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# Indicating Human Activity Intensity using Accelerometer

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## *Abstract*

*In this paper, we propose to develop a system that senses the human activity and indicates the intensity of action performed. Intention is to broadly classify human as inactive, underactive, overactive and hyperactive by simply turning on the LED of the system corresponding to the data received on the controller from ADXL345. The focus is on the fact that energy expenditure is related to the sum of integral of values of each axes of a tri-axial accelerometer. The objective is to know the activity intensity in terms of comparison and not as exact value. This simplifies our approach and also reduces the cumbersome algorithms used in Human activity recognition (HAR) based energy calculating systems. Indication of activeness and inactiveness of an individual is a multidisciplinary field finding application in more ways than one.*

***General Terms:*** *activity intensity, accelerometer, embedded system, gravitation constant, peripheral interface microcontroller (PIC)*
***Keywords:*** *sensor, microcontroller, activity intensity, indication, threshold, energy expenditure, human activity*

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## INTRODUCTION

Human activity recognition opens an altogether new domain of research which can be exploited for designing various applications. Calculation of the energy expenditure associated with performing various human activities has been an area of research that can be used to characterize the measure of human being active or inactive. The existing system mainly focuses on calculation of parameters associated with the signals to recognize the activity and calculate the energy spent in performing it [1]. The day to day activities no matter how simple or complex require the movement of body which results in stretching of muscles and hence results in consumption of body stored fats. The energy released can be hence manipulated to infer the relative amount of activity performed by an individual. Energy consumption in performing any kind of movement in a way defines the activeness of an individual. The various traits such as stamina, strength, agility are in terms of energy spent by an individual in a period of time and the pattern of energy consumption. Although there are existing models to calculate the energy expenditure such as calorimeters, pedometers, and heart rate meters, they pose several limitations. Such systems are either bulky, expensive, power consuming or vulnerable to environment. Moreover many such existing systems require large amount of training data for efficient operation [2]. These systems have been extensively used in conjugation with the accelerometers to determine the accuracy of results inferred by comparing the results of both systems [3].

Body worn sensors such as accelerometers have been widely used for activity recognition and energy along with entropy, standard deviation, mean, correlation and tilt angle has been used as parameter to classify human postures. The parameters associated with the signal are calculated using MATLAB inbuilt functions and algorithms are developed to classify the data. The data are used to train the system using fuzzy logic to determine posture of human body. Extensive calculations are done with data to determine exact value of energy spent by the human. Thus the concept of using accelerometers that are robust, miniaturized, low power consuming and inexpensive comparatively are a smart choice [4].

  

The output of accelerometer represents the vector sum of the gravity and kinematic accelerations. Accelerometers are built in electronic component based on electromechanical principle that measures the value of acceleration due to gravity (g) in various axes (x, y and z). Nowadays modules are available with a sensor along with the processing unit to give us digital values of x, y and z axes. Modules such as ADXL345 have a sensor for sensing the signals, analog to digital converter to digitalize the signals, filter to reduce noise and interference, 32-level FIFO to store the subsequent values, power management system, control and interrupt logic and serial input output. Such modules enable faster development of applications as they are ready to use and we get a digital output of values of g in all three axes. Several researches from various fields have proved that the data from accelerometers i.e. the inclination of sensors with respect to gravitational axes can be used to calculate the energy associated with signals generated. Moreover the correlation between axes can also be used effectively to further improve the estimation of intensity of human activity. The movement of human body in any direction produces a signal according to the sensor being used A continuous stream of data is stored in the data registers of the ADXL module. Accelerometer supports SPI as well as $I^2C$ to communicate with the application development board [5].

Predicting the activity intensity as an indicative factor provides effective feedback and intervention in domain that requires knowledge about not the exact energy spent in doing a certain set of activity but an idea of level of activity performed.

## RELATED WORK

Determining the activity intensity or the amount of energy expended or number of calories burnt while performing and activity using accelerometers and gyroscopes has been explored. It has been substantially proven that the expenditure of energy is correlated to the acceleration produced by body. Carlijn V. C. Bouten [1] describes the development and accuracy of one such system in terms of energy expenditure [4]. It highlights the fact that piezo-resistive accelerometers require calibration due to its DC response. The connection between the data unit and the TA is established via a 0.5 m flexible 12 conductor shielded cable. Individual outputs from the three measurement directions of the TA are amplified and high pass (0.11 Hz, 5.6 dB/octave) and low pass (20 Hz, 9 dB/octave) filtered to attenuate dc-response and frequencies. Acceleration signals are then digitized and the data logger unit is programmed to calculate IMA tot for the assessment of daily physical activity. The time period for integration is variable and can be adjusted at the start of a measurement period. After processing, the obtained data are stored in a 512 KB, 16 bit data memory chip can be read out with the serial interface to a computer. The data unit enables the amplification and filtration of acceleration signals from the TA as well as the storage of IMA tot over periods of days or weeks to study patterns of daily physical activity. The values of actual energy expenditure EE act were calculated from IMA tot and compared to the predicted value.

An existing model by Taekyun Kim has calculated the integrals of signal sets and determined the regression coefficients to calculate the energy spent [6]. It implies that that the body mass and acceleration of legs and arms correlates to the amount of energy expenditure. Sensors have been placed at various locations and results have been compared to gas analyser, treadmill, heart rate meters and calorimeters to judge the accuracy of prediction by accelerometers.

A comparative paper by Harshvardhan Vathsangam [7] compares the results from various methodologies for energy expenditure while walking on a treadmill and deduces the following:
Firstly, Tri-axial information yields better and more accurate results than uni-axial sensor. It improves prediction and provides higher dimensional feature space.

Secondly, it compares algorithms to determine regression coefficients and predicts that Bayesian linear regression and Gaussian process regression are less prone to error but require more training data. Nonlinear techniques are compared to linear ones wherein GPR has reduced average RMS prediction error.

Thirdly, it compares use of accelerometers, gyroscopes or both. Use of gyroscopes reduces average RMS value and both give better prediction by reducing prediction errors.

Another paper by Alka R. Kaushik, [8] states that Triax accelerometer estimates energy expenditure with approximate 90% correlation. It attempts to bring out similar results from non-contact infrared sensors. It states that the energy expenditure can be calculated as the integral area under each AC component of output signals.

$$EE = \alpha IA = \alpha\left(\int |a1|\,dt + \int |a2|\,dt + \int |a3|\,dt\right) \quad (1)$$

It uses various models to cumulatively calculate the regression coefficients to assess the relation between energy expenditure and sensor data.

Another research work by Marco Altini, introduces a new methodology for activity specific modelling [2]. In this work an algorithm has been designed by clustering groups of activities and then model sedentary and non sedentary activities separately. Sedentary activities are based on anthropometric variables (AV) and are assigned static Energy Expenditure (EE) whereas Non sedentary are on basis of the accelerometer data (ACC) or heart rate (HR). The summation of ACC, HR, MET (metabolic equivalent) and AV helps in activity classification.

Many researchers have sought to the use of accelerometers to calculate expenditure of energy [9] and compared to data collected from some standard methodologies.

Apart from this, a lot of literature [4,9,10] is available on the human activity recognition systems that serve as the foundation to design of intensity indicating system.

## PROBLEM STATEMENT

The existing systems are mainly based on Human activity Recognition or Posture Classification based on complex algorithms such as HMM, Forward-Back Algorithm, Linear Discriminant analysis, Support Vector machine, Decision tree to generate test data to train systems using concepts of Neural Networks and Fuzzy Logic. Once the posture is decided, the energy corresponding to it is calculated using mathematical formulas. The exact values of energy are calculated and a detailed analysis of posture is required.

## SOLUTION APPROACH

In this paper we attempt to counter the problem stated above by designing a model that acquires the value of movement in x, y, z axes in terms of gravitation force (g) using a gravitation sensor ADXL345. The data from the data registers of the ADXL module is transferred to the Flash Memory of PIC18F452 via SPI. The values stored in the memory are averaged to generate resultant values. The resultant values trigger the corresponding Light Emitting Diode (LED) to be turned ON according to the threshold set in the program code. LED's help to indicate the intensity of action in contrast to the energy expedited during movement of human body as per the Table 1 given below.

***Table 1:*** *Intensity Indication According to LED.*

| COLOUR OF LED | INDICATION |
|---|---|
| Red | Inactivity |
| Green | Underactivity |
| Yellow | Overactivity |
| All | Hyperactivity |

## METHODOLOGY

### Hardware

The hardware consists of PIC18F452 microcontroller with its basic hardware connections interfaced to ADXL345 accelerometer unit which is an inbuilt sensing and processing unit. The output is displayed by the pattern of LED's. The system is also serially connected to the PC via RS232 using MAX232 and DB9 connector. The output values are collected on the hyper-terminal and processed for future validation of system accuracy.

### Hardware Description

**PIC18F452:** The microcontroller has been used because it can send data via UART to PC as well as it supports SPI to communicate with the ADXl345. It works on 5V with its basic hardware connections [11].

**ADXL345:** It is a module which senses as well as processes the acceleration due to gravity in all 3 axes and gives a digital output. It has a built in power management and data storage 32 level FIFO. It works on 3V [5] and is connected via ribbon cable to the hardware.

**LED:** Three different colored LEDs form an array of LED that indicates the activity intensity of the subject.

**Power Supply:** A separate power supply section is developed that sources the hardware with 5V and accelerometer with divided voltage 3.3 V. A potentiometer is used to divide the reference voltage.

The basic block diagram of system is shown in Figure 1.

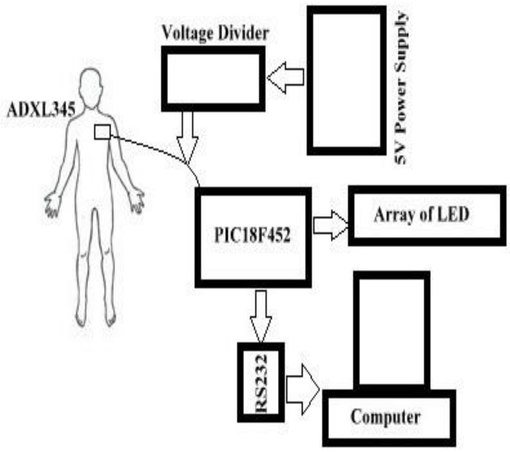


***Fig.1:*** *Block Diagram of Hardware.*

## SOFTWARE

### Program Flow

The software has been modeled to capture the relative changes in all three axes. The software uses the hardware sensed values of g in terms of x, y, z axes using ADXL345. ADXL has data registers to store the value of g according to the configuration of the inbuilt registers set using program code. These values are fetched by the microcontroller PIC18F452 using SPI protocol and stored at its internal memory locations. The values of g for each axis are summated after every 10 values and then finally a cumulative sum is calculated for all three axes. The value is then compared to the three threshold values namely Th1, Th2, and Th3. The sum is compared to these thresholds and according to the flowchart; LEDs are switched ON to indicate the intensity of movement produced by human body.

The flow of software is shown in Figure 2.

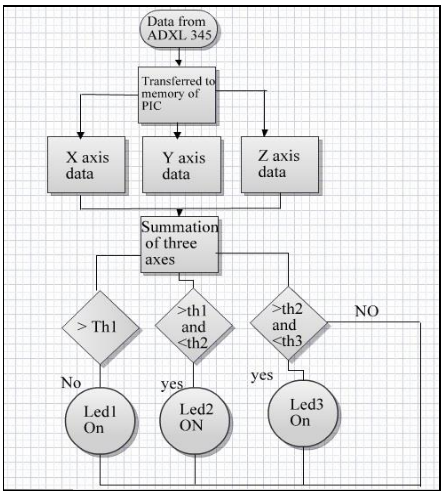


***Fig. 2:*** *Flowchart of Algorithm.*

The values of g are also serially transmitted to the computer such that we can calculate the tilt angle, standard deviation, entropy and correlation of signals among the axes to further consolidate exact posture of body i.e. HAR.

We use MPLAB 8.70 for programming of PIC and WinPIC800 to burn the code onto the hardware using an ICP. The hyper-terminal used to receive the data is of Flash Magic. The code has been written in C language.

## RESULTS

The values acquired from the data registers are in terms of hex values of 8-bit. These values have a resolution value in terms of either g/LSB or mg/LSB where g=9.8 (acceleration due to gravity).

Three subjects were asked to place the accelerometer on their shoulder and demonstrate any kind of movement. Light movements such as lying down or sitting straight showed less changes in g and hence red LED glows. Walking and moving around were among the under-activity category with green LED glowing. Intense movements such as brisk walking and light jumps made yellow LED to glow. In case of jumping, hopping, dancing i.e. fast and intense movements, all three LEDs were ON as shown in Table 2 above. Thresholds were set at 2, 4 and 8g.

***Table 2:*** *Indication of Movement with Respect to Activity.*

| **Activity** | **∑x** | **∑ y** | **∑ z** | **∑(x+y+z)/30** | **Result** | **LED** |
|---|---|---|---|---|---|---|
| Running | 110 | 90 | 130 | 11 | Hyperactive | Red, Yellow, Green |
| Jumping | 150 | 70 | 80 | 10 | Hyperactive | Red, Yellow, Green |
| Brisk walking | 100 | 75 | 65 | 8 | Overactive | Yellow |
| Walking | 50 | 40 | 30 | 4 | Underactive | Green |
| Moving | 55 | 45 | 20 | 4 | Underactive | Green |
| Standing | 20 | 30 | 10 | 2 | Inactive | Red |
| Sitting | 10 | 40 | 40 | 3 | Inactive | Red |
| Lying | 20 | 20 | 20 | 2 | Inactive | Red |

## CONCLUSIONS

We conclude that a model developed is to estimate the intensity of movement of humans without actual calculation of energy spent on performing the said activity. A simple technique has been brought to use for determining the amount of activeness of an individual.

## FUTURE SCOPE

The unit is further serially connected to a laptop unit for processing of data for analysis of the posture of human body. The parameters of signal are calculated and then processed to calculate the amount of energy that has been spent while performing the activity. MATLAB R2009 has toolbox to calculate the tilt angle, power, standard deviation, variance and correlation. It also has Fuzzy logic toolbox to apply fuzzy logic and cluster the values to generate specific results. The amount of energy can be calculated by estimating the regression coefficients as discussed in the literature above. We may calculate exact value of energy if required in future using the values obtained in this study. This is beyond our scope of discussion and may contribute to future work in this field.

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