HUMAN ACTIVITY MONITORING USING SMARTPHONE

Implementation in Matlab using signal processing and statistical analysis algorithm

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ABSTRACT

The main aim of the project is to develop an algorithm which will classify the activity performed by a human who is carrying a smartphone. The day to day life made humans very busy at work and during daily activities, mostly elderly people who are at home have an important need to monitor their activity by others when they are alone, if they are inactive for a long time without movement, or in some situations like if they have fallen down, became unconscious for sometime or seized with a cardiac arrest etc… will help the observer to know the state of activity of person being monitored. In this project we develop an algorithm to know the activity of a person using accelerometer available in Smartphone.

We have extracted the Smartphone accelerometer data using an application called accelerometer data logger version 1.0 available in Smartphone market and have processed the data in Matlab for classifying the different activities of human being into static and dynamic activity, if the activity is dynamic then further classification into walking or running is performed with the algorithm.

We implemented smoothening filters for data analysis and statistical techniques like standard deviation, mean and signal magnitude analysis for activity classification. This classification algorithm will let us know the type of activity either static or dynamic and then classify the position of the user, such as walking, running or ideal, which can provide useful information for the observer who is monitoring the activities of wearer, and which will help the wearer for his daily living.

To bring out the extensive use of algorithm and to provide valuable feedback for wearer regarding his activities, energy spent by user during the activities was calculated at a given time using regression methods and was implemented in the algorithm. The developed model was able to estimate the energy spent by the user, the observations recorded were almost similar to the treadmill data which is taken as a standard for our model and the mean error is not more than ±2 for 30 observations. The final results when compared with the standard model was proved to be 93 % accurate on average of 30 subjects data which is used for verifying the algorithm developed. With these set of results we have come to a conclusion that algorithm can be easily implemented in a real time Smartphone application with low false predictions and can be implemented with low computational cost and fast real-time response.

In future our classification algorithm can also be used in military applications where one can know what the soldier is doing without actually seeing him and additionally it can be proved as a support system in athlete’s health monitoring and training.
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1 INTRODUCTION

In rehabilitation medicine, accurate monitoring of the human mobility status over a long-term is important in evaluating the quality of life, since regular physical activity helps to maintain both physical and mental health of a person. In recent research and development, the human activity monitoring is done by an accelerometric method, which was first, suggested in the 1970s but has only been refined and perfected during the last 10–15 years. Accelerometers provide quantitative measures of motion; they are capable of identifying specific movement changes and can be used to objectively quantify ambulatory activity levels. Human movement is an important neuro-musculo-skeletal event which incorporates mechanical, physiological, anatomical, sociological, environmental and psychological factors (Godfrey et al 2000).

Accelerometers have proven to be an appropriate and viable means of determining various movements. This has been made more readily possible due to its current state of a miniature low power device coupled with light weight compact data acquisition instruments with the help of MEMS technology.

MEMS accelerometer technology offers significant advantages over conventional sensors, mainly in terms of high sensitivity and low noise due to its miniaturization and rich functional integration. So accelerometers has become a relatively non-intrusive means of assessing ambulatory movement, posture, postural transitions, energy expenditure, rate and intensity of movement (parkka et al 2007).

In our project we have used an accelerometer available in Apple iPhone4 with ios version 6.1.2 as a hardware system for collecting the accelerometer data in order to develop the algorithm. Matlab algorithm is developed for human movement classification. An analysis based on the posture details and nature of activity (static or dynamic) over a period time gives valuable information about activity performed. Thus the developed signal processing algorithm forms a basic platform for activity classification. The results obtained can be used in conjunction with other real time physiological parameters to monitor the overall health status, particularly in the case of rehabilitation medicine.
1.2 APPLICATIONS

1.2.1 Clinical

Human groups such as those suffering from back-pain, Parkinson’s disease, obesity, stroke, etc., and old age people can be monitored at home for their various movements. This monitoring can be helpful in detecting the fallers. Based on activity analysis, the extent of disability and severity of disease can be detected, which can be used as vital information for rehabilitation medicine.

1.2.2 Non Clinical

Fire fighters and other law enforcement personnel involving various movements during their activities have all been monitored by accelerometers in non-clinical based studies. This is useful in eliminating the false perception of video graphic and imaging techniques.

1.2.3 Military

In military, the soldiers are monitored for the effectiveness of their activity in the warfront from parameters like energy expenditure, heart rate etc. This helps in safeguarding the life of the soldiers by rescuing them quickly during injuries. This is used to track the motion of the soldiers in the warfront from the remote place and rescue them from the fatal conditions and prevent risks when they are injured or harmed by enemies.

1.3 NEED FOR ACTIVITY MONITORING

Human groups such as those suffering from back pain, Parkinson’s disease, obesity, stroke etc., and fire fighters and other law enforcement personnel performs various movements during their activities can be monitored using existing tri axial accelerometer based activity monitoring systems specific to limited number of application.

In the field of defense and medicine, there is a need for human activity analysis. By analyzing the motion, energy efficiency the effectiveness of rehabilitation therapy in patients can be measured (Sharma, A 2008).

A wide range or long term analysis is required to analyze the movements of a person, for this video graphic method had been used. But it fails to perform continuous monitoring in long
term, so to overcome the drawback, MEMS accelerometric method plays a vital role in fine tracking of human motion.
2 LITERATURE SURVEY

Carlijn V.C. Bouten et al (1997) developed a tri-axial accelerometer and portable data processing unit for the assessment of daily physical activity. The tri-axial Accelerometer (TA) composed of three orthogonally mounted uni-axial piezo resistive accelerometers and can be used to register accelerations covering the amplitude and frequency ranges of human body acceleration. The data unit enables the on-line processing of accelerometer output to a reliable estimator of physical activity over eight-day periods. From mechanical testing it was concluded that the TA was reliable and valid for the measurement of accelerations within the frequency and amplitude range of human body acceleration.

B.G.Celler et al (2001) described that accelerometers can be used to monitor physical activity in the home over prolonged periods. They described a novel system for objectively and continuously monitoring movement, suitable for patients with chronic obstructive pulmonary disease. The key design criteria were ease of use and comport for, the patient together with provision of clinically relevant information. The patient’s posture, energy expenditure and movement are clinically important parameters that can be measured by accelerometer. A data processing schema in which these parameters are extracted is described. So objectively by continuously monitoring patient movement in a home environment that classifies the patient’s posture, energy expenditure and movement. This integrated system is being used in a home based telemedicine trial for patients with heart diseases.

M. J. Mathie et al (2002) described that tri-axial accelerometers have been employed to monitor human movements in a variety of circumstances. It is necessary, however, to be able to extract useful information from the acceleration measurements. In a controlled environment, use an energy expenditure method to identify and separate dynamic activities, including changes in posture and ambulation. They have shown that it is possible to identify dynamic activities in a tri-axial accelerometer monitoring experiment using a signal energy thresholding approach, for the case of controlled movements. It was found that there were three basic parameters of interest, the length of the median filter, ‘1’; the width of the window ‘w’ and the energy threshold value, ‘th’. These parameters are the most sensitive for the tuning of the analysis. Upon tuning these parameters using a training subset of their measurements, it was found that a sensitivity of 0.99
and a specificity of 0.94 were measured in the test group. This shows the robustness of the technique for separation of the activities in the case of controlled movements.

M.Karantonis et al (2006) described that, Human movement classification system based on the data acquired from a single, waist-mounted tri-axial accelerometer was developed for use in a real-time environment. The classification algorithm employed was designed specially to perform the required signal processing using embedded intelligence. Despite the inherent limitations in implementing such a system, their experimental results demonstrated the technical feasibility of their approach in performing the task of long-term ambulatory monitoring in the home as a method of determining an individual’s functional status. A laboratory-based trial involving six subjects was undertaken, with results indicating an overall accuracy of 90.8% across a series of 12 tasks (283 tests) involving a variety of movements related to normal daily living.

Wan-Young Chung et al (2008) described that Activity classification was performed using MEMS accelerometer and wireless sensor node for wireless sensor network environment. Tri-axial MEMS accelerometer measures body’s acceleration and transmits measured data with the help of sensor node to base station attached to PC. On the PC, real time accelerometer data is processed for movement classifications. In this paper, Rest, walking and running are the classified activities of the person. Both time and frequency analysis was performed to classify running and walking. The classification of rest and movement is done using Signal magnitude area (SMA). The classification accuracy for rest and movement is 100%. For the classification of walk and Run two parameters i.e. SMA and Median frequency were used. The classification accuracy for walk and running was detected as 81.25% in the experiments performed by the test persons.

Wee-soon yeoh et al (2008) presented a new algorithm for real time tracking the flexion angle from wearable accelerometer sensor data using wireless body sensor network (BSN). The proposed algorithm uses dynamic filter for tracking the flexion angles of which the human body dynamics is described by its system model. In this work, the extended Kalman filtering is used to demonstrate the superiority of this approach. Results from a thigh tracking experiment show that the flexion angle estimated closely followed that of the video data.

Jee Hyun Choi et al (2005) presented a novel algorithm estimating the calorie expenditure during physical activities is introduced. The physical activity is quantified by the integration of the accelerometer signals obtained from the 3D accelerometer fixed at the waist level of the
human body. Simultaneous measurements of activity and calorie expenditure using 3D accelerometer and gas analyzer show the activity calorie expenditure increases as the activity increases with different rates depending on the type of activities (e.g., walking, running) as well as the physical characteristics of the subjects (e.g., gender, age, mass, and height). Based on the experimental data gathered from 94 subjects, they suggest a new algorithm estimating the activity calorie expenditure dependent on the demographic data of the subjects and the types of the activity.

Taekyun Kim et al (2009) aimed, for estimating energy expenditure with tri-axial accelerometers during exercise, to compare determination coefficients of equations of the estimated regression according to several locations of the accelerometers on the body and then to present an estimation model on the location where there is the least restriction on physical activities. A small device that is able to obtain acceleration data during exercise was developed. It was attached on the back, wrist, knee and ankle of the body and then sub maximal exercise was conducted on treadmills with the Bruce protocol. For the experimentation, seventeen males of twenties and thirties in good health (27.23±2.18) participated and wore the equipment to analyze respiratory gas, so that the values of acceleration and energy expenditure from the respiratory gas analyzer could be obtained at the same time. The energy expenditure values from the outputs of the respiratory gas equipment were set as a base value, and the accelerations and the physical features of the participants (age, weight, height and BMI) as variables, to check each correlation, and for each of the four locations of the accelerometers on the body, regression analysis was carried out. The results of the experiment are as follows: the correlation between the acceleration and the energy expenditure was the highest on the knee and the lowest on the wrist; but, the determination coefficients (R2) of the regression equations using the continued hours of exercise, weight and acceleration values did not show significant difference among the locations on the body, as the highest R2=0.873 on the back and the lowest R2=0.852 on the wrist. This study has shown two possibilities. First, it is possible to predict energy expenditure using accelerometer sensor without respiration gas analyzer in laboratory situation. Second, these findings can be applied to application about predicting conveniently energy expenditure during outdoor activities using accelerometer on watch or shoes.

Li Meina et al (2009) developed and evaluated the patched type sensor module for estimating the energy expenditure. The relation test on the heart rate for the motion artifact
shows the error rate within 5%. The purpose of this study was to use the combined heart rate and movement sensors method for measuring energy expenditure against indirect calorimetry. The subjects were participated in gradual exercise test on treadmill. The energy expenditure was considered as 5kcal per liter of O2 consumed. The preliminary results of correlation equations for the Airbeat3 systems provided similar estimates of activity and energy compares with the indirect calorimetric system. But deduced algorithms show poor accuracy repeatability than the calorimetric system and more experiments should examine to enhance the precise estimates of energy expenditure.

Scott E. Crouter et al (2005) developed a new two regression model relating actigraph activity counts to energy expenditure over a wide range of physical activities. Forty eight participants performed various activities chosen to present sedentary, light, moderate, and vigorous intensities. Eighteen activities were split into three routines being performed by 20 individuals, for a total of 60 tests. Forty-five tests were randomly selected for the development of a new equation and 15 tests were used to cross validate the new equation and compare it against already existing equations. During each routine, the participants wore an actigraph accelerometer on the hip, and oxygen consumption was simultaneously measured by a portable metabolic system. For each activity, the coefficient of variation (CV) for the counts per 10s was calculated to determine whether the activity was running, walking or some other activity. The new algorithm is more accurate for the prediction of energy expenditure than currently published regression equations using the actigraph accelerometer.

Dongwoo Kim et al (2007) designed the wireless networked multisite triaxial accelerometry system to estimate activity energy expenditure during daily life. Proposed system used different estimation algorithms according to activity classification based on measured acceleration signal. The estimation results showed higher correlation (R=0.98) and smaller standard deviation errors of estimation (SEE=0.98kcal) than any other system in preceding reports.
3 SYSTEM ARCHITECTURE

The system includes hardware for data acquisition which is an iPhone 4s 16Gb with ios 6.1.2 and an application called accelerometer data logger version 1.0 for data logging. This hardware system iPhone has an internal embedded MEMS tri-axial accelerometer (LIS331DLH).

3.1 HARDWARE SYSTEM DESIGN

The Tri-axial accelerometer signal was acquired from the iPhone and the acquired data has been saved as an excel sheet. The basic components of the hardware block showing the explained process are depicted in Figure 3.1.

3.1.1 Sensor and Signal conditioning circuit inside the iPhone

The digital accelerometer LIS331DLH is used in iphone 4. It is a device with 3mm x 3mm x 1 mm thick LGA package. This works on ultra-low power (10µA), 3-axis accelerometer (x, y, z) with high resolution, measurement at upto ±8g. Digital output data is formatted as 16-bit twos complement and is accessible through either a SPI (3- or 4-wire) or I2C digital interface. Supply voltage range: 2.16 V to 3.6 V and I/O voltage range: 1.8 V to VS with a wide temperature range (−40°C to +85°C).[19]

The LIS331DLH is well suited for mobile device applications. It measures the static acceleration of gravity in tilt-sensing applications, as well as dynamic acceleration resulting from motion or shock. Its high resolution (3.9 mg/LSB) enables measurement of inclination changes less than 1.0°.

Raw data obtained from sensor are received through USB cable in the form of digital samples which are sampled at 50 samples per second is then fed to the computer through USB version 2.0 ports.
3.1.2 Theory of operation

The LIS331DLH is a complete 3-axis acceleration measurement system with a selectable measurement range of ±2 g, ±4 g, ±8 g. It measures both dynamic acceleration resulting from motion or shock and static acceleration, such as gravity, that allows the device to be used as a tilt sensor.

The sensor is a silicon surface-micro machined structure attached to substrate in few points which are known as anchors, which are free to move in the direction of acceleration produced. Silicon springs suspend the structure over the surface of the wafer and provide a resistance against forces due to applied acceleration. To avoid the blocking during the plastic encapsulation a cap is placed on sensing element. Deflection of the structure is measured using charge integration in response to voltage pulse applied to capacitor. Acceleration deflects the proof mass and unbalances the differential capacitor, resulting in a sensor output whose amplitude is proportional to acceleration. Phase-sensitive demodulation is used to determine the magnitude and polarity of the acceleration.

Signal conditioning is inbuilt with the help of onboard digital filters; there is no requirement for external passive components (resistors and capacitors) to set the output signal bandwidth (25 Hertz). The values of capacitors load varies from few pF in steady state to fF.
4 METHODOLOGY

The output data of an accelerometer worn on the body is dependent on four factors as listed as follows:

- Position at which it is placed
- Its orientation at this location
- The posture of the subject
- The activity being performed by the subject

Proper protocol has been followed while data collection to ensure the sensor output to be accurate enough to analyze the human activity.

4.1 DATA COLLECTION PROTOCOL

Protocol has been followed while data collection such that, thirty subjects with age limit 22-35 years were chosen for data collection by placing iphone in pocket at thigh and suspended
from the neck as shown in the Figure.4.1. The subject is then advised to relax for some time during which data is collected for duration of ten seconds and it is used for offset correction.

4.2 OFFSET CORRECTION

Accelerometers are mechanical structures containing elements that are free to move. These moving parts can be very sensitive to mechanical stresses, much more so than solid-state electronics. The 0 g bias or offset is an important accelerometer metric because it defines the baseline for measuring acceleration. Additional stresses can be applied during assembly of a system containing an accelerometer. These stresses can come from, but are not limited to, component soldering, board stress during mounting, and application of any compounds on or over the component. If calibration is deemed necessary, it is recommended that calibration be performed after system assembly to compensate for these effects.

Accelometer output is calibrated by rotating the sensor to set an offset of 0g, -1g, 0g for X, Y and Z axis respectively as shown in the Figure.4.2.
Figure 4.2: Orientation on the x, y and z

Now the subject is made to perform various actions like sitting, standing, walking, running and jumping. As we are having a sampling rate of 50 samples per second it works for 5 seconds also. For every action, data is collected for duration of one minute and stored for further analysis. This procedure is repeated for many subjects and the data is collected in a similar manner.

4.3 ALGORITHM DEVELOPMENT

In the algorithm development the first stage is the activity classification algorithm in which the person posture and movement is classified. The second stage is the calculation of Energy Expenditure using SMA (Signal Magnitude Area) for the activity classified over the period of time. The third stage is the calculation of actual EE estimation using Regression model in which the measured Energy Expenditure using accelerometer is validated with the standard technique. The flow diagram of the algorithm development is shown in the Figure 4.3.

4.4 ACTIVITY CLASSIFICATION

Once the optimum placement of sensor is identified, the nature of activity namely static and dynamic with sensor placed at thigh is determined. The subject is requested to perform any activity and the ‘g’ values are collected as per the data collection protocol.

Using a one second moving window, which is moved over the acceleration signal, standard deviation $\sigma$ of acceleration signal was computed for that one second period. The $\sigma$ indicates the variability of the accelerometer signal for each one second window of recorded data (high variability would be expected during dynamic activities and low variability would be expected
during static activities). If the value of $\sigma$ lies above the threshold then the activity is dynamic, if it falls below the threshold, then the activity is static. The same procedure is repeated for entire data and the nature of activity is determined.

The acceleration signal consists of Gravity Acceleration (GA) due to gravity and Bodily motion Acceleration (BA) due to body motion. These two components are linearly combined in the acceleration signal. The BA component is used in distinguishing activity from rest because in this case, we are not interested in the effects of gravity. The GA component provides information on the tilt angle of the tri-axial accelerometer available in the Smartphone, which can be used to make inferences about the postural orientation of a subject. The static activity is further classified into lying, sitting, standing then the orientation is determined by the equation (4.1)
\[ \theta_{\text{degrees}} = \frac{180}{\pi} \cos^{-1}\left(\frac{a}{g}\right) \]  

(4.1)

Where ‘a’ is the acceleration of y axis and ‘g’ is the earth gravity (Jee Hyun Choi et al 2005). The posture of the person is determined by y axis output of the thigh accelerometers. The body component is used to find the movement of the person. The dynamic activity is further classified into walking and running. The walking and running activity is classified by calculating step frequency in the time domain signal. The Activity classification Flow chart is shown in the Figure 4.4.

Figure 4.4: Flow diagram of activity classification algorithm
4.5 ENERGY EXPENDITURE ESTIMATION

A typical model used for the estimation of metabolic Energy Expenditure (EE) in accelerometer systems is its linear relationship with the SMA of the body component accelerations. This relationship has been demonstrated with triaxial accelerometers in several studies (Haapalainen et al. 2008). The SMA of the combined triaxial accelerations proved most accurate for a range of daily activities. However, the accuracy of such SMA based estimations is greatly variable under free-living condition. Signal magnitude area is defined as the Integral of Absolute value of Accelerometer output (IAAout). The equation (4.2) is

\[
SMA = \frac{1}{t} \int_{0}^{t} |x(t)| \, dt + \int_{0}^{t} |y(t)| \, dt + \int_{0}^{t} |z(t)| \, dt
\]  

(4.2)

Where x(t), y(t), and z(t) refer to the body components of the x-, y-, and z-axis samples respectively and ‘t’ is time period of the activity. Even though the body component is derived on the accelerometer unit, the body acceleration frequency range of 2-20 Hz was obtained when applying a High Pass Filter (HPF) on the local computer because a filter of much higher order could be implemented. The HPF employed was a seventh-order IIR elliptic filter with cut-off frequency of 1Hz (0.01dB ripple in passband; 100 dB in the stop band). The flow chart of energy expenditure estimation algorithm is shown in the Figure.4.5.

4.6 VALIDATION

The measured accelerometer EE is validated with EE measured from the treadmill. The subject is performed the running activity at different speed in the treadmill and simultaneously data are logged in to the computer from the thigh accelerometer sensor. The speed and calorie consumption are noted for validation then the actual Energy Expenditure is determined using the regression model.

4.6.1 Treadmill

A Treadmill is an exercising device that consisting of belt which moves continuously on which a person can walk or jog while remaining in one place. It is used as cardiac exercise equipment. This equipment resembles a path on which a person may walk, jog and run. A treadmill is also used to measure the work done by the exerciser.
In modern days treadmill helps us to analyze a person’s ECG, Ergospirometry, blood pressure monitoring. This equipment display the calories spent, heart rate, speed and time during the exercise.

**4.6.2 Regression analysis**

Regression is the process of fitting models to data. The regression problem belongs to the family of the most common practical questions. The goal is to get a model of the relationship between one variable $Y$ and one or more variables $X$. The model gives the part of the variability of $Y$ taken in account or explained by the variation of $X$. A function $f$ represents the central part of the knowledge. The remaining part is dedicated to the residuals, which are similar to a noise. The model is $Y = f(X) + e$. Here the predictor variable is treadmill data $Y$ and the response variable is accelerometer data $X$. After fitting data with one or more models, we will evaluate the goodness of fit. The flow chart of the energy expenditure algorithm is shown in figure 4.5:

![Flow diagram of energy expenditure estimation algorithm](image)

*Figure 4. 4: Flow diagram of energy expenditure estimation algorithm*
4.6.3 Residual Analysis

The residuals from a fitted model are defined as the differences between the response data and the fit to the response data at each predictor value. Where r is Residual, y is data, y* is fit. Residual is derived by subtracting fit from data.

Mathematically, the residual for a specific predictor value is the difference between the response value y and the predicted response value y* the equation (4.3) is

\[ r = y - y^* \]  

Assuming the model you fit to the data is correct, the residuals approximate the random errors. Therefore, if the residuals appear to behave randomly, it suggests that the model fits the data well. However, if the residuals display a systematic pattern, it is a clear sign that the model fits the data poorly.

4.6.4 Goodness of fit statistics

To evaluate the goodness of fit, we should examine the goodness-of-fit statistics and the implemented techniques are as follows:

The sum of squares due to error (SSE)

This statistic measures the total deviation of the response values from the fit to the response values. It is also called the summed square of residuals and is usually labeled as SSE. A value closer to 0 indicates that the model has a smaller random error component, and that the fit will be more useful for prediction.

\[ SSE = \sum_{i=1}^{n}(X_i - \bar{X})^2 \]  

R-square:

This statistic measure shows how successful the fit is in explaining the variation of the data. Put another way, R-square is the square of the correlation between the response values and the predicted response values. It is also called the square of the multiple correlation coefficients
and the coefficient of multiple determinations. R-square can take on any value between 0 and 1, with a value closer to 1 indicating that a greater proportion of variance is accounted for by the model.

For example, an R-square value of 0.8234 means that the fit explains 82.34% of the total variation in the data about the average.

\[
R^2 = \frac{SS_{\text{regression}}}{SS_{\text{total}}} \tag{4.5}
\]

**Adjusted R-square:**

This statistic uses the R-square statistic defined above, and adjusts it based on the residual degrees of freedom. The residual degrees of freedom is defined as the number of response values \( n \) minus the number of fitted coefficients \( m \) estimated from the response values. The equation (4.6) is

\[
V = n - m \tag{4.6}
\]

\( V \) indicates the number of independent pieces of information involving the \( n \) data points that are required to calculate the sum of square

**Root mean squared error (RMSE)**

This statistic is also known as the fit standard error and the standard error of the regression. It is an estimate of the standard deviation of the random component in the data. Just as with SSE, an RMSE value closer to 0 indicates a fit that is more useful for prediction.

\[
RMSE(v,w) = \sqrt{\frac{\sum_{i=1}^{n}((v_{ix} - w_{ix})^2 + (v_{iy} - w_{iy})^2 + (v_{iz} - w_{iz})^2)}{n}} \tag{4.7}
\]
5 RESULTS AND DISCUSSION

The results of the algorithm proposed are based on the different set of experiments which are conducted on 30 different subjects to know the actual limits of threshold for classifying the activity using an accelerometer.

The initial sets of experiments were conducted on 10 different subjects by considering the weight and height of person. The subject’s data is acquired as per the data collection protocol as described below:-

1. The subject is made to sit for 1 minute when the accelerometer is on and data recorded for 1 minute at 50 samples per second.
2. The subject is then made to walk for 2 minutes with the same sampling rate.
3. Again the subject is allowed to take rest for 1 minute.
4. The subject is then allowed to run on a treadmill for 2 minutes.

The data collected was then implemented in matlab algorithm which we developed; the initial plot is shown in Figure 5.1, it illustrates the raw data which is obtained from iPhone and the data lot of the offset corrected data for further processing.

![Figure 5.1: Raw data before processing and offset corrected](image)
The second stage of algorithm actually performs the filtering of data with filter specified in chapter 4.5 and is processed for further analysis of recognizing activity, the Figure 5.2 illustrates the plot of filtered data of a subject:

![Figure 5.2: The data plot with filtering](image)

The third stage of algorithm implements the standard deviation classification for the analysis of finalizing the threshold limits for a given activity, Figure 5.3 gives us the standard deviation plot helping further for classifying individual activity:
The minima and maxima were detected for a given activity and the limits of threshold of a given activity were tabulated accordingly with the obtained standard deviation graph by plotting a stem graph as shown in Figure 5.4.
Interpretation of Limits of threshold:

The data collected from different subjects were processed in algorithm and resultant values of standard deviation were tabulated in table (5.1) to find out the Maxima and Minima for a given activity being performed by the subject.

Table 5.1: Standard deviation output values for individual activity

<table>
<thead>
<tr>
<th>S.no</th>
<th>Name</th>
<th>BMI</th>
<th>Minima</th>
<th>Maxima</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Rest</td>
<td>walk</td>
</tr>
<tr>
<td>1</td>
<td>Subject No.1</td>
<td>21</td>
<td>0.0001</td>
<td>0.01</td>
</tr>
<tr>
<td>2</td>
<td>Subject No.2</td>
<td>25</td>
<td>0.0007</td>
<td>0.01</td>
</tr>
<tr>
<td>3</td>
<td>Subject No.3</td>
<td>27</td>
<td>0.0009</td>
<td>0.02</td>
</tr>
<tr>
<td>4</td>
<td>Subject No.4</td>
<td>19</td>
<td>0.0003</td>
<td>0.01</td>
</tr>
<tr>
<td>5</td>
<td>Subject No.5</td>
<td>23</td>
<td>0.0007</td>
<td>0.01</td>
</tr>
<tr>
<td>6</td>
<td>Subject No.6</td>
<td>22</td>
<td>0.0002</td>
<td>0.02</td>
</tr>
<tr>
<td>7</td>
<td>Subject No.7</td>
<td>26</td>
<td>0.0008</td>
<td>0.01</td>
</tr>
<tr>
<td>8</td>
<td>Subject No.8</td>
<td>24</td>
<td>0.0007</td>
<td>0.03</td>
</tr>
<tr>
<td>9</td>
<td>Subject No.9</td>
<td>22</td>
<td>0.0003</td>
<td>0.03</td>
</tr>
<tr>
<td>10</td>
<td>Subject No.10</td>
<td>20</td>
<td>0.0002</td>
<td>0.01</td>
</tr>
</tbody>
</table>

The data which is obtained from initial 10 subjects is further used for the analysis of activity prediction the limits of threshold were finalized for implementing in algorithm which is being developed. The table 5.2 gives us the range of thresholds for differentiating the activity performed by user.
The data collected from the other 20 subjects is used for further analysis and system verification of our previously obtained results. The 20 subjects were asked to perform the protocol mentioned activities like sitting, walking and running. The observed data is recorded accordingly with a protocol as mentioned below:

a. The subject’s physical details are recorded and device is set ready for data collection and time is noted at the start of activity.
b. The subject is made to rest for 15 seconds and 15 seconds of walk and 30 seconds of running.
c. This procedure is followed by individual subject for the total time period of 3 minutes of data collection repeating the same activities continuously for every minute.
d. The time of the given activity is recorded and observed by a video recording for all the subjects while performing activity.

This data is compared with initially analyzed data of ten subjects to verify and is used to analyze the designed algorithm for its accuracy in determining the activity and to test the algorithm for its further implementation into real time model.

In the table 6.1 we have shown the results of 20 subjects compared with respect to initial ten subjects. When the subject’s action is standing, our model shows that he is standing with accuracy of 99% in case of walking the model has 98% of accuracy and in case of running 97% accuracy were observed for the data collected.
Energy Expenditure Estimation:

A model used for the estimation of energy expenditure in accelerometer is Signal Magnitude Area (SMA) of body component acceleration. The integral of absolute value of accelerometer output is giving the linear relationship with the standard techniques. Here we taken the running treadmill calorie is the standard reference value. The subject is performed the running activity in the treadmill and simultaneously data are logged in to the computer from the thigh accelerometer sensor.

The power of the FFT value is used as a reference indicative value for a given activity to derive the regression analysis and the resultant periodogram for walking and running activities are shown in figures 5.5 and 5.6 respectively and with the FFT derivation we can further know the exact limit for finalizing the threshold as we obtain power of the magnitude for the duration of activity performed, it is used as a re verification tool for finalizing thresholds of activity.

![Periodogram](image)

Figure 5.5: Frequency of walking activity by FFT method
Initially linear regression lines were used to predict the actual energy expenditure of accelerometer technique. Measured Energy expenditure is validated against the reference calorie values taken from the treadmill during the activity. So the predictor value is calories obtained from the treadmill and the response value is calories estimated in accelerometer technique.

Two regression equations are derived using the data collected from the 10 different subjects. The data obtained is tabulated in the table 5.3. The FFT power value obtained is stored as a reference value for predicting the energy expenditure calories at a given time. The predictor FFT power values and calories obtained from treadmill were used to derive the individual regression equations for walk and run activities respectively for 10 different subjects.
Table 5.3: Data collected for deriving the regression equations for estimating the energy expenditure

<table>
<thead>
<tr>
<th>Subject</th>
<th>Time</th>
<th>Walk function</th>
<th>Treadmill calories</th>
<th>Time</th>
<th>Running function</th>
<th>Treadmill calories</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10.52–10.54</td>
<td>246</td>
<td>90</td>
<td>10.57–10.59</td>
<td>477</td>
<td>135</td>
</tr>
<tr>
<td>3</td>
<td>13.50–13.52</td>
<td>243.8</td>
<td>78</td>
<td>13.55–13.57</td>
<td>481</td>
<td>147</td>
</tr>
<tr>
<td>4</td>
<td>16.03–16.05</td>
<td>248</td>
<td>100</td>
<td>16.08–16.10</td>
<td>478.6</td>
<td>140</td>
</tr>
<tr>
<td>5</td>
<td>16.41–16.43</td>
<td>247</td>
<td>94</td>
<td>16.46–16.48</td>
<td>483</td>
<td>151</td>
</tr>
<tr>
<td>6</td>
<td>08.15–08.17</td>
<td>245.4</td>
<td>86</td>
<td>08.20–08.22</td>
<td>476.3</td>
<td>131</td>
</tr>
<tr>
<td>7</td>
<td>08.29–08.31</td>
<td>246.2</td>
<td>90</td>
<td>08.34–08.36</td>
<td>480.5</td>
<td>145</td>
</tr>
<tr>
<td>8</td>
<td>09.42–09.44</td>
<td>243.9</td>
<td>74</td>
<td>09.47–09.49</td>
<td>484.6</td>
<td>158</td>
</tr>
<tr>
<td>9</td>
<td>09.31–09.33</td>
<td>245.6</td>
<td>88</td>
<td>09.36–09.38</td>
<td>478</td>
<td>137</td>
</tr>
<tr>
<td>10</td>
<td>09.43–09.45</td>
<td>246</td>
<td>87</td>
<td>09.48–09.50</td>
<td>481.4</td>
<td>149</td>
</tr>
</tbody>
</table>

Two regression models were derived for walking and running activities respectively and the regression models of walk and run with respect to calories were represented in figures 5.6 and 5.7.
The regression analysis provided the coefficient of determination and residual standard deviation sum of squares due to error are $R^2 = 0.9617$, RSD = 1.551 and equation (5.1) obtained for walking activity from this model is

$$ y = -1325.8611 + 5.7510 \, x $$

(5.1)

Where $y$ is the predictor variable which is energy expenditure in calories need to be estimated from the accelerometer data and $x$ is the response variable from which energy expenditure is being calculated.
The regression analysis provided the coefficient of determination and residual standard deviation sum of squares due to error are $R^2 = 0.9781$, \( \text{RSD} = 1.2749 \) and equation (5.2) obtained for Running activity from this model is

$$ y = -1314.5690 + 3.0382 x $$  \hspace{1cm} (5.2)

The two regression models were used in the data for further analysis of energy expenditure and the equations were tested on 20 different subjects for the walking and running activities respectively and proved to estimate the calories with reduced error.

![Graph showing the comparison between observed and derived calories for walking activity](Image)

**Figure 5.9: Walking activity by 20 different subjects.**

The data which is observed from 20 different subjects and the data which is obtained from our regression equation represent in equation 5.1 and equation 5.2, are within the limits of acceptance for estimating the energy expenditure as the results obtained from statistical analysis are as follows:

<table>
<thead>
<tr>
<th>Sample size</th>
<th>20</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correlation coefficient $r$</td>
<td>0.9492</td>
</tr>
<tr>
<td>Significance level</td>
<td>$P&lt;0.0001$</td>
</tr>
<tr>
<td>95% Confidence interval for $r$</td>
<td>0.8737 to 0.9801</td>
</tr>
</tbody>
</table>
The line of equality plot with the observed calories and derived calories is as follows for the running activity:

![Figure 5. 10: Running activity by 20 different subjects](image)

The obtained correlation coefficient is as acceptable for estimating the energy expenditure estimation for a given activity:

<table>
<thead>
<tr>
<th>Sample size</th>
<th>20</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correlation coefficient $r$</td>
<td>0.8805</td>
</tr>
<tr>
<td>Significance level</td>
<td>$P&lt;0.0001$</td>
</tr>
<tr>
<td>95% Confidence interval for $r$</td>
<td>0.7175 to 0.9520</td>
</tr>
</tbody>
</table>
6 MODEL VERIFICATION

Algorithm Verification:

The algorithm presented in thesis bears the attribute of extensibility. The same basic threshold-based steps that have been explained can be used to identify many other patterns of movements like standing, walking and running. The algorithm is tested on various different subjects following a standard protocol as mentioned in the methodology. The algorithm was tested extensively on 30 different subjects and it was 93 % accurate in detecting the activity as per our analysis.

The data was collected based on a the protocol so as to know, how well the data collected during different observations will fit into the derived model, and the standard observations of standing, walking and running were taken into consideration on all the different 30 subjects. The observations accuracy were mentioned in the below table (6.1) as per the observations.

<table>
<thead>
<tr>
<th>Subject Activity</th>
<th>Obtained activity</th>
<th>Standing</th>
<th>Walking</th>
<th>Running</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standing</td>
<td></td>
<td>99%</td>
<td>1%</td>
<td>0 %</td>
</tr>
<tr>
<td>Walking</td>
<td></td>
<td>0%</td>
<td>98 %</td>
<td>2 %</td>
</tr>
<tr>
<td>Running</td>
<td></td>
<td>0 %</td>
<td>3 %</td>
<td>97 %</td>
</tr>
</tbody>
</table>

Table 6.1: Offline observations accuracy with respect to our derived threshold based model.
Table 6.2: Observation and comparison of 20 subjects

<table>
<thead>
<tr>
<th>Subject</th>
<th>Time</th>
<th>Walk function</th>
<th>Observed calories from equation</th>
<th>Treadmill calories</th>
<th>Time</th>
<th>Running function</th>
<th>Observed calories from equation</th>
<th>Treadmill calories</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>14.52-14.54</td>
<td>247</td>
<td>94.63</td>
<td>101</td>
<td>14.57-14.59</td>
<td>476.2</td>
<td>135</td>
<td>138</td>
</tr>
<tr>
<td>2</td>
<td>08.15-08.17</td>
<td>245.3</td>
<td>84.85</td>
<td>87</td>
<td>08.25-08.27</td>
<td>476.8</td>
<td>134.04</td>
<td>146</td>
</tr>
<tr>
<td>3</td>
<td>16.07-16.09</td>
<td>244.6</td>
<td>80.83</td>
<td>76</td>
<td>16.08-16.10</td>
<td>480.5</td>
<td>145.28</td>
<td>147</td>
</tr>
<tr>
<td>4</td>
<td>10.52-10.54</td>
<td>247</td>
<td>94.63</td>
<td>93</td>
<td>10.57-10.59</td>
<td>478.3</td>
<td>138.60</td>
<td>136</td>
</tr>
<tr>
<td>5</td>
<td>13.46-13.48</td>
<td>245</td>
<td>83.13</td>
<td>86</td>
<td>13.51-13.53</td>
<td>482.1</td>
<td>150.14</td>
<td>147</td>
</tr>
<tr>
<td>6</td>
<td>11.35-11.37</td>
<td>244.3</td>
<td>79.10</td>
<td>77</td>
<td>11.40-11.42</td>
<td>477.3</td>
<td>135.56</td>
<td>141</td>
</tr>
<tr>
<td>7</td>
<td>17.28-17.30</td>
<td>245.2</td>
<td>84.28</td>
<td>86</td>
<td>17.33-17.35</td>
<td>482.5</td>
<td>151.3</td>
<td>153</td>
</tr>
<tr>
<td>8</td>
<td>17.58-18.01</td>
<td>243.6</td>
<td>75.08</td>
<td>80</td>
<td>18.04-18.06</td>
<td>483.6</td>
<td>154.7</td>
<td>150</td>
</tr>
<tr>
<td>9</td>
<td>08.49-08.51</td>
<td>244.6</td>
<td>80.83</td>
<td>82</td>
<td>08.54-08.56</td>
<td>479</td>
<td>140.7</td>
<td>140</td>
</tr>
<tr>
<td>10</td>
<td>14.26-14.28</td>
<td>248</td>
<td>100.38</td>
<td>99</td>
<td>14.31-14.33</td>
<td>483.4</td>
<td>154.09</td>
<td>153</td>
</tr>
<tr>
<td>11</td>
<td>08.25-08.27</td>
<td>246</td>
<td>88.88</td>
<td>86</td>
<td>08.30-08.32</td>
<td>478</td>
<td>137.6</td>
<td>139</td>
</tr>
<tr>
<td>12</td>
<td>16.33-16.35</td>
<td>247.4</td>
<td>96.93</td>
<td>95</td>
<td>16.38-16.40</td>
<td>480</td>
<td>143.7</td>
<td>145</td>
</tr>
<tr>
<td>13</td>
<td>10.18-10.20</td>
<td>245.3</td>
<td>84.85</td>
<td>89</td>
<td>10.23-10.25</td>
<td>485</td>
<td>158.9</td>
<td>161</td>
</tr>
<tr>
<td>14</td>
<td>13.36-13.36</td>
<td>246</td>
<td>88.88</td>
<td>91</td>
<td>13.41-13.41</td>
<td>476</td>
<td>131.6</td>
<td>128</td>
</tr>
</tbody>
</table>
Matlab results during observations with respect to individual activity are shown in below figures:

<table>
<thead>
<tr>
<th></th>
<th>13.38</th>
<th>13.43</th>
<th>15</th>
<th>16</th>
<th>17</th>
<th>18</th>
<th>19</th>
<th>20</th>
</tr>
</thead>
<tbody>
<tr>
<td>15</td>
<td>09.11-09.13</td>
<td>245</td>
<td>83.13</td>
<td>85</td>
<td>09.16-09.18</td>
<td>482.3</td>
<td>150.7</td>
<td>145</td>
</tr>
<tr>
<td>16</td>
<td>17.35-17.37</td>
<td>244.4</td>
<td>79.68</td>
<td>82</td>
<td>17.40-17.42</td>
<td>476</td>
<td>131.6</td>
<td>136</td>
</tr>
<tr>
<td>17</td>
<td>08.57-08.59</td>
<td>247.2</td>
<td>95.78</td>
<td>93</td>
<td>09.2-09.04</td>
<td>481</td>
<td>146.8</td>
<td>142</td>
</tr>
<tr>
<td>18</td>
<td>08.15-08.17</td>
<td>249.9</td>
<td>111.31</td>
<td>109</td>
<td>08.20-08.22</td>
<td>480.5</td>
<td>145.2</td>
<td>148</td>
</tr>
<tr>
<td>19</td>
<td>09.55-09.57</td>
<td>245.8</td>
<td>87.73</td>
<td>86</td>
<td>10.00-10.02</td>
<td>475.2</td>
<td>129.18</td>
<td>132</td>
</tr>
<tr>
<td>20</td>
<td>16.33-16.35</td>
<td>249</td>
<td>106.13</td>
<td>105</td>
<td>16.38-16.40</td>
<td>476.8</td>
<td>134.04</td>
<td>132</td>
</tr>
</tbody>
</table>

Figure 6. 1: Plot of matlab output illustrating the orientation of the subject’s activity “Standing”
The overall prediction of the Model is always successful for any different kind of data provided, hence we would like to take this to real time Android Based application in our future approach.
7 CONCLUSION

In this model we have developed an algorithm for activity classification and energy expenditure estimation, which helps us in monitoring daily human activity with greater accuracy. The results are validated with standard energy expenditure technique and activity classification video observations. We want this model to be integrated in smart mobile phones to give the end user a friendly atmosphere without adding any complicated features for the handling of equipment.

This model is very useful in clinical monitoring of patients, it will help us to monitor old, sick, and mentally retarded subject’s activity identification and helps us in close monitoring of patients though physically being away from them. Our portable MEMS based triaxial accelerometer system based smartphone compatible algorithm along with other physiological monitoring parameters will provide accurate motion monitoring and energy expenditure estimation for clinical analysis.

This model is useful in analyzing and monitoring group and individual subjects, which will lead to tracking their motion and a successful rescue operation to rescue them from fatal conditions and prevent risks when they are injured.

Future work will be continuous monitoring of subjects individual activity along with the group activity. Identifying posture transition of various activities in a short time span like running to sitting, sitting to standing, standing to crawling etc.
8 REFERENCES


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14. Wee-Soon Yeoh; Jian-Kang Wu; Pek, I.; Yong, Yi-Han; Xiang Chen; Waluyo, A.B., "Real-time tracking of flexion angle by using wearable accelerometer sensors," Medical Devices and Biosensors, 2008. ISSS-MDBS 2008. 5th International Summer School and Symposium on , vol., no., pp.125,128, 1-3 June 2008


