer data. Instead, we first must transform the raw time series data into examples [18]. To accomplish this we divided the data into 10-second segments and then generated features that were based on the 200 readings contained within each 10-second segment. We refer to the duration of each segment as the example duration (Ed). We chose a 10-second ed because we felt that it provided sufficient time to capture several repetitions of the (repetitive) motions involved in some of the six activities. Although we have not performed experiments to determine the optimal example duration value, we did compare the results for a 10-second and 20-second Ed and the 10-second Ed yielded slightly better results (as well as twice as many training examples). Next we generated informative features based on the 200 raw accelerometer readings, where each reading contained an x, y, and z value corresponding to the three axes/dimensions.

The features are described below, with the number of features generated for each feature-type noted in brackets:

• **Average [3]:** average acceleration (for each axis)

• **Standard Deviation [3]:** standard deviation (for each axis)

• **Average Absolute Difference [3]:** average absolute difference between the value of each of the 200 readings within the Ed and the mean value over those 200 values (for each axis)

• **Average Resultant Acceleration [1]:** average of the square roots of the sum of the values of each axis squared over the Ed

• **Time Between Peaks [3]:** time in milliseconds between peaks in the sinusoidal waves associated with most activities (for each axis)

• **Binned Distribution[30]:** we determine the range of values for each axis (maximum – minimum), divide this range into 10 equal sized bins, and then record what fraction of the 200 values fell within each of the bins.

2.6Metabolic Equivalent (MET) For Each Activity:

A unit of metabolic equivalent, or met, is defined as the ratio of a person's working metabolic rate relative to the resting metabolic rate. Mets values correlate with oxygen requirements. Starting with 1, which is the least amount of activity (such as resting), the values increase with the amount of activity. Here the calories are estimated based on metabolic equivalent (Mets) conversion method. For each activity, there is a corresponding met value

TABLE 1

METS VALUE AND USER CONTEXT

CONTEXT	METS
IDLE	0.9
WALK	0.272*WALKING SPEED(M/MIN)+1.2
RUN	0.93*RUNNING SPEED(M/MIN)-4.7

2.7Calorie Estimation:

Based on this METS value, we can estimate the energy:

Energy (kcal) =1.05× METS × Weight (kg)× Exercise Time (hr)

Total energy expenditure (TEE) is also estimated. It is the addition of calories burned due to each activity.

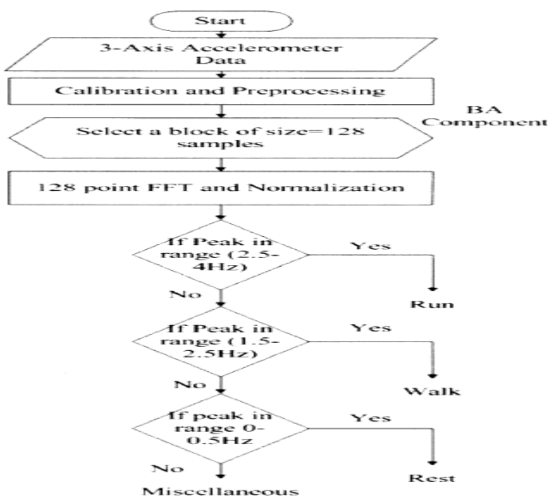
2.8Algorithm

(a) ***Heart Rate Calculation:***

Require: *signal* — time series of the average green component values of captured by camera frames; *frame rate* — frame rate of captured data; *n* — maximum number of the peaks in the chosen set (default value equals 20); *max diff* — maximum deviation of distances between peaks from their average value (default value equals 25%).

deriv = derivative of the *signal*
for *value* ∈ *signal* **do**
  if *value* == max of the *value*'s 2-neighbourhood **then**
  peaks += *value*
  end if
end for
for *k* = 5: *n* **do**
  distances = distances between adjacent peaks of *k* highest peaks from *peaks*
  variances += variance of the *distances*
end for
if min(*variances*) == *n* **then**
  chosen set = set of distances that variance equals to first local minimum in *variances*
else
  chosen set = set of distances that variance equals to min(*variances*)
end if
remove all values that are lower than *frame rate*×10=33 from *chosen set*
  repeat
  R = values of *chosen set* that differ from mean(*chosen set*) for more than *max diff*
  remove *R* from *chosen set*
until *R* = 0
heart rate = 60×*frame rate*=mean(*chosen set*)
return *heart rate*

(b) Peak Range Calculation:



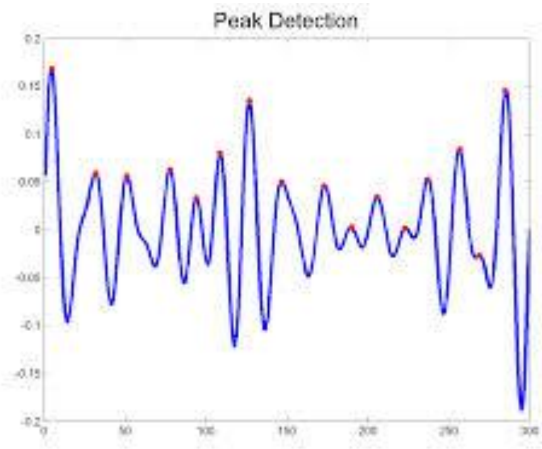


Figure 3 *Peak Detection*

3. CONCLUSIONS

Here a real time system for monitoring the heart rate, breath rate and the daily calorie expenditure of a person is designed using smart phone. This system will be very useful for the people who are suffering from cardiovascular disease, obesity; type 2 diabetics' mellitus to balance their dietary intake and calories burned. Here the tests were conducted by keeping the user's index finger in the cell phone camera and by keeping the smart phones in their pants pocket.

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