HUMAN ACTIVITIES & POSTURE RECOGNITION

Innovative algorithm for highly accurate detection rate

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in

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I acknowledge Professor Subhas Mukhopadyay and my parents Mr & Mrs Ranhotigamage for giving me the motivation to complete this research project successfully.

TABLE OF CONTENTS

Contents

EXECUTIVE SUMMARY

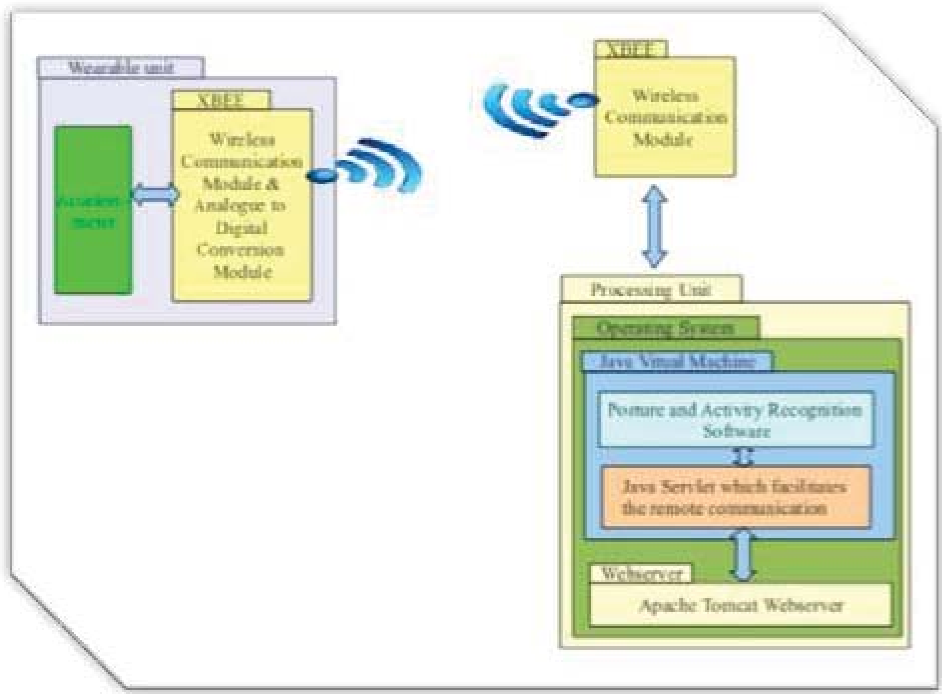
The main purpose of thesis is to introduce new innovative algorithm for "unintentional fall detection" with 100% accuracy of detecting falls on hard surfaces which can cause severe and sometimes fatal injuries. Furthermore this thesis explains how to detect deliberate human activities such as running, walking etc using the same algorithm with near perfect accuracy. Subset of the above mention algorithm is used for posture recognition as well.

The above mentioned algorithm is converted into computer software using java programming language for real time detection. A graphical user interface is developed to display human posture and activity information.

Most pre-existing algorithms need expensive and wide range of sensors to achieve this level of accuracy. In this thesis it explains how to use just one tri-axial accelerometer with wireless zigbee communication module and achieve far better accuracy. Most of the other sensor types violate human privacy therefore they are unethical to be used at residence of vulnerable elderly or sick individual and majority of them are very expensive when compared to a tri-axial accelerometer which costs just around NZ$5.

Intended target audience: Engineers with mathematical and data analysis background.

Overview of the developed system



1. INTRODUCTION

According to the United Nation, population of the developed countries are aging fast [50]. Therefore it has become a timely necessity to develop automated care systems for the elderly.

Growing number of elderly people prefer to live in their own homes, all alone, in their golden age. This is not an ideal way for an elderly person to live. But the urbanization and resultant change of the social and cultural behaviour makes it a more frequent occurrence.

In 1996, approximately one third of older New Zealanders were living alone [51]. According to the same source, in 1960s the percentage of older people living alone was only 20%. And in the developed European countries like Germany and Holland the number of aging people living alone are far more alarming and it reaches 40% mark. According to the UN report this is an upward trend [50].

As the people age, the tendency of developing diseases such as poor eye sight, arthritis, cardiovascular diseases, diabetes and neurodegenerative diseases increase and this can impact the mobility of the elderly in a very negative manner. These diseases can reduce their reaction time, reduce the balance, can affect their decision making as a result they become more prone to falling. Furthermore there are other environmental factors such as obstacles lying on the ground, stairways, wet floors, and poor lighting conditions can pave the way to increase risk of falling even for healthy individuals.

The real problem occurs when an elderly person who is living alone get severely sick or in a worst case fall and get injured making him or her unable to ask for help. In some unfortunate situations, after they fall or got very sick they might even have to live through that agony and physical pain until their final breath without any sort of help.

It is reported that nearly one third of people over the age of 65 fall each year [52]. Among those who fall at the age over 65, 47% is reported to have head or neck injuries and 27% hip injuries. Head and neck injuries can cause instant unconsciousness making the faller unable to ask for any help. Similarly a broken hip would disrupt their ability to move to a phone to alert emergency services unless the phone is already with them at the time of fall. Due to this reason it is much essential to have a reliable fall detection system for elderly people who are living alone so that the guardian of the elderly can dispatch immediate emergency medical assistance as soon as possible. This would probably save the life of the elderly, reduce the recovery time and minimise the unwanted complications.

Human beings are creatures of habits. Behavioural experts have found out that an average human being follows a predictable pattern of daily physical activities unless there is a considerable change in the circumstances or environmental factors around them. So by observing and analysing the daily physical activity patterns, one can deduce whether there are uncharacteristic behavioural changes in an individual. So by having a daily activity monitoring system, it can be easily identified whether an elderly person living alone is becoming ill and need to be given assistance.

There are many different methods of tracking the behavioural patterns which have been widely researched by the engineering community such as, Image based behavioural patterns tracking, RFID based behavioural patterns tracking, Ultrasonic distance based behavioural patterns tracking, Radio wave signal strength based behavioural patterns tracking, Accelerometer/Gyroscope based behavioural patterns tracking, Strain sensitive clothing based behavioural patterns tracking, Magnetic sensor based behavioural patterns tracking, Electrostatic sensor based behavioural patterns tracking to name few.

Every one of those technology has their own strengths and weaknesses in strictly technological terms, for example, the image based tracking highly depends on the room illumination level can be regarded as a huge disadvantage.

In the economic sense the hardware costs of the image based system as well as RFID based system far exceeds the hardware cost for the ultra-sonic sounds based system and accelerometer based system.

When considering the ethical implications of the chosen technology, both image based and RFID technology has been viewed as a violation of privacy and harmful to human dignity and therefore treated as unethical.

Among those technologies, accelerometer based system is deemed to be ethically acceptable, cost effective and reliable.

This undertaking is to utilize an existing sensor technology in a novel way to help vulnerable elderly who are living alone while protecting their dignity and independence.

2. Research on available technologies

2.1. Image based human posture recognition

Technology in a nutshell

This technology relies on the real time images taken from cameras which are mounted in the living space of the human subject who is being monitored. The captured image is processed to extract the subject in order to find the posture/activity of the individual. In the database, data of different postures are stored and to find the relevant posture, the extracted image of the subject is compared with postures in the database to find the most accurate match.

Technical limitations and Implementation complexity

A system developer cannot dictate to the end user how to illuminate the living space of the end user, so amount of illumination at the end users living space is an unknown from the system developers' point of view. Especially if the end user has very poor eye sight he or she might not to opt to switch on a light source when it is dark to move around because it does not make much difference to them. But to a system which heavily depends on the background illumination for its video camera inputs, it is very cumbersome to get accurate representation of the moving object every time. Furthermore any attempt to nullify the effect of varying lighting level by introducing extra algorithms makes the computer application unnecessarily high taxing for the data processing unit [55].

Overlapping of other moving objects with the target subject would give false results. But research has been done to overcome this limitation by utilizing 3D imagery [53].

The size of the elderly individuals can have a high variation across the spectrum; therefore it is required to work on considerable amount of setting up tasks even after the implementation of the system is completed [54].

Cost of the implementation

It requires minimum of one camera for an each separate living space (bedroom, dining area, kitchen etc.). This can be very expensive to implement. It needs a high end computer processing system to process imagery in real time.

Ethical issues

The amount of ethical implications of the use of cameras in the living spaces of an individual has no bounds. Even though such practices are widely used by the intelligence community and law and order community, it is not any way acceptable technological tool for the engineering discipline from the ethical standpoint. In the engineering research community there are arguments which validate the use of cameras in common living areas such as kitchen and dining rooms. But also the counter arguments highlight the issues the elderly individuals with the dementia find themselves in most of the time. It would make no difference whether the cameras are only placed in common areas such as kitchen. Therefore for an engineering undertaking which is bound to provide service to the human individuals while protecting the dignity of the individuals, the image based posture recognition system is not acceptable.

2.2. Ultrasonic based system

Technology in a nutshell

An ultrasonic sensor sends an ultrasonic sound wave and receives the echo of the sound wave. The time interval between the sending the sound wave and receiving the echo is used to calculate the distance between the sensor and the object which the sound wave just bounced off.

The target living area is mapped to a 2D distance sensor matrix. In order to achieve this, multiple ultrasonic transceivers are placed on the roof of the target area. Each individual sensor calculates the distance to its' nearest object and those collected results are used to create an accurate 2D distance matrix of the target living area. Just like in the image processing, human subject can be identified by subtracting the background 2D matrix from the current 2D matrix. By this way it can track the movement of the human subject [58].

Technical limitations and Implementation complexity

Having to rely on 2D matrix, rather than 3D matrix would make the processing and interpretation of data very trivial. Because in the 2D matrix, analysis is primarily based on the body height and body width of the human subject. So just like in the image based system, in this case also any object overlapping can cause incorrect analysis. For example having a large pet dog or human subject carrying large basket of laundry would give inaccurate posture analysis in the 2D matrix based system. The obvious solution for this is to implement 3D matrix system, which means implanting ultrasonic sensors on the side walls as well, but this comes with a huge cost increase [57].

Accuracy of the 2D system depends on the resolution of the ultrasonic matrix which is created by the processing computer which uses the ultrasonic sensor data. In other words to get a higher resolution you need to have higher number of sensors installed. So the higher the number of sensors the higher the accuracy of the processed output but also the cost of implementation is also higher. But the advantage of this technology is, in terms of algorithm and analysis the increased number of sensors would not require drastic increase in processing power of CPU as the required processing is very less power hungry compared to the image processing [57] , [58].

Ethical issues

One of the main advantages of this system is, it is considered to be ethically suitable and non-intrusive to personal privacy when compared with image based system.

2.3. Radio wave signal strength based system

Technology in a nutshell

This technology uses RSSI (Receive Signal Strength Indicator). Radio signal sending and receiving nodes are placed throughout the body. Periodically the radio signal sending units send out a burst of signal and receivers track the signal strength of each received signal. Then these RSSI values are sent to the processing computer by the receiving units.

The processing computer uses those data to calculate the distance between the different body parts and based on that, it calculates the posture of the human subject [56].

Technical limitations and Implementation complexity

In order to achieve any sort of success, multiple sending units and receiving units have to be placed on the human subjects' body. This can be very uncomfortable to the human subject as well as it carries unnecessary amount of cost burden too. The other issue is, selecting a proper period for the signal burst. Sending the burst of signal quite frequently would deplete the batteries very quickly. On the other hand not sending signals frequently enough would also cause the system to miss very important data [56]. Therefore this sort of technology would be ideal only to find static postures.

Ethical issues

Having multiple nodes placed throughout the body would not be an ideal solution for an elderly. The physical discomfort which might cause from wearing these nodes throughout the body, day in and day out can be easily imaginable but whether any psychological discomfort which might arise from wearing these technical tools is yet to be properly researched.

2.4. Thermal Infrared based system

Technology in a nutshell

In an ordinary image based system, the image is retrieved using the cameras which rely on the reflected photons of the light whose frequency range lies within the visible spectrum. But infrared cameras record electromagnetic radiation emitted by the human subject and the pixels of the image represent the temperature footprint of the human subjects' body heat.

Just like in ordinary image processing, first, the human silhouettes are extracted from the background. Then human posture is deduced from the image and using multiple subsequent images the activity is statistically determined [59].

Technical limitations and Implementation complexity

Unlike ordinary image based system, the infrared thermal imaging system is not vulnerable to the changing lighting conditions in the surrounding. This is a big advantage it has over the ordinary image based system.

Non-transparent solid objects block visible light photons hence in an ordinary image based system it creates blind spots where the camera cannot see the human subject even within a close proximity. But using infrared camera system this issue can be avoided. In essence the number of cameras needed for the undertaking can be largely reduced [60].

Ethical issues

Infrared cameras are far more widely accepted than the ordinary cameras. Yet infrared cameras are also considered to be an intrusion of privacy to a certain extent, therefore not an ideal tool to be used in private households.

2.5. Strain Sensitive based system

Technology in a nutshell

The strain sensitive materials such as ethylene-vinyl acetate and ethylene-propylenediene rubber and many more change their resistance to the electron conductivity under the different strain levels on the material. This property of these materials is exploited to create strain sensitive wearable sensors, so by simply measuring the resistance, the researcher can find the amount of strain which the material is under [61].

Technical limitations and Implementation complexity

The application of this technology is fairly straightforward. But selecting an appropriate strain level sensor needs a great deal of attention. Carbon black-composite strain level sensors have relaxation time of several minutes; therefore strain sensors made out of this type of materials are not ideal for relatively high frequency activities such as human activity monitoring. Yet strain sensors made out of thermoplastic elastomer materials do not require curing period so it makes a suitable candidate for strain sensors for monitoring human postures. The other main external factor which can affect the sensor output is humidity, where it is recorded that, humidity can cause up to 40% variance in resistivity. The other issue with this type of sensor is, it is a mechanical sensor which undergoes continuous force and this ages the sensor fairly quickly due to the mechanical stresses. The aging has bearing effects on the accuracy of the sensor output. Therefore the long term reliability of this type of sensors are highly variable and it depends on the sensor material, how sensors are attached to the wearer, whether the sensors are washed and of course the frequency of high intensity strain levels on the sensor [61].

Ethical issues

This type of sensing technology is non-intrusive and also can be attached to the garment of the human subject which would avoid any discomfort to the human subject.

2.6. RFID based system

Technology in a nutshell

Most commonly, the implementation of Radio Frequency Identification technology in posture recognition context consists of many passive RF tags and single RF reader. Unlike active RF tags which rely on internal battery for power, passive RF tags depend on the energy emitted from the transmitting electromagnetic signals of a RF reader.

Human subject wears multiple RF tags across the body. The RF reader has to be placed strategically and most common position for that would be in one of the hands. Based on the RF reader sensing data, the RF readers' location relative to the different region of the human subjects' body can be found. The analysing software can use this location information to extract human posture details and by tracking continuous posture details, the human subjects' activity can be found [63].

Technical limitations and Implementation complexity

One of the main advantage of this technology is the fact of passive RF tag costs only few cents and the size-wise RF tags also very small (few millimetres). Since the introduction of washable RF tags, it is feasible to place the tags in most of the clothes of the human subject.

But there is a considerable limitation in this technology when it comes to correctly find the activity of the human subject because only the relative positions of the human body parts to each other is tracked in this sort of system. Therefore in an event where the human subject is falling down, it is extremely difficult to find a common behavioural trend to find how a human would place their most dominant limb (Usually the most dominant limb is where the RF reader is placed because the most dominant limb is the most moved part of the human body in majority of the human activities). For example, if the RF reader is placed on the human subjects' right wrist, one cannot guarantee when the human subject is falling down unexpectedly, he/she would try to grab some object which is fixed at a higher place within his/her reach to avoid him/her falling down or use the hand to minimise the impact of the fall by placing it towards the ground. Therefore this sort of posture recognition technology is only relevant to find deliberate human posture/activity where it can be useful as a Human Computer Interface tool [62].

Ethical issues

There are many common concerns about using RFID tags on human subjects and those raised ethical issues are quite accurate and logical. But in this case that sort of ethical issues are not very relevant because the RFID tags which are used in this sort of system can only provide data to the implemented system only because those data makes no sense to a 3rd party and even if the RFID tags contains memory elements, only "Read Only" memory elements are needed for the implementation of the system. Therefore unless some undesirable individual deliberately physically tampered with the RFID tags induced clothes, it can be considered that this sort of system is acceptable in a home environment.

2.7. Accelerometer based system

Technology in a nutshell

An accelerometer is capable of detecting the instantaneous acceleration of an object. There are wide ranges of different methods of developing accelerometers. But in essence all modern day accelerometers are designed to output an electrical signal which reflects the acceleration of the object [65].

Technical limitations and Implementation complexity

Usages of accelerometers are fairly straightforward. The cost of a good quality accelerometer would cost less than $10 and the size of an accelerometer would be in few millimetres only. So in that regard accelerometers are very cost effective devices which take very small space in the circuit boards hence it is ideal as a wearable system.

Ethical issues

The accelerometers only provide the instantaneous acceleration of the wearer therefore, even in strict ethical code and conduct; one cannot find evidence of invasion of privacy by this type of sensor. Only ethical issue might be the fact that accelerometer based sensing unit has to be worn, so if the wearable unit is heavy or large in size that might cause discomfort to the wearer, especially if the wearer is an ailing elderly. But since the advancement of the technology, accelerometers are highly miniaturized; therefore the above mentioned issue can be discarded due to the sophisticated new accelerometer designs.

3. Criteria for selecting sensing technology

Diverse technologies are researched in order to find the most effective and ethically acceptable sensing technology for this undertaking.

Image based systems are widely used in this context by the scientific community for over a decade. But this type of application has severe ethical issues and also the implementation cost of it, is relatively very high compared to the some other technologies. Furthermore normal image based systems are vulnerable to light illumination levels as well as solid obstacles and there are many more shortcomings in this type of sensing technologies as this author has pointed out in the previous section. Therefore image based system is not chosen for this undertaking.

Ultrasonic sensors based systems are relatively ethically safe but this type of system needs sensors to be mounted in the entire usable living space of the subject to make the system robust, which is not very practical application of the technology therefore usability of this type of technology is bit questionable.

The existing research work which utilises radio wave signal strength for human posture recognition has provided a unique and novel perspective for the usage of radio wave signal strength. One of the main disadvantage of this type of system is user has to wear many wireless nodes throughout his/her body in-order to get any sort of meaningful working system and this can be grossly uncomfortable for the user specially if the user is an elderly. Considering this shortcoming this type of technology is discarded.

Thermal Infrared based systems can overcome the issue of light dependency in the normal image based system but cost of the components needed for the system is relatively very expensive. Furthermore it has considerable ethical issues as discussed in the previous chapter. Due to the cost ineffectiveness and privacy issues this technology is discarded.

Strain Sensitive sensor based system can be implemented with relatively low cost specially if mass produced. And in ethical sense this type of sensor is acceptable. But again the practicality of this technology is questioned because Strain sensitive sensors have to be embedded within the clothes, therefore the user has to wear specially made clothes which are attached with strain sensitive sensors in order to make the system function properly. This is quite a huge sacrifice from the users' side. Furthermore the durability of these sensors is highly debatable because mechanical properties of the strain sensitive sensors do change with the time due to multiple washing and other normal wear and tear. Because of the durability issues and the impracticality this technology is discarded.

RFID based system is not a very effective tool for human posture recognition, because it tracks merely the relative position of the targeted limbs of the user to RFID tag reader. The user has to wear multiple tags around his/her body which can be uncomfortable. Because of this reason this technology is discarded.

Accelerometers are quite cheap and very small in size (few millimetres). In ethical sense they do not invade privacy of the user. There are many scientific researches done on the topic of human posture recognition using accelerometers but almost all of them require the user to wear multiple accelerometers around the body which can be uncomfortable to the user. But the need of multiple accelerometers around the body is not a compulsory requirement and it is just done that way to increase the accuracy of the system. But this author believes by implementing a more robust computer algorithm to analyse the accelerometer data, one can achieve the same level of accuracy with just one accelerometer. Therefore for this undertaking accelerometer is chosen as the sensor to be used.

4. Research on available accelerometer technology

As the name suggests accelerometers are sensors which measure acceleration of an object.

Acceleration is the rate of change of velocity with respect to the time. As Newton's second law (F=ma) explains, the acceleration of the object is proportional to the force which the object is under. Every moment, our human body is under some form of force. When we are motionless the only force which is acting on our body parts are earths' gravitational force. But when we are moving (excluding any kind of vehicular transportation) our body parts are under the force which is generated by our muscles. These muscular forces can be a result of a deliberate action which means we consciously move our limbs or it can be habitual which means the movements occurs as we have used to work them throughout our lives or these movements can be unintentional like in the case of seizures or we are under free fall. The in-depth understanding of the above mentioned subjects are very important to make the human posture recognition system accurate. Because for example habitual motions such as walking and running usually follow a pattern which is periodic, whereas in the case of seizure specially tonic-clonic seizures the patient would have jerking movements followed by period of motionless state. Naturally human body system would not experience constant velocity (unless the human is on a vehicle moving in constant velocity, which is not relevant variable in this study). Therefore any motion a human makes has acceleration. Therefore using accelerometers one can re-track the human motion fairly accurately.

In physics the acceleration is calculated by differentiating the velocity vector with respect to time and acceleration has the unit of meters per time squared. But in Engineering, acceleration is found directly using an accelerometer which is a sensor specifically designed to measure the acceleration of an object. In Engineering, the unit of acceleration is G and not m/s2. 1 G is the gravitational acceleration acting on an object at the sea level, which is 9.8m/s2.

There are many different technologies which are used to make accelerometers such as piezoelectric, piezo-resistive, Hall Effect, magneto-resistive, heat transfer, capacitive etc.

Piezoelectric materials produces electricity upon a pressure is exerted on it. Engineers have used this property of this special kind of materials to make wide range of sensors. Piezoelectric accelerometer is one of those sensors. One of the main advantages of piezoelectric accelerometer is that, it does not have moving mechanical parts because most of the modern piezoelectric accelerometer designs utilize heavy liquid to provide the pressure which will be exerted on the piezoelectric elements. Not having mechanical parts increase the durability of the sensor. Most of these types of accelerometers have high sampling rate of kilo hertz so these are ideal for sampling high frequency dynamic systems [67]. But one of the downside of this type of accelerometer is that it is relatively expensive and cheapest available from the suppliers (www.farnell.com) cost around $1000 mark.

Piezo-resistive accelerometers are made of piezo elements whose resistivity changes upon the pressure exerted on it. Just like piezoelectric accelerometer the manufacturing cost of piezo-resistive accelerometers are relatively high because of the problems associated with temperature coefficients and drift properties of piezo-resistive materials so complex packaging and compensation circuits are used to properly manufacture these sensors [67].

Hall Effect accelerometers are made using the discovery of E. H. Hall, which is, a measurable voltage builds up across the two sides of a current carrying conductor under a magnetic field which is perpendicular to the current. This Hall voltage is proportional to the measured acceleration [68].

Magneto-resistive accelerometers utilize the discovery made by William Thomson, which is, some materials change its' resistivity under different magnetic field. Manufacturing of magneto-resistive accelerometers follow similar fabrication technology as Hall Effect accelerometers. Both Hall Effect accelerometers and magneto-resistive accelerometers are rarely found in the market place. One of the reasons for this is that these sensor units are susceptible to external magnetic field distortions, especially if the external magnetic field noises are very high than the internal magnetic unit within the sensor [69].

Heat transfer accelerometers are made by tracking the location of heated mass during acceleration. The location is tracked by placing thermo resisters around the heated mass at equal distance and under zero acceleration the heat gradient is symmetrical and under acceleration heat gradient becomes asymmetrical due to heat transfer [66].

Capacitive accelerometers are made by measuring the electrical capacitance which changes due to the acceleration. These accelerometers are manufactured by placing movable beam which is placed between two fixed beams in an equal distance, in essence this forms two back to back capacitors. The movable beam is attached with a moving mass where the mass is moved by the acceleration. As the movable beam moves between the fixed beams the distance between one fixed beam and movable beam is increased and the opposite holds true for the other fixed beam. This change in distance difference is used to find the capacitance values using the formula $C = A\varepsilon/D$ where C is capacitance, A is the area of the beam, ε is the dielectric constant, and D is the distance between the beams. These capacitance values are translated into acceleration data. The capacitive accelerometers are widely available and the manufacturing process is relatively simple. Since these accelerometers are micro-machined the size is very small and the cost is also very affordable. The main weakness of these types of accelerometers is that they are based on mechanical moving parts and hence relatively fragile and sudden shock which is above the specified threshold value can permanently damage the accelerometer [70].

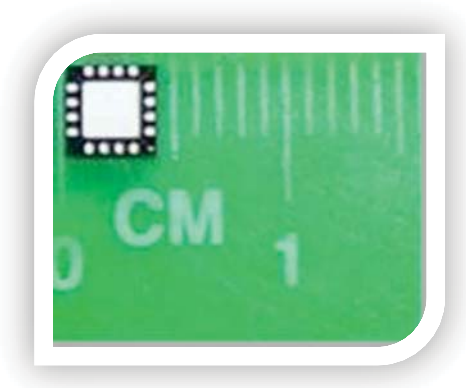
4.1. Criteria for selecting an accelerometer

The following criteria were considered when selecting an accelerometer. Maximum measurable acceleration, linearity of the sensor output with the actual acceleration, frequency response, number of sensitive axes, size, mass, cost, durability, immunity to external noises such as magnetic/electrical noise and thermal sensitivity.

One of the main drawbacks of the piezoelectric and piezo-resistive accelerometers is that they are far too expensive [67]. Hall Effect and magneto-resistive accelerometers are susceptible to external magnetic field noises [69]. Heat transfer accelerometers have low frequency response [66]. Capacitive accelerometers are fragile in nature and not ideal for high impact applications [70]. But when the project objective which is posture tracking of human elderly subject is taken in to consideration, the author can safely regard the capacitive accelerometers cannot find an event which will make the accelerometers undergo a G force of 7 or more [71]. Therefore initial doubt of durability of the capacitive accelerometers can be discarded. When the cost, size and frequency response of the capacitive accelerometers are taken in to account, they are more than adequate for this undertaking. After careful consideration the capacitive accelerometer technology is chosen as the most relevant accelerometer technology for this project.

There are wide ranges of electronic parts suppliers in the market which provide capacitive accelerometers. After considering the cost, technical specifications, miniaturized design and also the reputation of the manufacturer, the accelerometer MMA7361L is chosen. As you can see in the picture below, this accelerometer is only 4mm x 4mm x 2mm in size with negligible mass. The cost is under NZ$5. Maximum measurable acceleration is 6G but this sensor can withstand up to +-5000G of acceleration without been damaged. MMA7361L consists of 3 axes with maximum measurable frequency of 300Hz. Micro-machined manufacturing means it is not susceptible to external magnetic field noises because the length of conductive wires are very minimum. MMA7361L has the operable temperature range of -40 to +85 Celsius [72]. All the features of this accelerometer fulfil the needs of this project.

4.2. Getting to know the chosen accelerometer MMA7361L



Sensitivity: 0.206 VG^{-1} (TA = 25°C, VDD = 3.3 V)

Sensitivity is how much the acceleration output voltage changes per the change in the acceleration it is under. For example, if the accelerometer undergoes an increase of 1G of acceleration, the output would increase by 206mV.

Maximum Acceleration: ±5000G

Maximum acceleration defines the extreme values of acceleration where this particular accelerometer fails.

V_{OFFSET} : 1.65V (TA = 25°C, VDD = 3.3 V)

Offset Voltage is the output of accelerometer when it is not under any form of acceleration. In other words when it is under 0G, it is said to be outputtingV_{OFFSET}.

Operating temperature range: -40 to +85 Celsius

Calculating the actual acceleration using the output voltage of the accelerometer can be done using the following formula.

$$Acceleration = {V_{\text{output}} - V_{\text{offset}}} / {V_{\text{sensitivity}}}$$

V_{output} and V_{offset} has the units of Voltage and $V_{\text{sensitivity}}$ has the units of Voltage per G, therefore the acceleration unit is G. As explained in a previous chapter, in physics the acceleration has the unit of ms^{-2}, where acceleration is found by differentiating the velocity with respect to the time. But in Engineering for the ease or as for the norm acceleration is measured in G, where 1G is the gravitational acceleration, which is $9.8ms^{-2}$.

Substituting the values of this particular accelerometer,

$$Acceleration\ (G) = {V_{\text{output}}(V) - 1.65(V)} / {0.206\ VG^{-1}} \qquad -\text{eq1}$$

V_{output} is an analogue output, and measured from the output terminal of the accelerometer. It is converted into 10bit digital value by using the analogue to digital converter (ADC). The xbee device (will be discussed in a later chapter), which is used for the wireless communication has 4 inbuilt ADCs and this xbee module has external voltage reference pin, which is connected to VDD, which is 3.3V. Which means when the ADC output is 1111111111Binary, the analogue voltage which is been measured is 3.3V. (Binary 1111111111 is equivalent of decimal 1023)

Therefore Voutput can be calculated using the following formula.

$$V_{OUTPUT} = \frac{V_{ADC}}{1023} \times 3.3V \quad \text{-eq2}$$

Substituting the eq2 in eq1,

$$Acceleration\ (G) = \frac{\frac{V_{ADC}}{1023} \times 3.3(V) - 1.65(V)}{0.206\ VG^{-1}}$$

4.3. Calculating acceleration using accelerometer data

4.3.1. Calculating X axis acceleration from received data packet

```
public static double getAccelerationX(String d)
{
    try{
        return ((Integer.parseInt(d.substring(Constants.ADC2_DATA_start,
                Constants.ADC2_DATA_end), 16)*
                Constants.CONSTANT_CONVERT_ADC_TO_VOLTAGE)-
                Constants.ACCELEROMETER_V_OFFSET)/
                Constants.ACCELEROMETER_SENSITIVITY;
    }
    catch(Exception ie)
    {
         return -1;
    }
}
```

4.3.2. Calculating Y axis acceleration from received data packet

```
public static double getAccelerationY(String d)
{
    try{
        return ((Integer.parseInt(d.substring(Constants.ADC1_DATA_start,
                Constants.ADC1_DATA_end), 16)*
                Constants.CONSTANT_CONVERT_ADC_TO_VOLTAGE)-
                Constants.ACCELEROMETER_V_OFFSET)/
                Constants.ACCELEROMETER_SENSITIVITY;
    }
    catch(Exception ie)
    {
         return -1;
    }
}
```

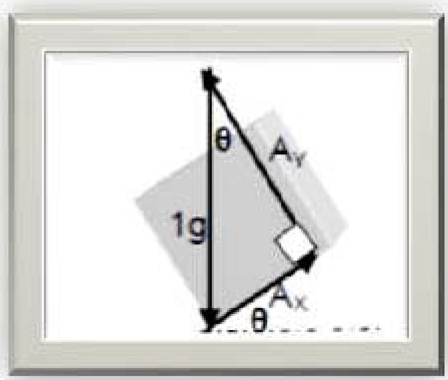
4.3.3. Calculating Z axis acceleration from received data packet

```
public static double getAccelerationZ(String d)
{
    try{
        return ((Integer.parseInt(d.substring(Constants.ADC0_DATA_start,
                Constants.ADC0_DATA_end), 16)*
                Constants.CONSTANT_CONVERT_ADC_TO_VOLTAGE)-
                Constants.ACCELEROMETER_V_OFFSET)/
                Constants.ACCELEROMETER_SENSITIVITY;
    }
    catch(Exception ie)
    {
         return -1;
    }
}
```

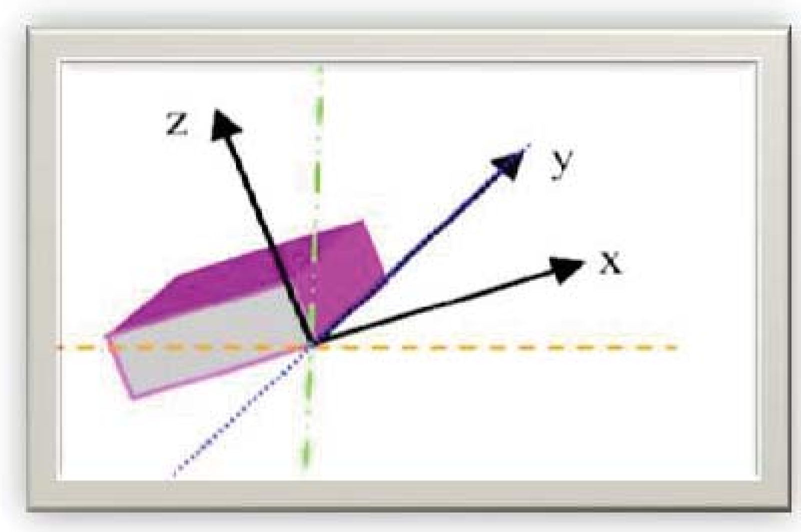
The sign of the acceleration gives the direction of the acceleration vector.

4.4. Calculating the tilt using the accelerometer data

Accelerometers measure acceleration, and gravity itself is acceleration and has the direction towards earth. This gravitational component is used to calculate the tilt angle of the accelerometer.



If paid attention to the image (provided by the datasheet of the accelerometer) above, the gravitational acceleration is acting on both Y and X axis. Y axis acceleration can be stated as G.cos(theta) and X axis acceleration can be stated as G.sin(theta).Since the acceleration of each axis can be calculated using equation 3 as stated above, we can use that to find the unknown angle theta.



The angles can be calculated using the following formula

$$\text{Angle of x axis} = \tan^{-1}\frac{Acceleration_x}{\sqrt{Acceleration_y{}^2 + Acceleration_z{}^2}}$$

$$\text{Angle of y axis} = \tan^{-1}\frac{Acceleration_y}{\sqrt{Acceleration_x{}^2 + Acceleration_z{}^2}}$$

Both x and y axis angles are calculated with respect to ground.

$$\text{Angle of z axis} = \tan^{-1}\frac{\sqrt{Acceleration_x{}^2 + Acceleration_y{}^2}}{Acceleration_z}$$

The x axis angle is calculated with respect to the gravity.

When the accelerometer is completely static the magnitude of the resultant accelerations vectors (Which is called Sum Vector) is equivalent to the gravitational acceleration as indicated by the following equation.

$$\sqrt{Acceleration_x{}^2 + Acceleration_y{}^2 + Acceleration_z{}^2} = 1$$

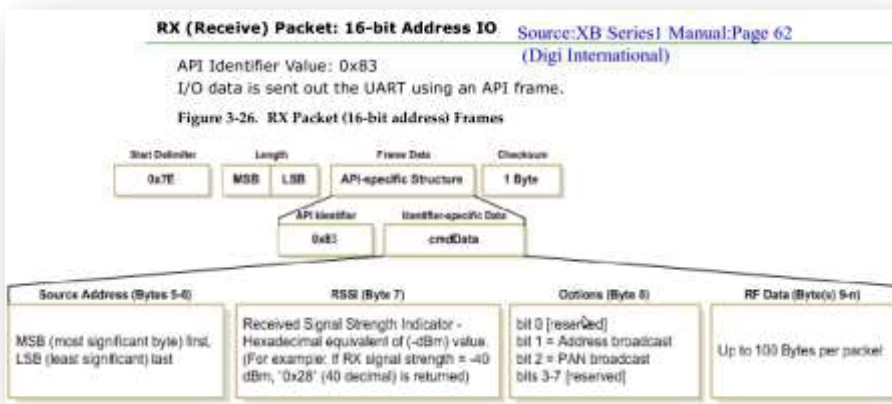
5. Wireless Communication

XBEE series 1 module is used for wireless data communication. One of the main reasons for that is, it uses IEEE.802.15.4 standard which is specified for point to point and point to multi-point communication. The point to point networking protocol reduces the overhead of mesh-network (XBEE series 2) hence increase the data throughput. IEEE.802.15.4 standard has employed packet collision avoidance technique which is called Clear Channel Assessment (CCA), therefore any node before sending the data checks to see if the channel is used by another node. This is done by measuring the energy at the present moment and comparing it with the pre-set value which identifies whether the channel is in use. If the channel is not in use then send the packet otherwise, attempt it again after a delay [74]. Due to this feature in a home like environment such as rest homes, small hospital wards, the wireless modules with IEEE.802.15.4 standard can be used simultaneously providing that number of modules operating in the given radius does not exceed the optimum node count for that particular environment. Optimum node count is a function of the given wireless communication radius, obstacles, other non-related wireless modules operating in the area, signal transmission strength and retry count [73].

One of the main advantage of these DIGI international XBEE modules is that they have inbuilt analogue to digital converters (ADC). Therefore it heavily reduces the need for incorporating additional ADCs into the printed circuit board (PCB), allowing us to make PCB smaller and also save the component costs. XBEE series 2 have hardwired reference voltage (which is 1.2V) for the ADC modules which are unsavoury in this particular application; because the accelerometer voltage range is between 0 to 3.3V (Positive acceleration ranges from 1.65V to 3.3V and negative acceleration ranges from 1.65V to 0V). Therefore to bring it to the level of 0 to 1.2V, a step down voltage converter is needed. As a low cost solution, a simple voltage divider using a resister bridge can be used for the purpose but resistors introduce random noise to the circuit and having the output current of the accelerometer in the order of micro amperes makes the matters worse due to the electron diffusion within the resistor lattice. Given the fact the accelerometer sensitivity is 0.206V per G, and when you factor in the multiplication of voltage factor (3.3V/1.2V), it multiplies signal to noise ratio by the voltage division factor. XBEE series 1 does not have a hardwired reference voltage hence far less components needed.

The operating frequency of the XBEE module is 2.4GHz band and it has 16 direct sequence channels to choose from. It has a data rate of 250 kilobits per second and has line of sight range of 90m. Typically it uses 50mA of current at 3.3V hence a battery with 100mAh 3.3V capacity would last around 2 hours. This battery life can be increase by enabling the cyclic sleep option in XBEE module, so that after every ADCs sampling session followed by the data transmission, XBEE module go into the sleep state and wakeup after predetermined amount of time and this process keeps on repeating. There is another option of increasing the battery even further by enabling the Pin sleep [74]. In this case additional micro-controller is needed to determine when to send wake up signal through pin sleep due to the fact that the nature of the accelerometer signal, where simple voltage cutoff point cannot be used (Voffset is 1.65 and 0V means maximum negative acceleration and 3.3V means maximum positive acceleration and simple voltage output does not convey whether person motion characteristic has changed or not).

5.1. Wireless Communication API packet deconstruction



Sample data packet where 3 ADC inputs

7E000E83AB132C00010E0003FF03FF03FF7D

Accumulating received data until end of packet byte is received

```
lic void run() {
    try{
            String accumilator="";
            String portion="";
            byte[] b = new byte[1];
            b[0]=0;
            while(true){
                do{
                    portion=Integer.toHexString(b[0]).toUpperCase();
                    if(portion.length()==1)
                        portion="0"+portion;
                    else if((portion.length()>2))
                        portion=portion.substring(portion.length()-2);
                    accumilator=accumilator+portion;
                    b[0]=(byte)comport.getSerialPort().readByte();
                    API.append(""+new String(b, "US-ASCII")+"");
                    if(b[0]==13)API.append("\n");
                }while(b[0]!=126);
                API.append(accumilator+"\t\t\t\n");
                if(API_ADC_packetDECODE.validateCheckSUM(accumilator))
                {
                    API.append("                    CheckSUM VALID\n");
                    if(API_ADC_packetDECODE.isADC_DATA_PACKET(accumilator))
                    {
```

XBEE module has inbuilt packet data integrity validation technique, which is done by adding checksum at the end of every data packet. By checking whether the checksum is valid, one can guarantee that data is not corrupted. Checksum is calculated by adding all the bytes in the data packet excluding the frame delimiters and length bytes and then subtract if from 0xFF. (Source:XB Series 1 Manual: Page 57)

```
public static boolean validateCheckSUM(String d)
{
    boolean result=false;
    int total=0;
    int i=6;

    String data=d.replace(" ","");

    while (i<data.length()-2)
    {
        total=total+Integer.parseInt((data.substring(i,i+2)), 16);
        i=i+2;
    }

    String checksum=Integer.toHexString(0xFF-total).toUpperCase();

    if(checksum.length()>2)
        checksum=checksum.substring(checksum.length()-2);

    if(data.substring(data.length()-2,data.length()).compareTo(checksum)==0)
        result=true;
    else
        result=false;

    return result;
}
```

6. Research on existing fall detection systems

A system to detect falling has been developed using accelerometers by a team from Seoul National University. According to their journal [5] their system is composed with accelerometer, gyroscope and tilt sensor as sensors. Sensors have been only attached to the chest of the human subject. The accelerometer is used to measure kinetic force on human subject and tilt sensor detects human body orientation. Their algorithm for fall detection is based on the threshold values. In their algorithm for fall detection, first they check whether the average value of buffered tilt sensor data are over the pre-set threshold and then check whether the buffered acceleration values has maximum values which are over the pre-set threshold. Then after pre-set timer level is expired they check whether the new acceleration data maximum values are below a pre-set threshold value. If all three tests are passed they consider the person has fallen. When developing this algorithm they have made several assumptions. First major assumption they have made is after the human subject have fallen human subject would stay motionless. The other assumption they have made is human subject bend their upper body when a human subject is falling.

Another fall detection system has been developed by a group from University of Virginia. They also have employed accelerometers and gyroscopes as sensors [6]. But oppose to [5] who have only placed sensor nodes on chest, [6] have placed sensor nodes on chest as well as thigh of the human subject. According to their journal report their system is developed to recognize four kinds of static postures: standing, bending, sitting, and lying. They use the assumption that a person who has just fallen would end up in a static lying posture. And based on that assumption they have devised an algorithm. Their algorithm uses pre-set threshold value to compare with the sensor data to find whether the human subject is motionless or dynamic. If the human subject is motionless then they use body angle measurement to find whether the human subject have taken the lying posture. If those criteria are satisfied they check the previously recorded dynamic activity was intentional or not. If it is not intentional they would consider the human has fallen.

Another research work about human mobility monitoring is reported by a group from University of Limerick [7]. Their work mainly focuses on detecting whether the human subject is moving or inert and if the human subject is inert what posture the human subject is currently at. They have not reported any work on distinguishing the different dynamic activities or detection of falling. They have placed the accelerometer at trunk and thigh of the human subject. They utilize the standard deviation of the buffered accelerometer data to determine whether the human subject is moving or not by comparing the calculated standard deviation with the pre-set threshold value. If the human subject is found to be motionless they use body angle data to find the human subjects posture. One of the shortcomings of this developed system is that it does not try to detect falling of the human subject.

A human posture identification system has been developed by a group from University of Bologna [8]. Unlike previous reported works ([5,6,7]), the primary focus of this research work is to develop a novel Human Computer Interface using the human posture monitoring system. They have mounted accelerometers at trunk, shin-bone and thigh-bone. Since this implementation is made for a Human computer interface purposes, the reported algorithm is developed to detect intentional static postures. So the algorithm looks for the angle of 3 body parts which the accelerometers are placed on and then deduce which command the human subject is giving by detecting whether the angle of the body parts adhere to the set angle ranges.

A system is developed employing both accelerometer as well as image based posture recognition technology [9]. As this author have discussed previously having image based system can be deemed as a violation of privacy of the human subject depending on the circumstances of the individual. The accelerometer based human posture recognition work in such a way that, to detect a falling of a human subject the algorithm looks for sudden spike in the accelerometer data. By comparing with the pre-set threshold value this sudden spike in the data is either discarded as mere sitting down action or if it is above the threshold value it is considered as falling.

A group from Netherlands have reported of developing a daily activities monitoring system using accelerometers [10]. They have placed accelerometers on thighs, trunk and both arms. Instead of transmitting the sensor data to an external data processing unit, they have opt out to use a digital portable recorder to record data for up-to 48 hours which suggests this system is not developed for real time monitoring of human activity. But their algorithm is quite different to previously mentioned attempts of other developers. Their algorithm is reported to have 3 steps such as feature extraction, posture/motion detection and post processing. In the feature extraction stage they first take the average of 1 second sample data and using arcsine transformation to find the angular position of the limb the sensor is placed on. Then they filter the data through a high pass filter and take the average of the filtered data. Then they send the data through a band pass filter and filtered data is used as the input for fast time frequency transform (FTFT) procedure and take the average of the resultant output. Then they use pre-set range on the above mentioned extracted features to find the posture/motion detection.

A system to monitor fall detection of elderly human subjects has been reported by a group from Sweden [11], [46]. A triaxial accelerometer has been placed on the waist of the human subject. When generating the algorithm, they have calculated three components from the accelerometer data and they have called them as sum vector, dynamic sum vector and vertical velocity Z2.

They have used the following formula to calculate the sum vector and dynamic sum vector.

Ax, Ay, Az is the acceleration in the x, y and z axis respectively.

The difference between dynamic sum vector and sum vector is that dynamic sum vector is calculated after the data is passed through and high pass filter.

A group from Ireland has developed waist mounted tri-axial accelerometer based fall detection algorithm [13]. They have identified that there are four stages of a fall such as pre-fall phase, sudden movement toward ground phase , vertical shock phase , motionless phase where body is lying. As in [11] they have calculated the root sum of square of the tri-directional accelerometer data.

A group from Erasmus University also has reported of developing a posture and movement detection system using accelerometers [14]. They have used the technique of relying on the limb angle to determine the posture. But one distinguishing feature in their algorithm is that they have used multi-correlation analysis to find whether the human is in a repetitive motion such as walking.

A group from University of Virginia has also developed a human activity monitoring system. They have used multiple accelerometers as well as gyroscopes in their system [18]. They have also used the pre-set threshold values to distinguish between dynamic and static activities and they have also categorized falling as a sudden change in acceleration followed by static posture of lying down.

A group from National Yang-Ming University has also reported to have developed Fall Detecting System for the Elderly Residents [19] and [20]. They have placed the sensor unit on the head. For an elderly individual this can be an quite uncomfortable. As in [11] they have calculated sum vector of all 3 axes and also sum vector of x and y plane excluding z plane. They have calculated the maximum velocity while falling to avoid false positive readings such as misidentifying quickly sitting down with falling.

A group from Academy of Military Medical Science, China has also developed a fall detector for elderly based on accelerometers [21].They have classified the falls into two categories such as linear fall and non-linear fall. An example for linear fall is someone is fainting; an example for non-linear fall is someone is falling down a staircase. They detect linear falls if the accelerations of x, y, and z axis are within the ±4% of zero g for at least 50ms.They detect nonlinear fall if sum vector of the three axis data is within 3% to 10% of zero g for at least 100ms.

A group from Texas Tech University has also developed a fall detection system [22]. They also have used threshold values to determine whether a fall has happened. Along with accelerometers they have used gyroscopes as sensors too and a similar approach is taken by a group based in Singapore [26].

A group from Singapore [23] has made a similar algorithm to [22] but have not used gyroscopes but have used network of accelerometers around the body.

Another similar attempt of making fall detection using thresholding are made by the following groups [24] and [25]. [25] has proposed that in order to save the resources of the processing unit the commonly used sum vector should be used without calculating the square root.

A group from University of Portsmouth has tried to develop an activity monitoring system using the off-the shelf wrist worn watch [27]. They have stated the sample frequency of the accelerometer signal is 10Hz and they have used fast Fourier transformation to analyse frequency components of the signal. According to the paper they have published their attempt was a failure and they could not properly identify human activity. This author cannot verify whether their failure is due to a series of human errors or faulty equipment.

A group from University of Bologna has developed a fall detection system using accelerometer which is placed on the waist [29]. They have used simple thresholding algorithm where they use pre-set value to compare sum vector to detect whether possible fall has occurred. Once this stage of fall alert is received they check whether body orientation after the impact is horizontal. If both cases are true, they identify it as a fall. They have used the sample rate of 100Hz to sample the accelerometer signals and used zigbee as the standard for wireless transmission.

A group from University of Limerick has developed fall detection system [30]. They have shown that some daily activities have a high resultant sum vector which is higher than certain situations of falling. They have also shown that having low threshold would be able to capture 100% of the falls but it also give false positives where an ordinary daily activity is identified as a fall.

A group from Seoul national university has developed a fall detection algorithm based on the acceleration data [31]. The placement of the accelerometer sensors are not on the body but in the shoes. The algorithm uses sum vector of the 3 axis accelerometer data and apply pre-set threshold values. The evidence and graphs they have supplied in the published paper is not adequate to gauge the usefulness of placing accelerometers in the shoes.

A group from National Yang-Ming University has also reported of developing a fall detection system [32]. The accelerometers are mounted on the waist of the human subject. They have used the same algorithm as in [20]. In [33] again they have used the same algorithm to develop fall detection but they have added a location finder to the system.

A group from Konkuk University has also developed a real time elderly activity monitoring system using waist-mounted accelerometer [34]. They have calculated the differential acceleration vector (SVM) from all directions of 3 axes to detect an abnormal peak of shock such as falls. Then they have calculated the signal magnitude area (SMA) to identify the periods of activity. They use pre-set threshold value on SVM and SMA. They identify running from walking by using variance of vertical acceleration as vertical acceleration is increased much more during running than during walking.

A group from Ireland also has developed fall detection system [35]. They are trying to prove that using only the vertical velocity; a fall can be accurately predicted. They have used a tri-axial accelerator for the sensor data and mounted it on the chest of the human subject. They have used threshold values on the vertical velocity to identify a fall.

A group consists of members from Sweden and Finland also has developed a fall detection system [36]. They have used thresholding method on sum vector data. But unlike other systems, they have run the field test on actual elderly people and have validated the practice of implementing fall detection algorithm using young/middles age subjects.

A group from Canada has reported of developing a fall detection system using accelerometers and gyroscopes [37]. They have used data mining tool called WEKA and implemented Naïve Bayes algorithm to analyse the sensor data. They have reported of achieving 97.3% of success rate.

A group from Taiwan has reported of developing a fall detection system using accelerometers which are mounted on 6 different places of the human subject [38]. They have integrated the sum vector in a specific time period to find out whether the human subject is static or dynamic. If static then they calculate the body limb angles and based on that determine human posture, and if dynamic they have used predetermined peak threshold values to identify a fall.

A group from UK has reported of developing a fall detection system [39]. Since mobile phones are common accessory they have utilized the inbuilt mobile phone 3D accelerometer as the sensor to gain accelerometer data. Their algorithm use simple thresholding of acceleration data.

Wu from University of Vermont has developed a fall detection system which is based on velocity characteristics [41]. He has experimentally shown that, in most common scenarios the horizontal and vertical velocity of the trunk stays within a definable range.

A group from University of Pisa has developed activity monitoring and fall detection system [42]. The basis of their algorithm is that human subject bend and arch their upper body in a distinct way while engaging in different activities and by finding the trunk inclination and rate of change of inclination they can identify the activity and also recognize accidental falling. They have reported of mounting the triaxial accelerometer on the upper trunk area. They have used Kalman filter to separate the gravity component in the signal from sensor data.

A group from Dongseo University has developed activity recognition system using accelerometers [43]. Their algorithm first converts the time domain discrete signal into frequency domain using power spectral density. Along with the PSD they have used signal magnitude area which is the area under sum vector graph. Then they have used pre-set threshold values on median frequency, average power and signal magnitude area to detect different activities. Their reported success rate is only 81.25%.

A group from Italy has developed an activity monitoring system [44]. They also have calculated signal magnitude area and the sensor tilt angles using the accelerometer sensor data. Then they have applied pre-set threshold values to detect different postures and activities as commonly done. They also have included accelerometer self-calibrating algorithm into their system.

A group from Rutgers University has developed activity recognition system using accelerometer which is worn near pelvic region [45]. They have calculated mean, standard deviation, correlation between axis and energy of the signal. The method they have used to calculate the energy is to calculate squared sum of FFT component magnitude. Then they have used those calculated features in different classification algorithms but best success rate they have achieved is 73.3% when different human subjects were involved for the learning and testing part of the algorithm.

A group from Netherlands has developed activity monitoring system using uni-axial accelerometers placed on multiple parts of the human subject [47]. Their analysis states that using mean and standard deviation values of the sensor data cannot properly distinguish between different dynamic activities. They have experimented with using the cross correlation between different set of sensor data (ie: thigh mounted vs waist mounted etc.) to see whether they can identify dynamic activities specifically from each other. Identification of different static postures is done using the raw thigh mounted uni-axial accelerometer data, using their magnitude alone and they have shown that each static posture does not overlap with others.

6.1. Summary of the existing activity monitoring system based on accelerometers data

Scientific and engineering community has been continuously researching on activity monitoring. The research articles which were published from year 1993 to 2011 on distinguished journal papers on the topic of activity monitoring using accelerometers have been studied as reported in the above section.

The research works published in 1990s era used single axis accelerometers and placed them in multiple parts of the body. Then as the manufacturing and fabrication technology of accelerometers became very advanced, the real miniaturization of the accelerometers began, and as a result the inevitable shift to three axial accelerometers can be seen in the year 2000s research works.

In the published works, the sensor placements vary from head of the human subject to foot of the human subject (foot wear) including hands and legs. Some works are based on single accelerometer data but in some cases many accelerometers (7+) have been employed.

When developing an algorithm for activity monitoring the most commonly used method is thresholding. Some researchers have applied thresholding to vertical acceleration straight from the sensor, while other researchers have applied thresholding to the calculated vertical velocity. But the most common approach is to apply thresholding on the sum vector of all three axis data.

Energy of the sensor signal is also widely looked at topic. Most common energy calculation method is to find the area underneath the sum vector graph. But calculating the mean value of the accelerometer data is also used to find the average energy.

Periodicity is another topic which is looked at. Discrete Fourier transform is the most commonly used tool to find the periodicity but power spectral density is also used. Wavelet transformation is also used by one research group to identify transition between static postures to dynamic activity.

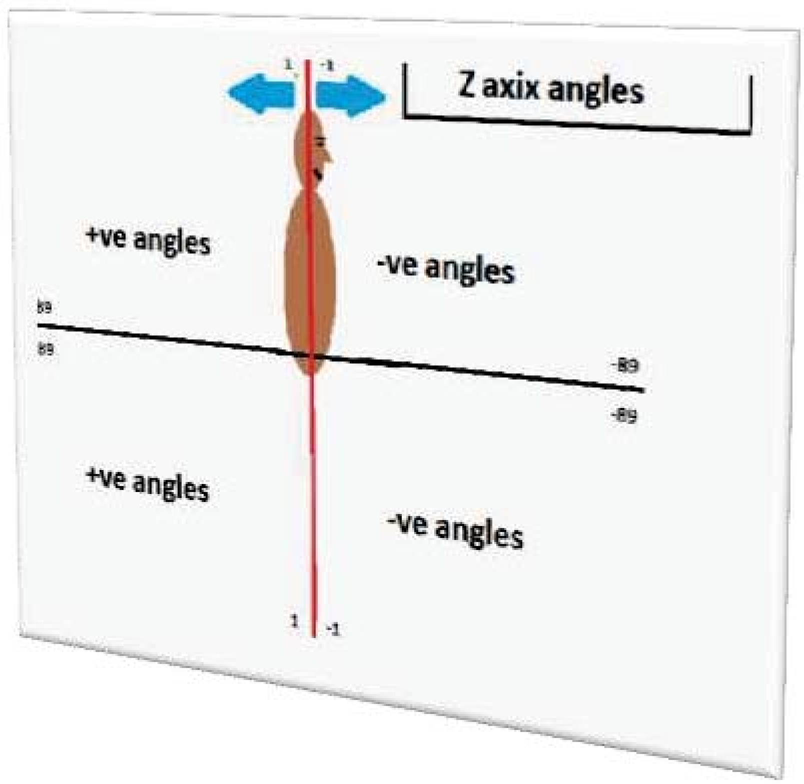
The other two commonly used statistical tools were standard deviation and correlation. The correlation is mainly applied to the two axes accelerometer data of the same sensor but standard deviation and mean is applied to many objects varying from raw accelerometer data to calculated sum vector array.

7. Detecting the positioning of the body

7.1. Z angles

As the picture illustrates below, when the human subject bends forward it results in negative Z angle values and bending backward results in positive Z angle values. The red line indicates the virtual line which the angle changes the sign.

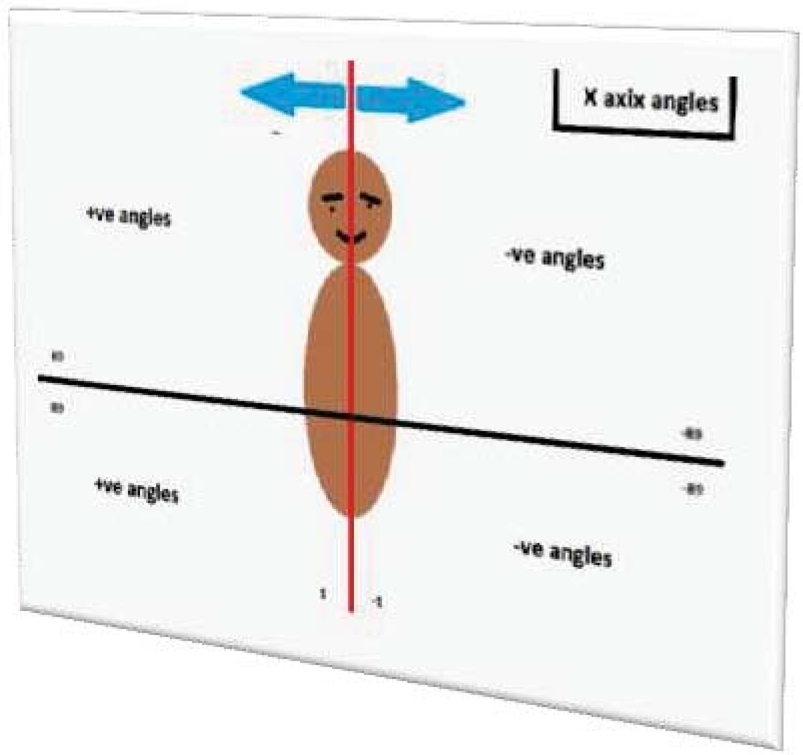
The blue arrows indicate the direction of the motion which the Z axis is sensitive of. When bending forward and the persons' trunk is perfectly horizontal to the ground Z angle registers -90 degrees. When the person is perfectly upright Z angle registers 0 degrees. When bending backward and persons' trunk is perfectly horizontal to the ground Z angle registers 90 degrees.



7.2. X angles

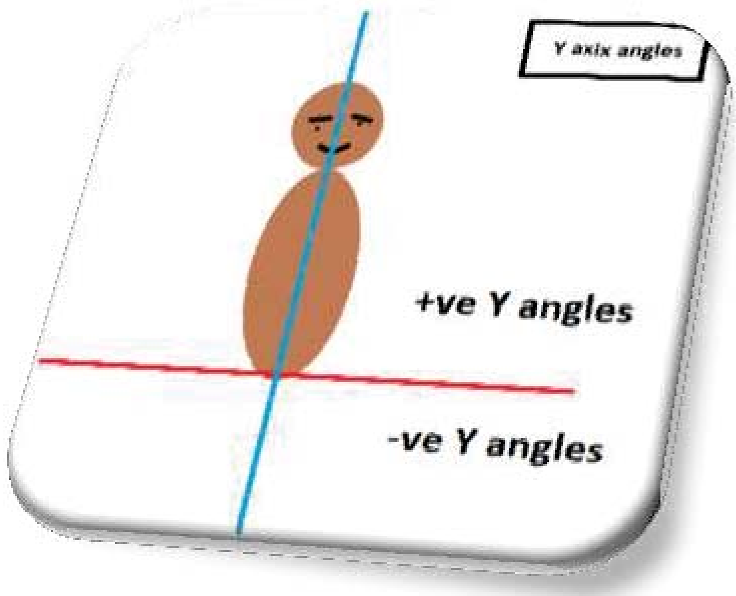
As the picture illustrates above, when the person is bending towards the right hand side, X angles become positive and when the person is bending towards the left side, X angles register negative values. The red line indicates the virtual line where the X angle changes its sign.

The blue arrow indicates the direction of the motion which the X axis angles are sensitive to. When a person has bent all the way to right and the body is perfectly horizontal to the ground the X angle registers 90 degrees. When the person has bent to all the way to left and the body is perfectly horizontal to the ground the X angles registers -90 degrees. When the person is perfectly up wright X angle register 0 degrees.



7.3. Y angles

Whether the person is bending forward, bending backward, bending to the right or bending to the left, Y axis angle is sensitive to all those directional movements. Therefore the only differentiating quality which is valuable for posture detection comes from the fact that as the persons' body becomes more horizontal to the ground, Y axis angle reaches to its extreme value (ie: +-90 degrees). The other vital information the Y angles tells is that whether the person is wearing the monitoring system in the proper side up or not.



8. Mathematical tools used for the data analysis

8.1. Discrete Fourier Transform and Inverse Fourier Transform [2]

A French engineer called Joseph Fourier found mathematical formula to represent any function in terms of infinite series of sin and cosine functions. It is documented that originally Fourier developed the Fourier series to solve differential equations present in heat conduction [2].
In this project, discrete Fourier transformation is used to find the frequency component of the acceleration signal. Weighted Fourier coefficients of the individual frequencies derived from the discrete Fourier transformation is used to find the energy of the data packet.
Furthermore the inverse furrier transformation is used to implement digital filters.

8.2. Moving window

The main purpose of the moving window is to assist with applying other mathematical tools which are necessary to identify patterns in the data.
The algorithm I have designed, analyse the data packet as a cluster. Each cluster has overlapping from its neighbouring clusters hence create the moving window. The reason for the moving window is to make sure data at the boundary of the data packet is not separated from its parents' underlying pattern of the packet and lose vital information during the clustering process. The packet size depends on the sampling rate and how the smoothing algorithm is developed. In this particular undertaking due to the nature of the sensors used, the smoothing is done through simple moving average filter. The sampling rate is 10Hz therefore the cluster size is chosen to be 16 data points (Aids Discrete FFT) per one data packet, with 50% overlap. Once each cluster is analysed, different mathematical parameters are generated for that particular cluster. Once a group of 64 clusters are accumulated, that cluster group is analysed for activity recognition. This dual layer approach has increased the algorithms' prediction accuracy in many folds.

8.3. Correlation

Correlation is a statistical tool which is very useful to identify how two set of data changes and whether those changes have an underlining pattern in them.
Cross axis correlation is especially useful when detecting transitional phase of sit to stand and stand to sit.

8.4. Mean and Standard Deviation

Mean is used more as a smoother/ripple filter. The mean does not get rid of high frequency signal but it integrates the high frequency signal and spread it throughout the moving window data. Standard deviation is the variation of the data around its' mean. Both mean and standard deviation are used in the data digitisation algorithm.

8.5. Outliers

Outliers are data points which are abnormally bigger or smaller than the median of the data set. The intensity of an outlier depends on its' distance from the centre of the dataset and the proportion of that distance to the variation of the data set.
Outlier detection is one of the key components employed in my algorithm for digitization of the data set to improve the efficiency of the algorithm as well as increase the accuracy of the predictions.

8.6. Filters

8.6.1. Frequency Domain

Frequency domain filters are generated by applying a selective function to the discrete Fourier transformation coefficient and then taking the inverse Fourier transformation. Depending on the selective function there are 3 types of frequency domain filters were created.

8.6.1.1. Low pass filter

Low pass filters are useful to separate the leisure activities in the daily activity pattern from sudden movements such as running and falling down.

8.6.1.2. High pass filter

High pass filters are useful to extract the high speed activities in the daily activity pattern such as falling down or running fast.

8.6.1.3. Band pass filter

Band pass filters are useful to separate the moderate speed activities such as transitional state activities such as sit to stand.

8.6.2. Time Domain

8.6.2.1. Smoothing filter

Smoothing filter is generated simply by calculating the moving average of data sample. The electronic circuitry which I have developed does not produce large noisy spikes. Therefore it is well within the limitations of the moving average filter to smooth out the data.

8.7. Digitization

There are three types of digitization techniques used in the analysis. I named the first type of digitization algorithm as “falling digital”. It runs on the Sum Vector data and when it identifies a downward motion data fragment it set that to -1, when it recognizes impact it sets that to 1 and every other data fragment is set to 0.The second type of digitization algorithm is applied to any form of raw data such as X,Y,Z accelerations as well as low complexity calculated data such as Sum Vector and also to high complexity calculated data such as Fourier energy. The outputs are -1, +1 and 0.The third type of digitization algorithm is applied only to correlation data. This algorithm has two steps, it filters the correlation data based on the Fourier energy (this is done because correlation data has lot of unwanted information), and then a threshold-based filter is applied on the filtered data again to digitise the values. The outputs are -1, +1 and 0.

Main purpose of the digitization is to improve the efficiency and the accuracy of the algorithm which is used for the prediction of the activities. Digitisation is not important for the posture recognition because even without digitization the accuracy of the posture recognition is very high.

9. Posture detection techniques

The posture detection is a very simple straightforward task once the necessary sensor data acquisition process is done properly. The only way the posture detection accuracy can go down is by trying to apply posture detection techniques to data which come from noisy sensors or communication medium which does not have checksum to verify the data integrity.

I have used XBEE devices with checksum to verify the data integrity and have removed high frequency noises using both electronic noise filtering circuit as well as software noise filtering techniques.

To detect a posture, the angles of X, Y and Z axis have to be calculated first.

Ideally, the human wearer has to be static in order to detect the correct angles of inclination in the 3D space using an accelerometer. Because as discussed previously angles are measured using the gravitational acceleration and when the human wearer is dynamic there are other acceleration components present which would make the angle measuring process theoretically inaccurate. But mathematically the acceleration data can be sent through a low pass filter and then process the data for angle to avoid the above mentioned issue. The best possible low pass filter for the best accuracy is using Fourier transformation of the time domain data and run it through "the low frequency selective function" which would nullify all the high frequency data. Then by applying the inverse Fourier transformation, data is ready to be processed for calculating the angle. In this way the sudden change in acceleration can be discarded and would be able to get more accurate angle readings. But the disadvantage of this mechanism is even the most efficient Fourier transformation needs N.Log(N) amount of mathematical steps where there are N amount of data and this data set has to be looped through N times in order to run the transfer function and then have to carry out the reverse Fourier transformation. This is computationally very expensive and the cost of computational expense does not justify the amount of accuracy practically needed in this situation because just mere simple averaging of raw data can smooth out the most of the dynamic activity ripples.

Computationally efficient and practical method of treating the data before angle calculation is to use moving average of the data set. As the tables and graph below illustrates, this method produces practically valid angle calculation output. As illustrated below, the running which is a repetitive action produces very little variation and as it indicates the human subject had slightly bend forward running action and this is correctly shown by the angle calculations. And in the falling to the left is a non-repetitive, dynamic activity which has very high frequency components which results from the impact, followed by the rebound and sudden change in the angles. As you can see from the data table and X axis graph the angle at the fall impact has registered as extreme left bending, followed by the rebound and then slowly damping out the kinetic energy and settles at extreme left bending.

This shows that this algorithm of posture detection can be easily be transferred to a microcontroller if needed due to its' computational efficiency and still get accurate results.

Person running

	Xangle	Yangle	Zangle
	1.66	35.05	-35
	1.31	35.95	-35.92
	2.91	33.73	-33.57
	2.79	31.35	-31.2
	2.22	37.4	-37.31
	2.57	29.36	-29.22
	2.4	29.03	-28.91
Average	2.27	33.12	-33.02
Standard deviation	0.59	3.28	3.31

Person falling to Left Hand side

X angle	Y angle	Z angle
-6.08	11.53	-9.76
-5.67	10.66	-9
-5.89	10.58	-8.75
-6.13	10.82	-8.88
-6.08	11.03	-9.17
-6.1	11.16	-9.3
-6.08	11.14	-9.31
-5.75	10.91	-9.24
-5.19	10.65	-9.27
-5.77	10.71	-8.99
-9.14	13.73	-10.15
-52.18	52.25	-2.01
-89.19	89.42	-0.56
-71.47	-73.64	-8.47
-81.29	-88.19	-8.52
-82.09	-87.24	-7.41
-83.21	-86.61	-5.88
-84.27	-86.69	-4.67
-84.73	-86.72	-4.12
-84.72	-86.72	-4.13
-84.8	-86.62	-3.94
-85.09	-86.64	-3.58
-85.31	-86.66	-3.28
-85.27	-86.6	-3.29

9.1. Upright Posture

To be upright the following conditions must be met.

Y angle must be positive.

Z angle must be between -10 and 10 degrees.

X angle also must be between -10 and 10 degrees.

9.2. Bending Forward

Y angle must be positive.

Z angle must be negative.

The magnitude of the Z angle indicates how far the person has bent forward.

9.3. Bending Backward

Y angle must be positive.

Z angle must be positive.

The magnitude of the Z angle indicates how far the person has bent backward.

9.4. Bending to right

Y angle must be positive.

X angle must be positive.

The magnitude of the X angle indicates how far the person has bent towards right.

9.5. Bending to left

Y angle must be positive.

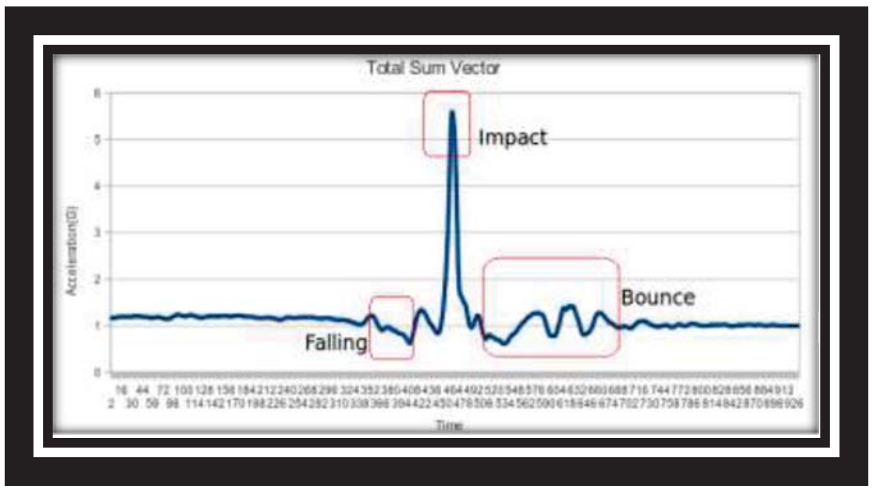
X angle must be negative.

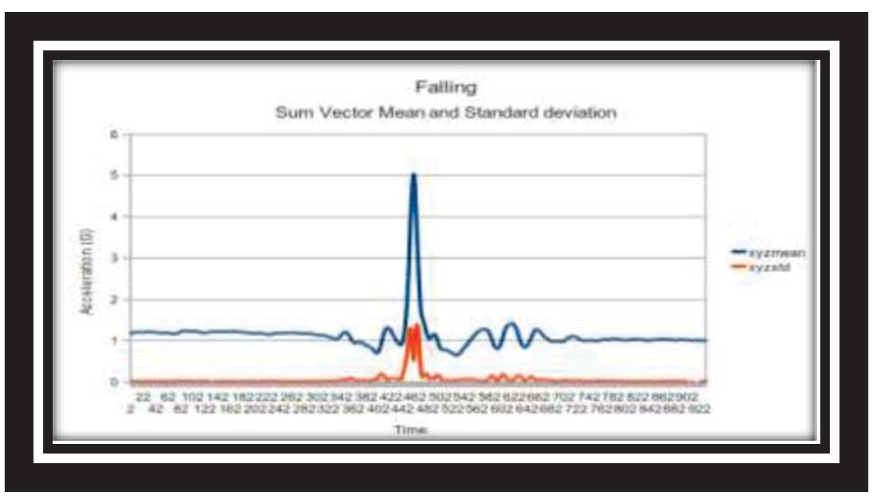
The magnitude of the X angle indicates how far the person has bent towards left.

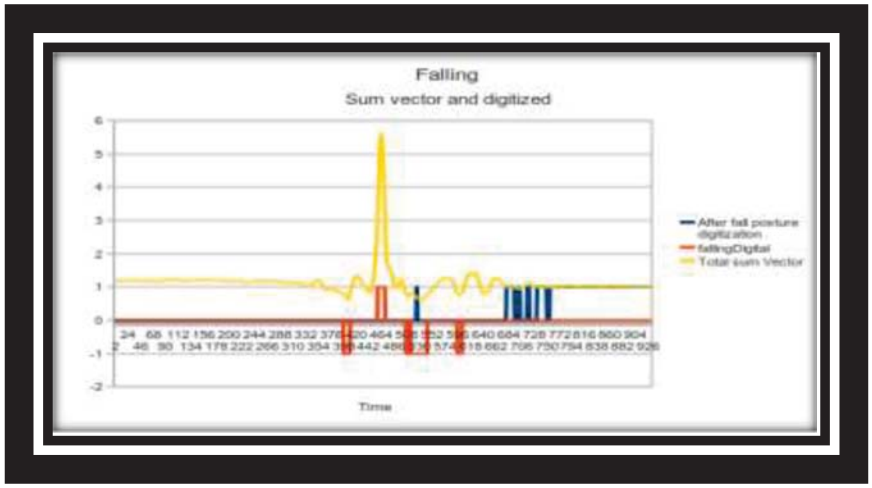
10. Fall detection

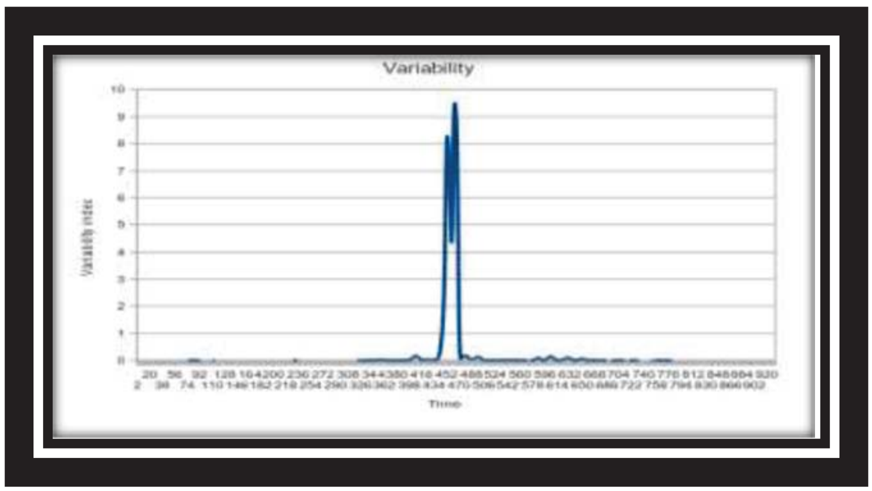
Falling is one of the most researched topics in this field of work for many years by the world wide scientific community. There are several different types of falling such as, falling due to slipping, falling due to tripping over some object, falling due to fainting, falling due to imbalance. Falling is categorized as free fall followed by the uncharacteristic impulsive impact, followed by very low activity after a time delay. By identifying the fall event one can automatically send necessary emergency help immediately thus possibly minimizing the medical complications of the fall.

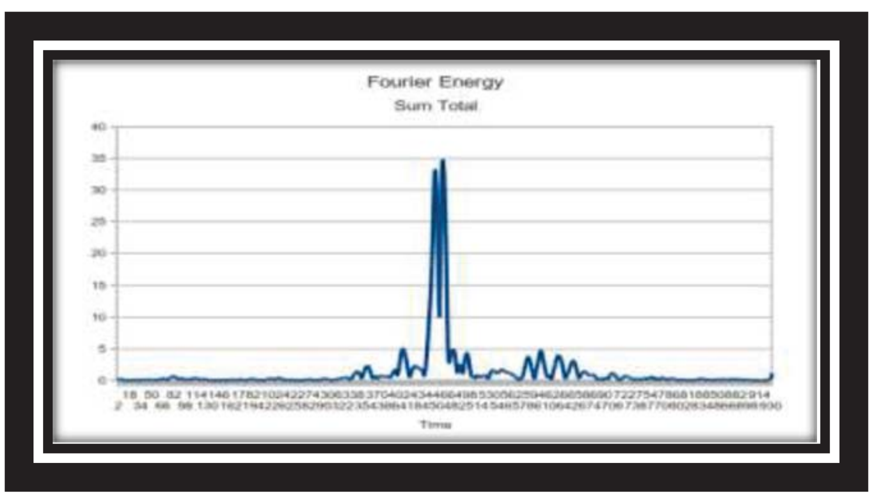
The following graphs show unique characteristics of a fall.

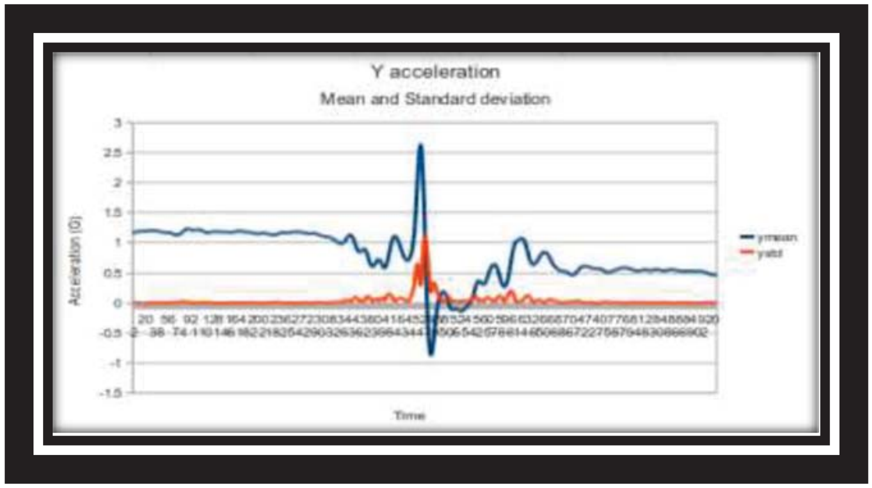


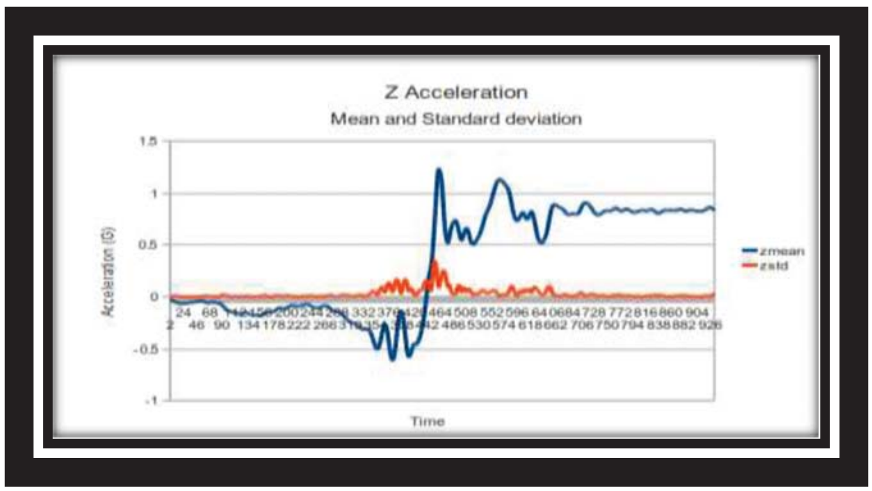


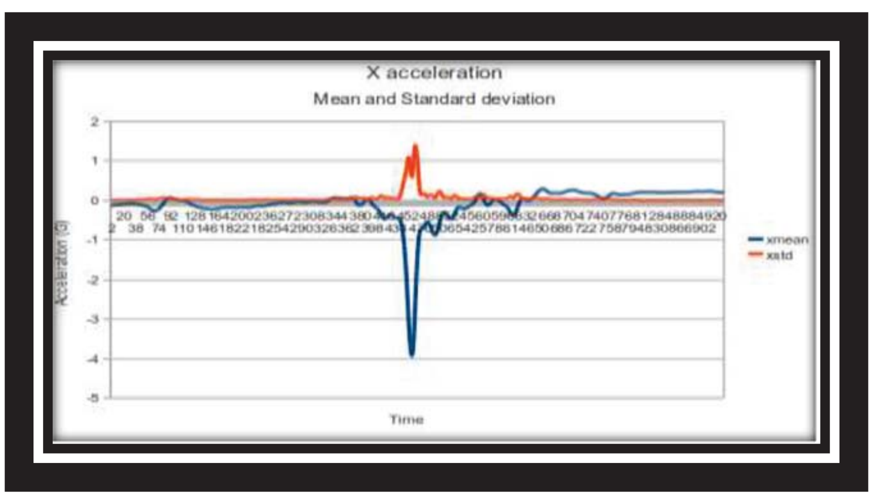

Falling
Sum vector and digitized
After fall posture digitization
fallingDigital
Total sum Vector
Time

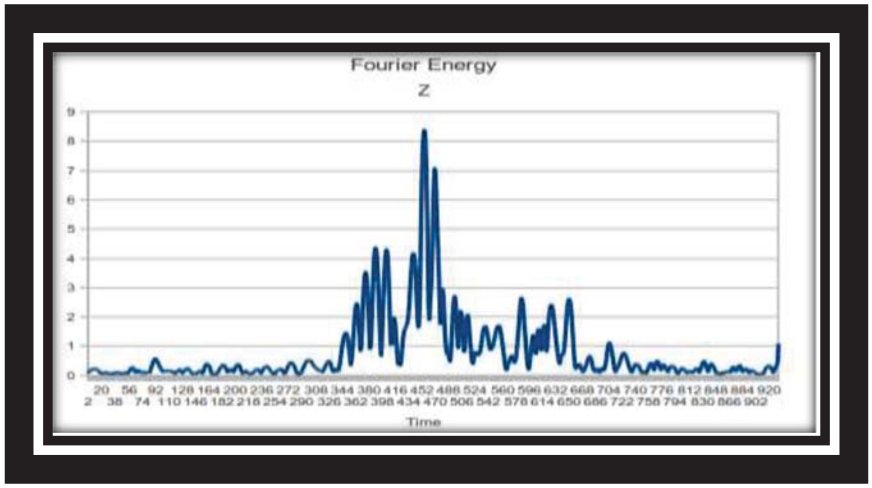

Variability
Time

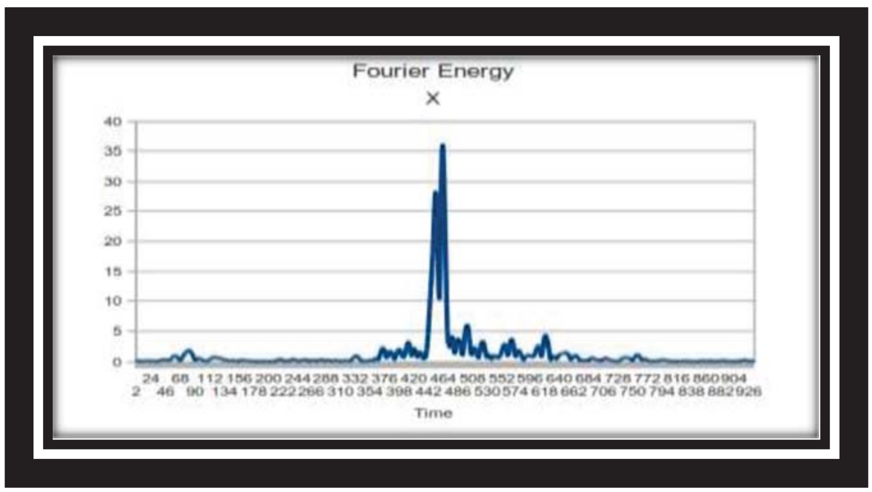

Fourier Energy
Sum Total
Time

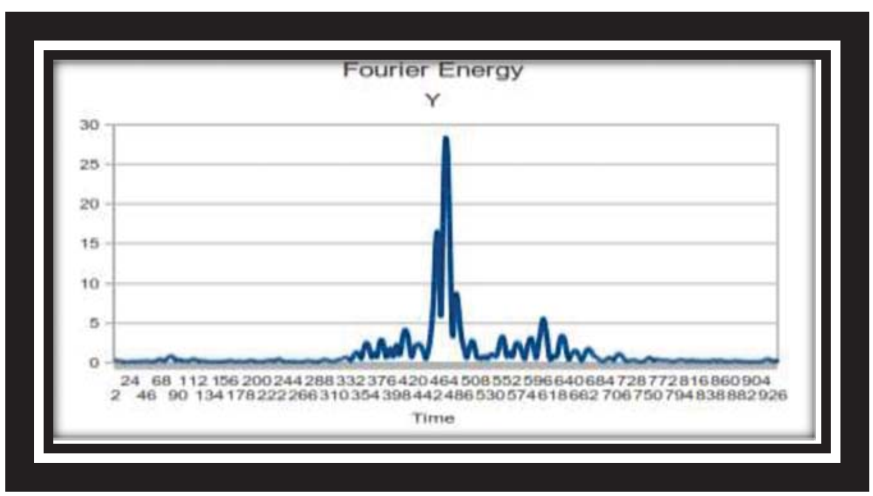

Y acceleration
Mean and Standard deviation
Acceleration (G)
Time
ymean
ystd


Z Acceleration
Mean and Standard deviation
Acceleration (G)
Time
zmean
zstd


X acceleration
Mean and Standard deviation
Acceleration (G)
Time
xmean
xstd


Fourier Energy
Z
Time


Fourier Energy
X
Time


Fourier Energy
Y
Time

Testing for falling

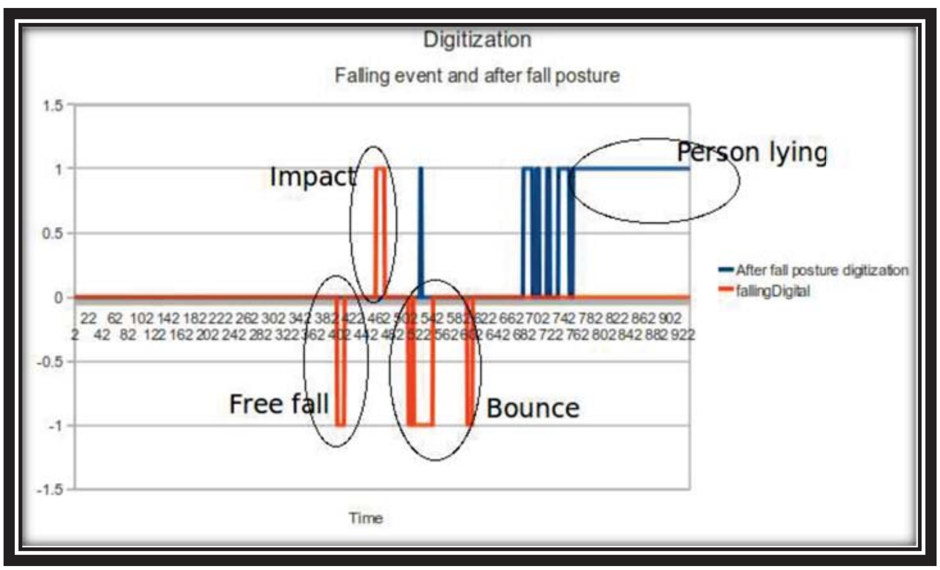
10.1. Test 1

In order to detect falling, the digitised information (falling digital) is analysed.
In falling digital, a negative pulse followed by lone positive pulse should be there. Negative pulse is the indication of fall and the positive pulse is the indication of the impact. The positive pulse should not be repeated, but negative pulse may repeat due to the bouncing after the positive pulse (this bouncing pulses are only present if the surface of the impact is made out of elastic material).

10.2. Test 2

Test 2 is carried out only if the test 1 is passed. In this test after the "t" elapsed time, the person lying indication should be a constant positive line, in other words person is fully or partially in an inclined posture (lying posture).

The following graph shows the summarised description of how fall detection works.

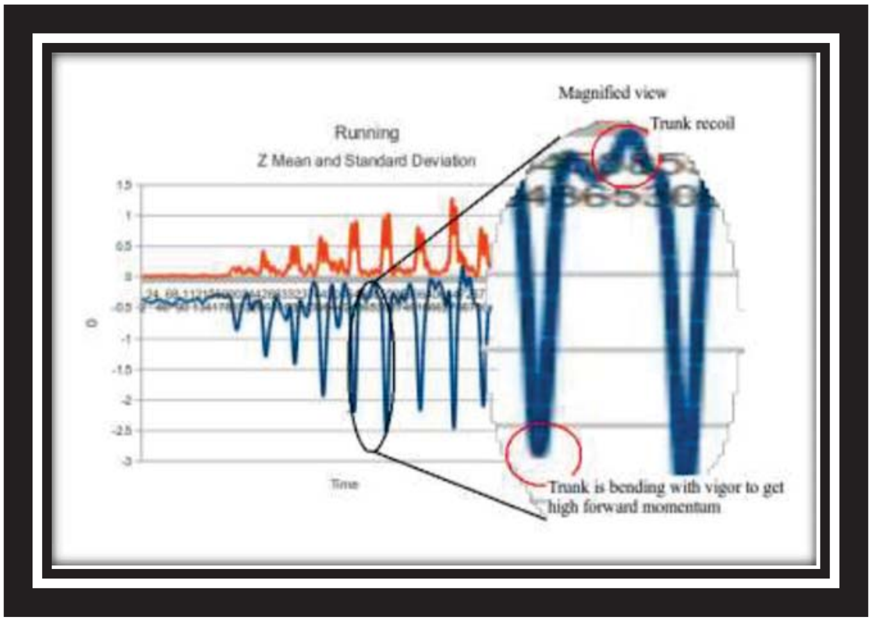


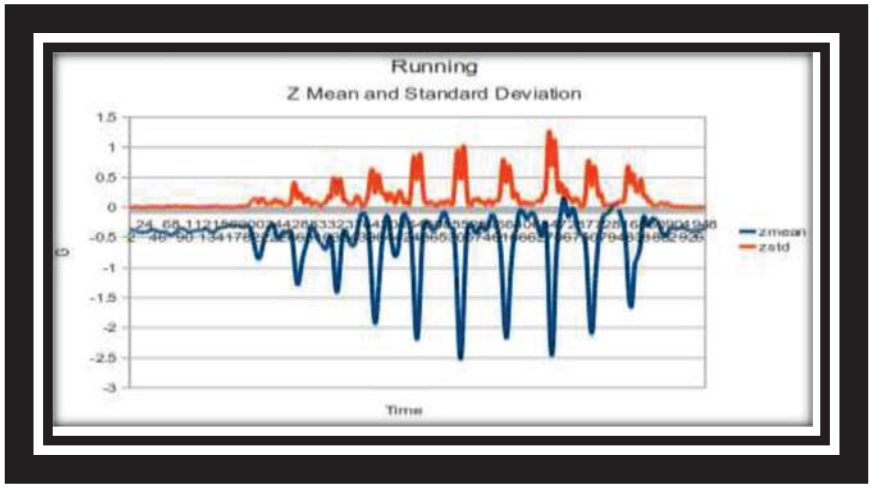
11. Detecting high intensity repetitive activity

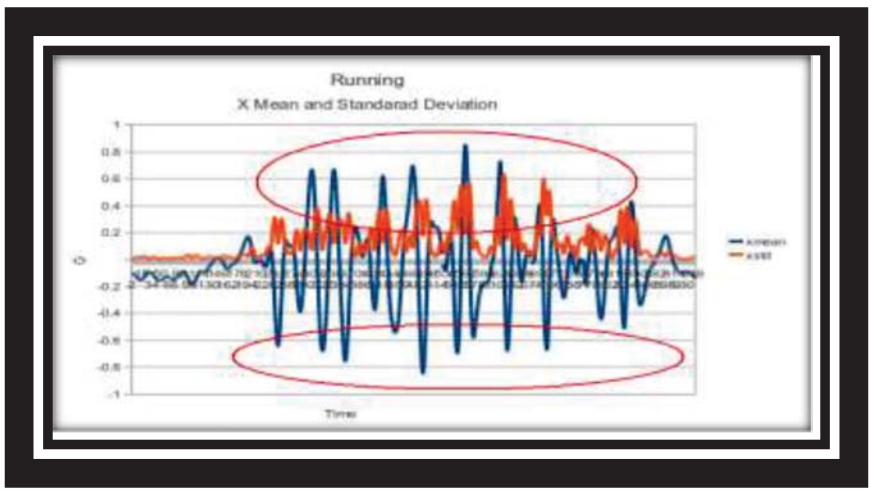
11.1. Running

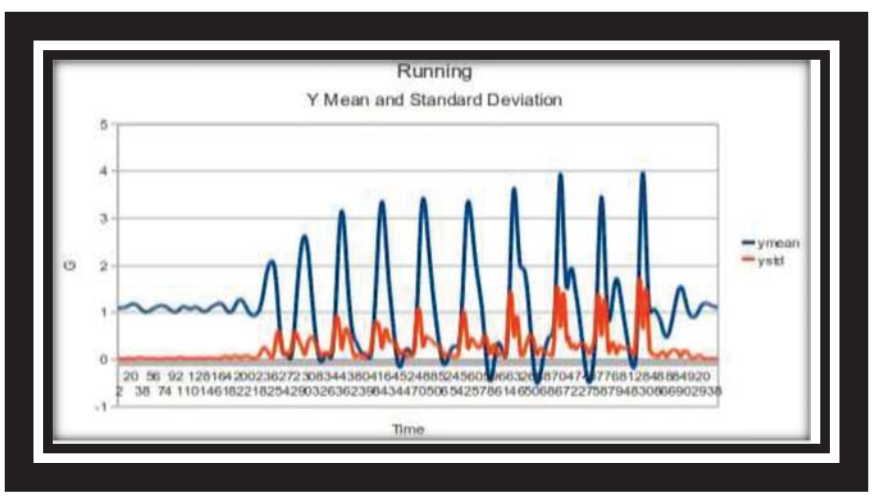
Running is a high energy, repetitive physical activity which has 3 distinct phases, which are upward motion, downward motion and high energy impact [77]. One of the common threads of running posture is all the participants who participated in the experiment had mild forward trunk bending while running.

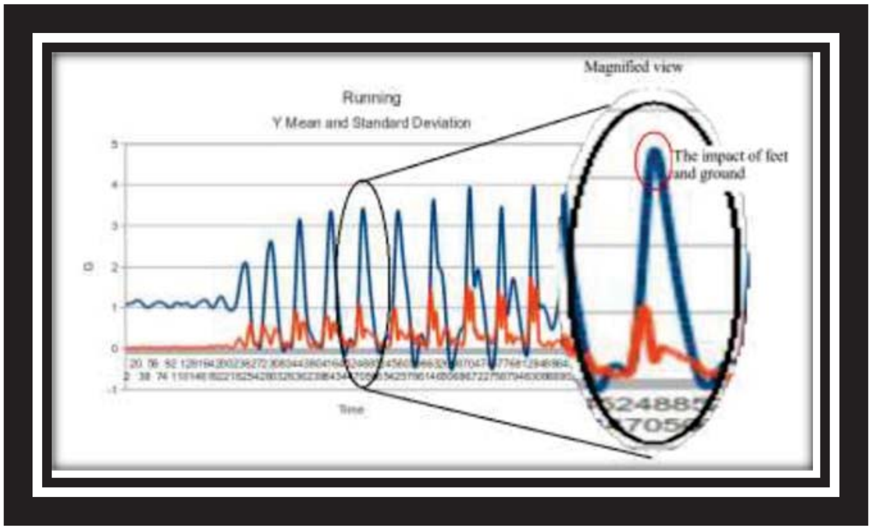
The following graphs show unique characteristics of running.

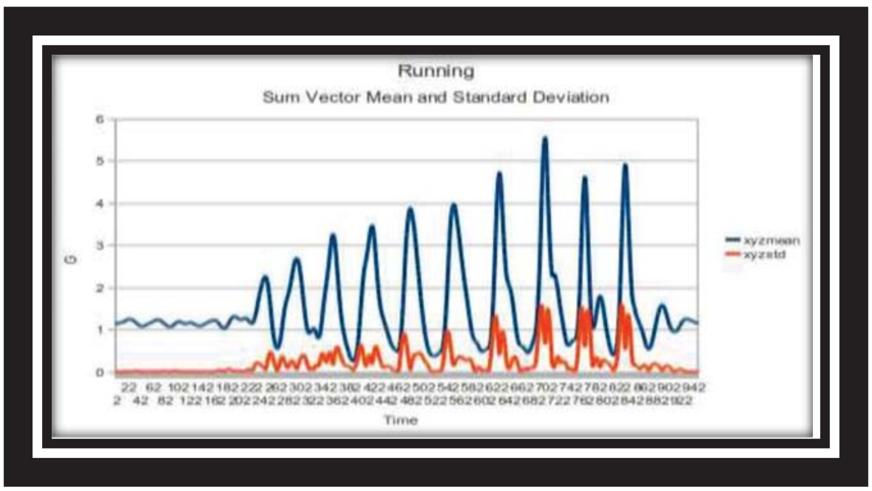


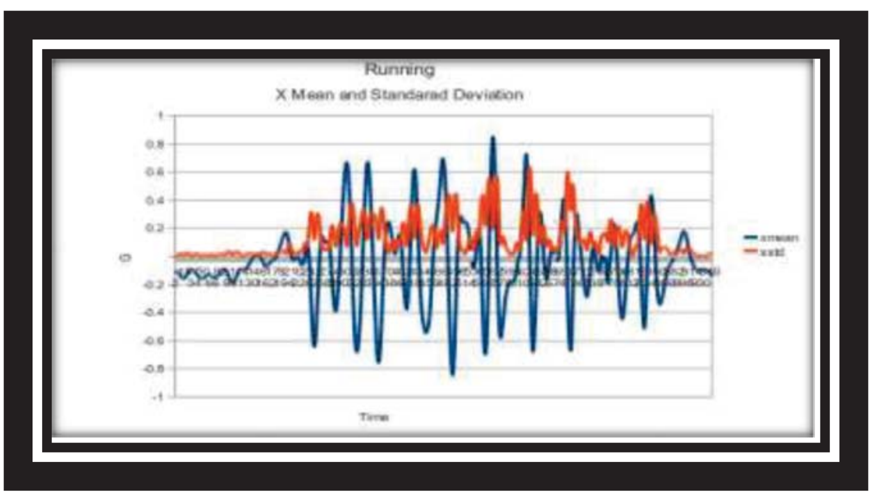

Running
Z Mean and Standard Deviation
G
Time
zmean
zstd

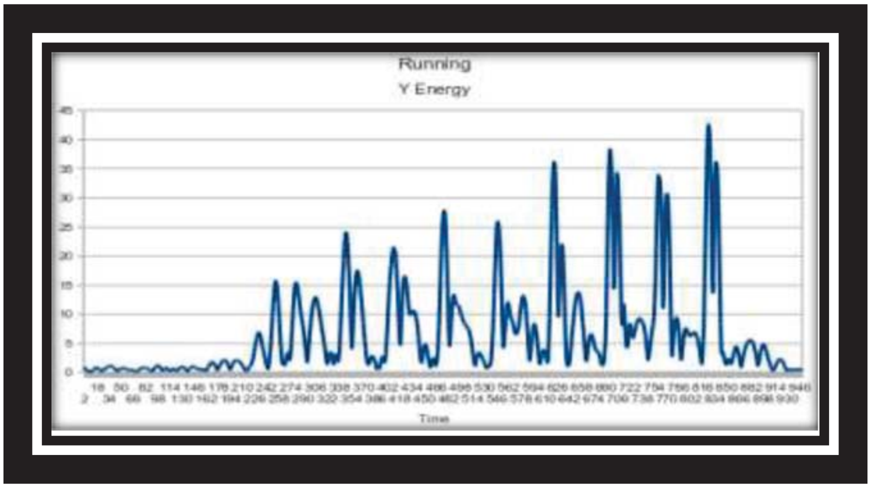

Running
X Mean and Standarad Deviation
G
Time

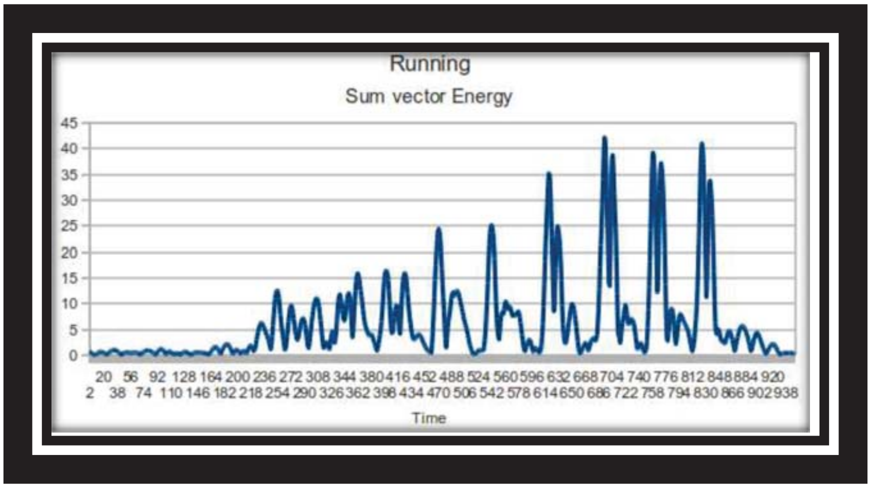

Running
Y Mean and Standard Deviation
G
Time
ymean
ystd

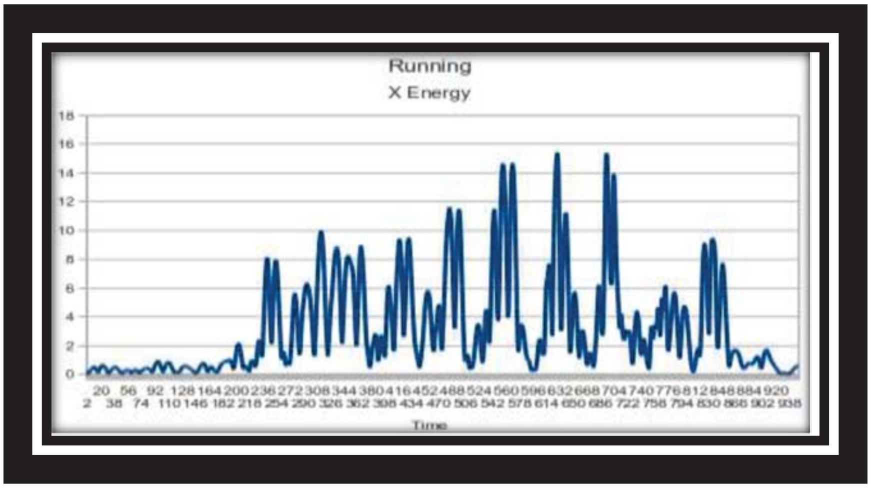

Running
Y Mean and Standard Deviation
Magnified view
The impact of feet and ground
G
Time

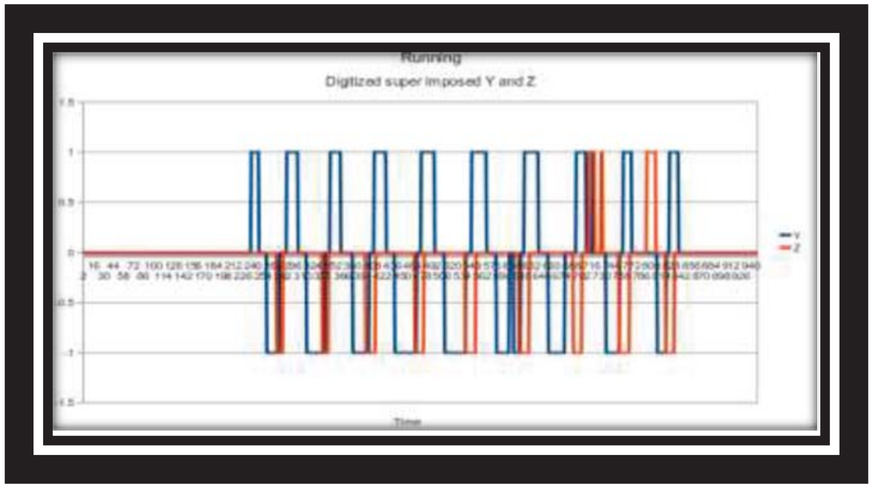

Running
Sum Vector Mean and Standard Deviation
xyzmean
xyzstd
G
Time

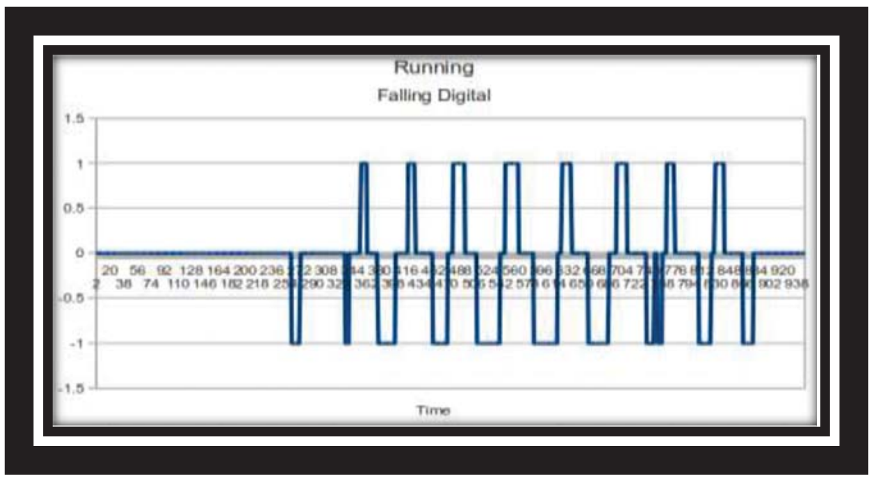

Running
X Mean and Standarad Deviation
G
Time

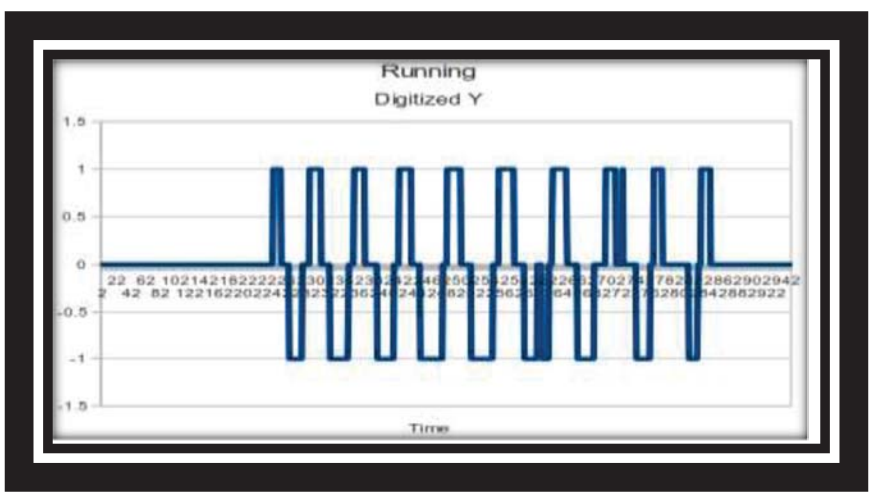

Running
Y Energy
Time

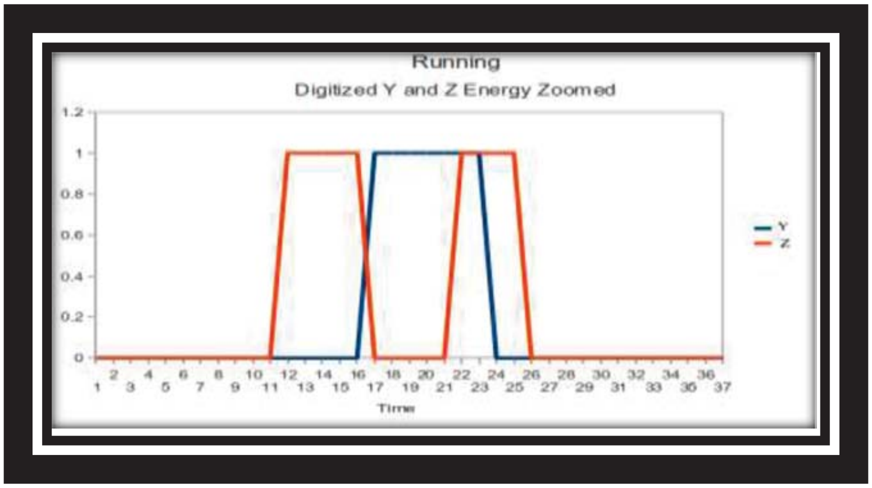

Running
Sum vector Energy
45
40
35
30
25
20
15
10
5
0
Time

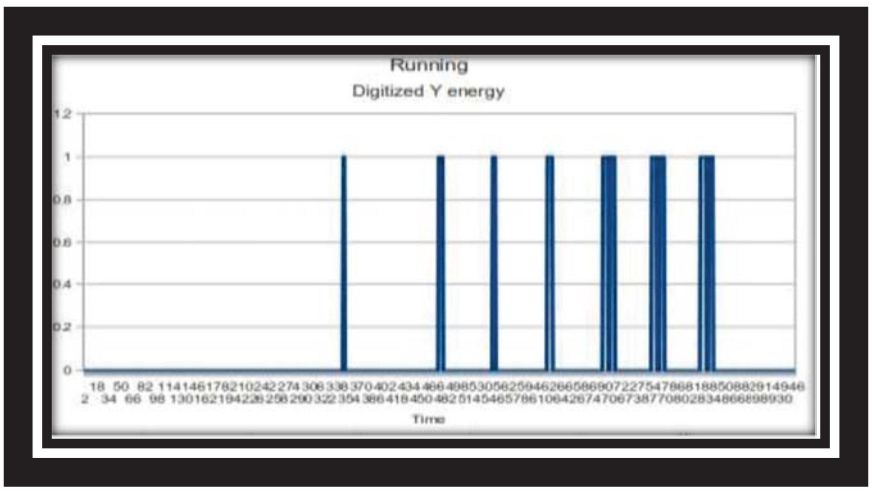

Running
X Energy
Time

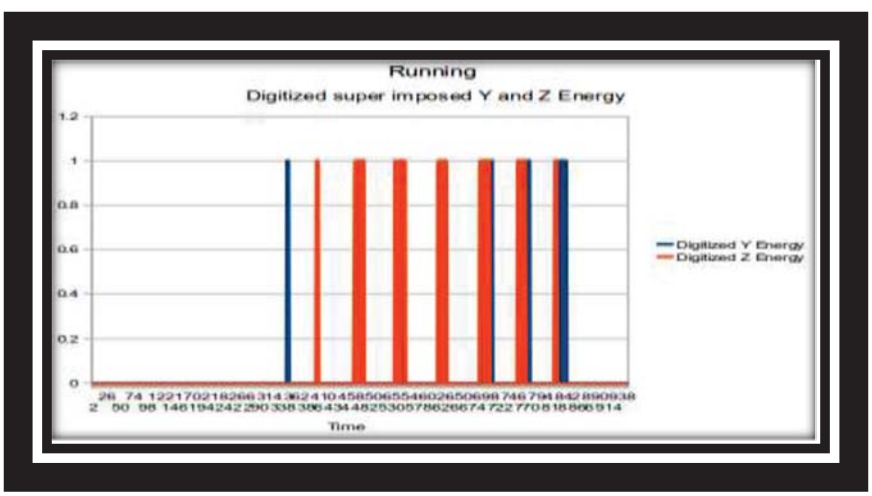

Running
Digitized super imposed Y and Z
Time

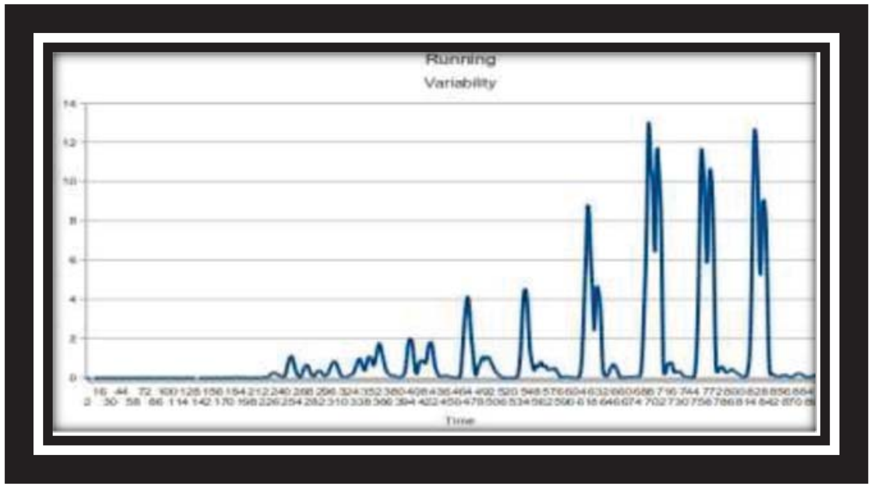

Running
Falling Digital
Time

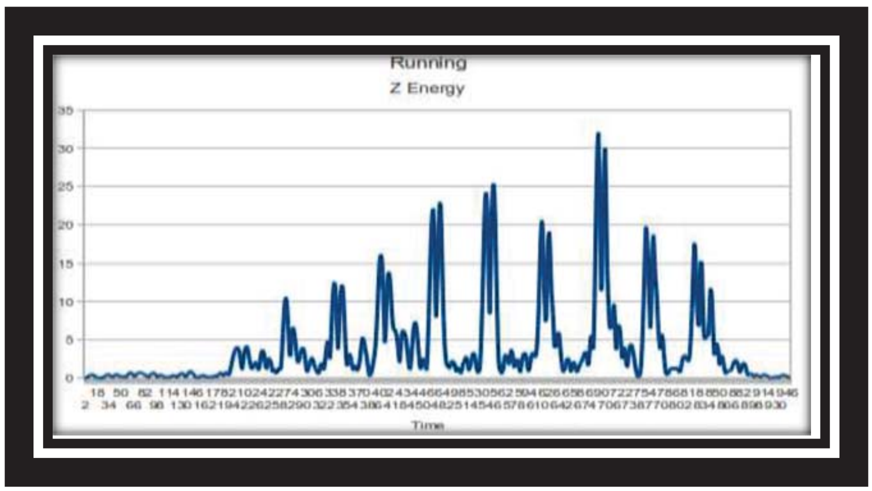

Running
Digitized Y
Time

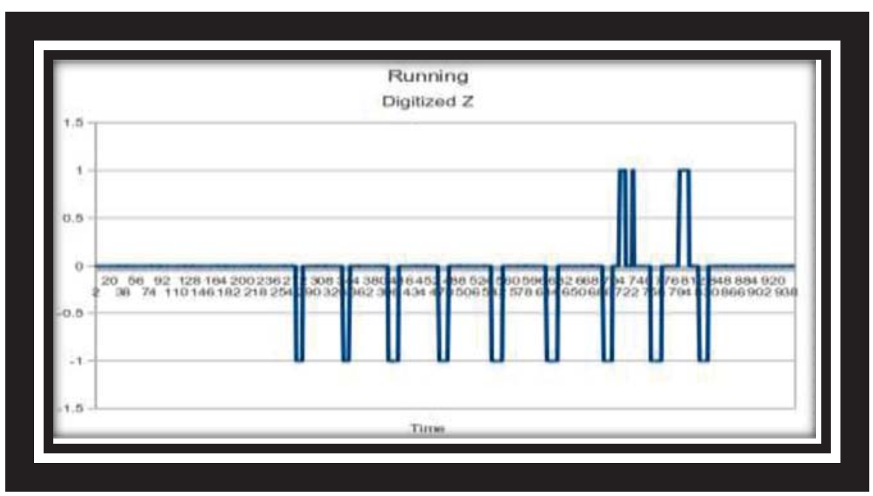

Running
Digitized Y and Z Energy Zoomed
Time
Y
Z

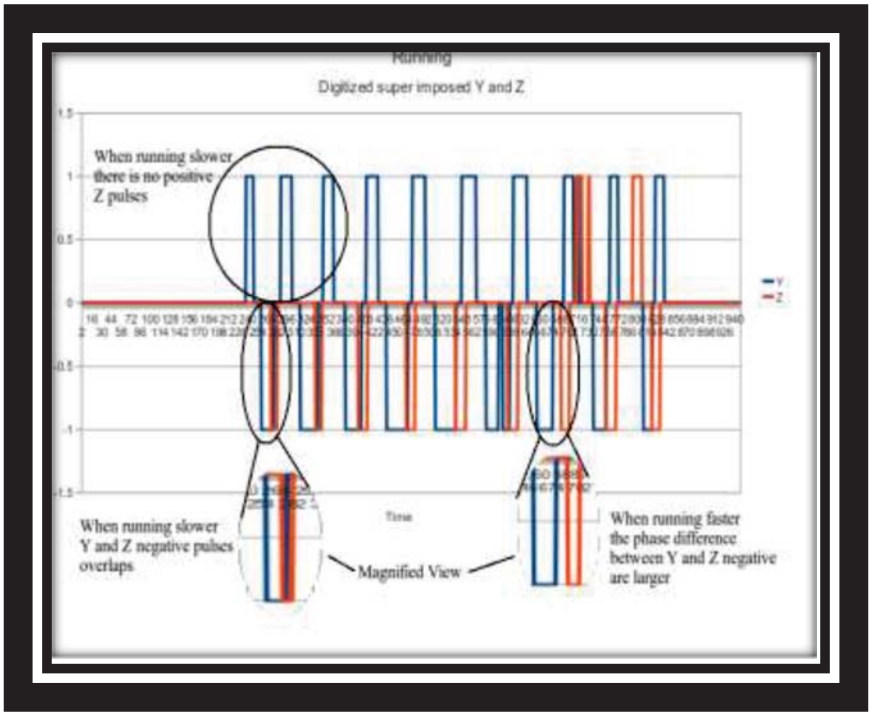

Running
Digitized Y energy
Time

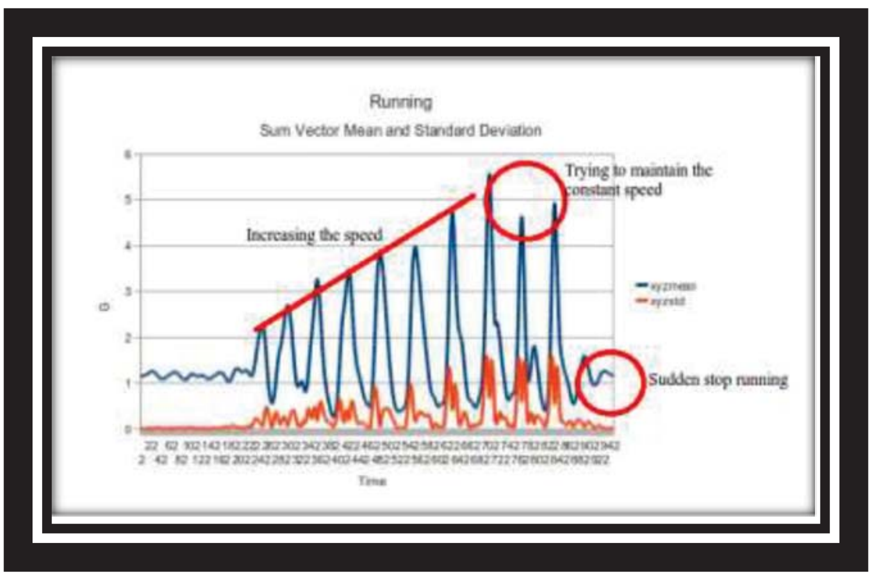

Running
Digitized super imposed Y and Z Energy
Time
Digitized Y Energy
Digitized Z Energy

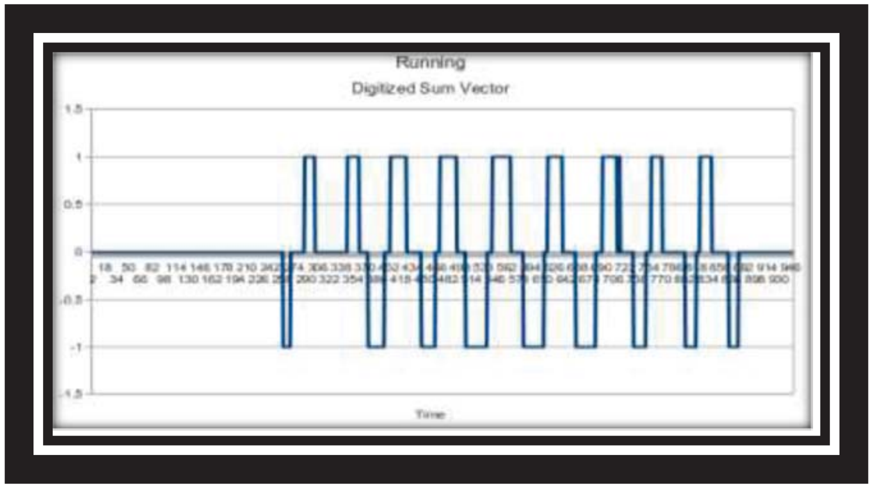

Running
Variability
14
12
10
8
6
4
2
0
Time

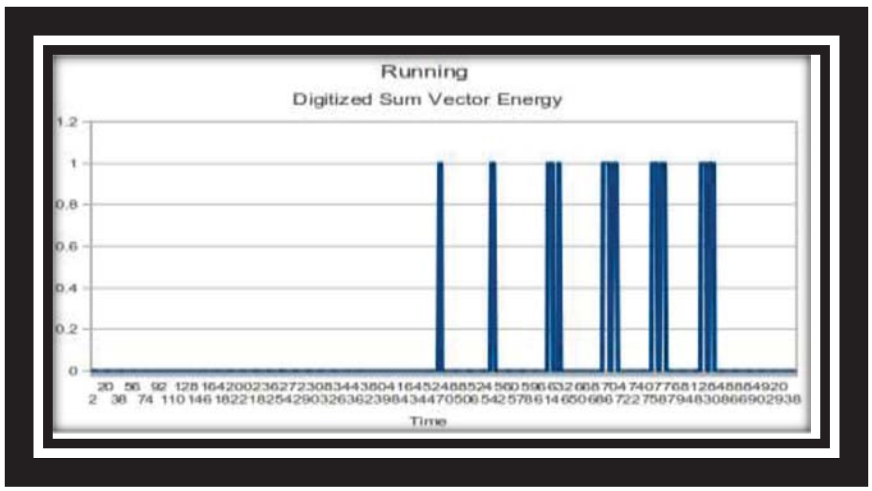

Running
Z Energy
35
30
25
20
15
10
5
0
Time

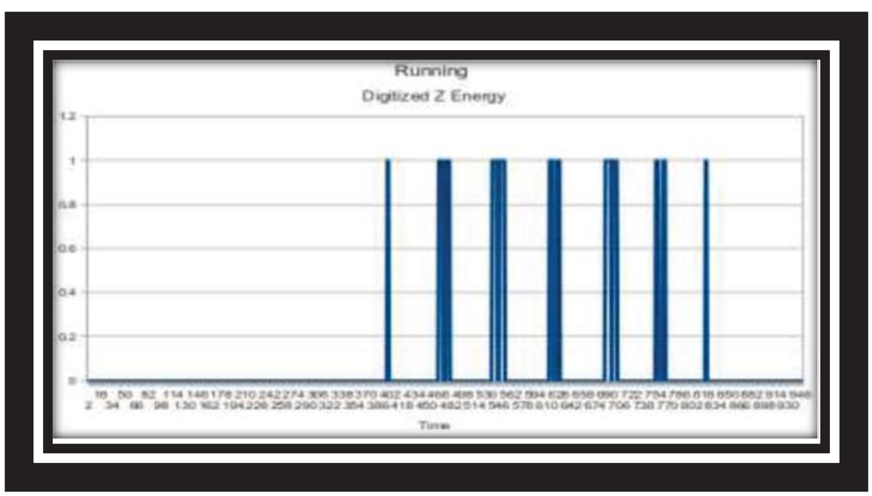

Running
Digitized Z
1.5
1
0.5
0
-0.5
-1
-1.5
Time


Running
Digitized super imposed Y and Z
When running slower there is no positive Z pulses
When running slower Y and Z negative pulses overlaps
Magnified View
When running faster the phase difference between Y and Z negative are larger
Time


Running
Sum Vector Mean and Standard Deviation
Increasing the speed
Trying to maintain the constant speed
Sudden stop running
Time


Running
Digitized Sum Vector
1.5
1
0.5
0
-0.5
-1
-1.5
Time

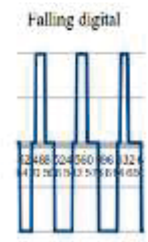

Running
Digitized Sum Vector Energy
1.2
1
0.8
0.6
0.4
0.2
0
Time


Running
Digitized Z Energy
Time

There are 8 tests for running.

11.1.1. Test 1

Falling digital should continuously have the negative pulse followed by the positive pulse pattern repeated. This is because when running the person has downward fall followed by the high impact and this process is continuously reoccurring during the entire duration of running; whereas when a person is falling it happens only once.



11.1.2. Test 2

When running, this pattern in variability data should be repeated periodically.

11.1.3. Test 3

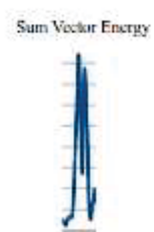
Check for the following pattern in Sum vector and Sum vector standard deviation. This pattern also repeats periodically.

11.1.4. Test 4

Check for the Z for the following pattern. This is due to the fact that when a person is running they usually have a forward tilt and when generating power for the forward momentum trunk is also exerted forward directional force.

11.1.5. Test 5

Check for the following pattern in the sum vector energy, this pattern is repetitive.

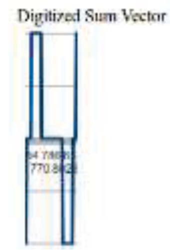


11.1.6. Test 6

Digitized Y has the following pattern repeated during the entire duration of running.

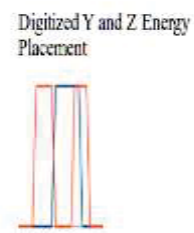
11.1.7. Test 7

This test is very similar to test 6 and uses digitized sum vector.



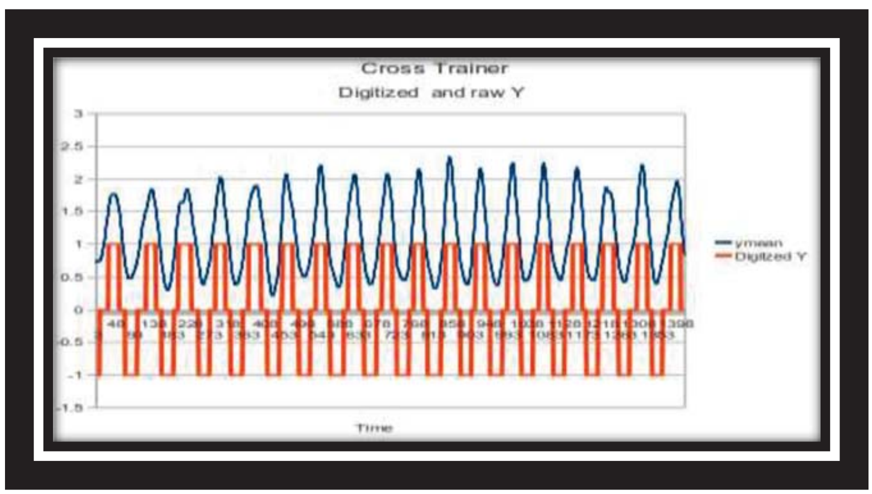
11.1.8. Test 8

This test uses the super imposed Y and Z energy and check their placement relative to each other. When a person is running trunk is bent forward and then afterward is straightened. In between this tilting of the trunk, the runner goes up and down and has an impact with the ground. So first Z energy pulse, which is the cause of trunk forward acceleration (to gain momentum) is followed by the Y energy pulse due to downward motion, ended with ground impact which ends with Z energy trunk straightening.

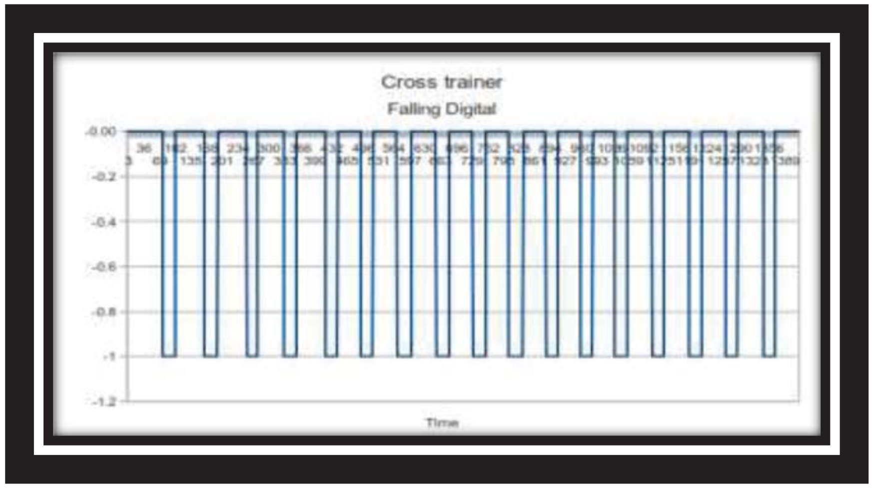


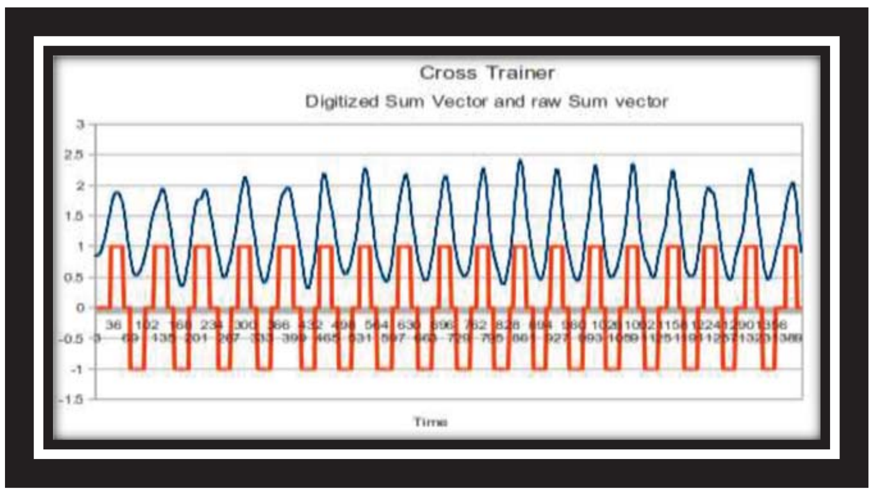
11.2. Cross trainer

Cross trainer is an exercise machine which is widely used by the people with low physical strength to gain muscle strength, burn fat and enhance cardiovascular health. Unlike thread-mils (running/walking machine) which can be hazardous , cross trainers suits the elderly peoples' exercise needs very well , where most of the modern cross trainers are equipped with heart rate monitors so it can avoid over exhaustion which can cause faint in elderly. The other well suited exercise machine for elderly is humble exercise-cycle, but a waist worn or wrist worn sensor is not very useful to detect that activity.

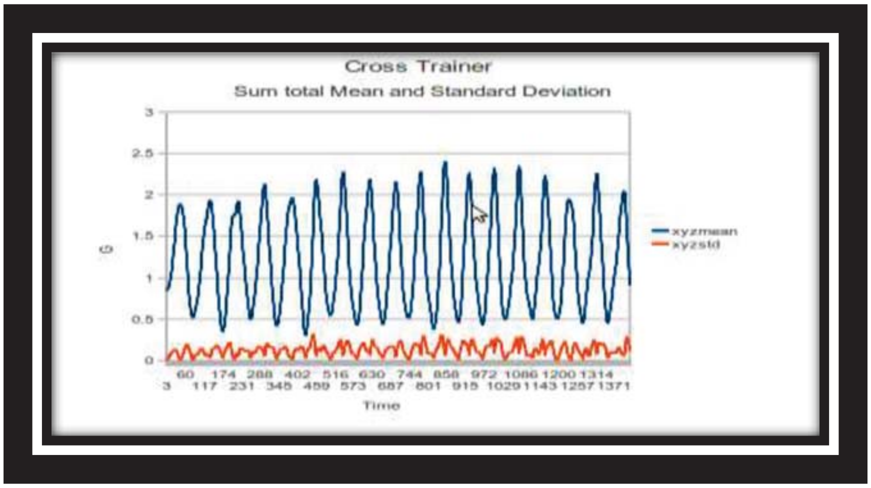


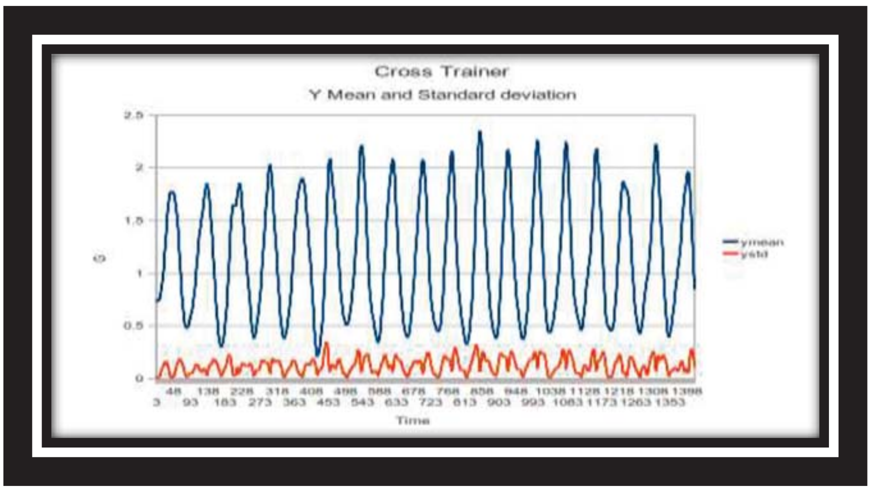
Cross trainers have a repetitive periodic motion and it can be separated from running by using the falling digital where in a cross trainer no impact is recorded and it can be separated from walking where in walking falling digital is flat line but in cross trainer there is a repetitive negative pulses which signifies the downward motion.

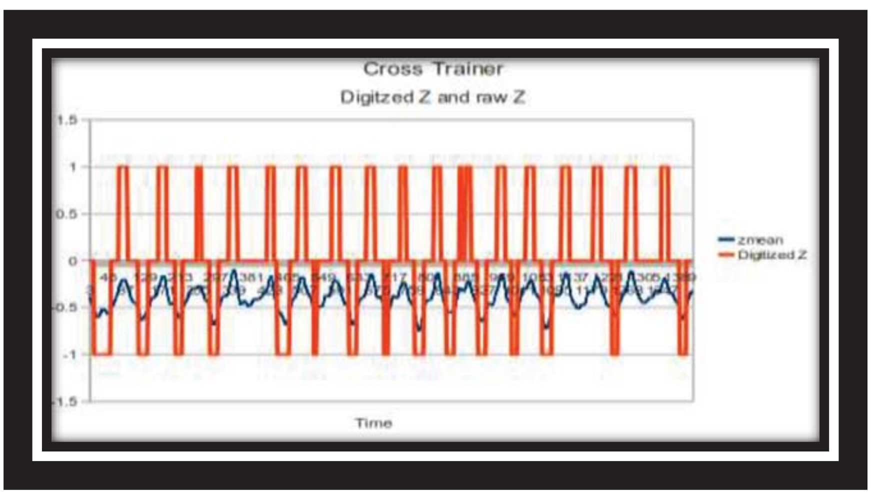

Cross trainer
Falling Digital
Time

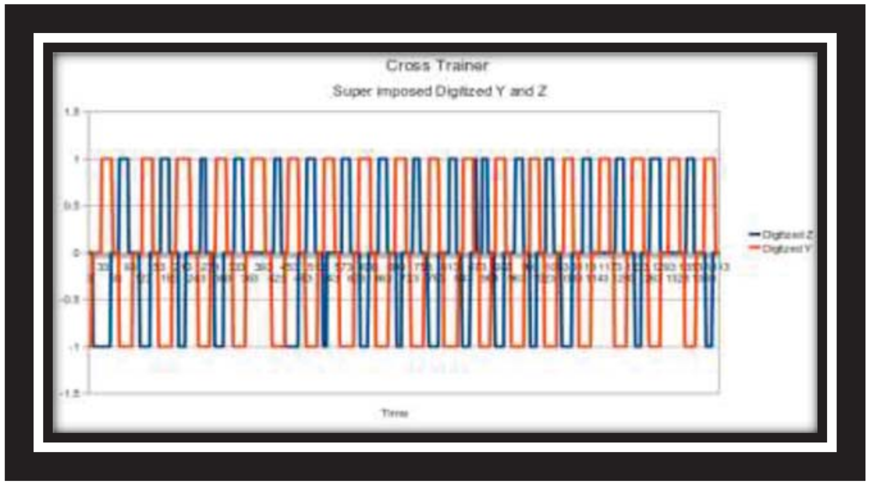

Cross Trainer
Digitized Sum Vector and raw Sum vector
Time

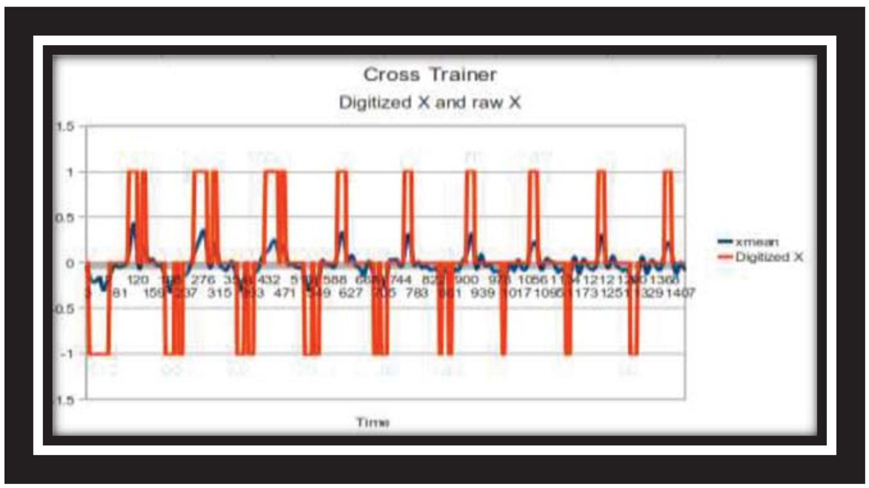

Cross Trainer
Z Mean and Standard Deviation
Time

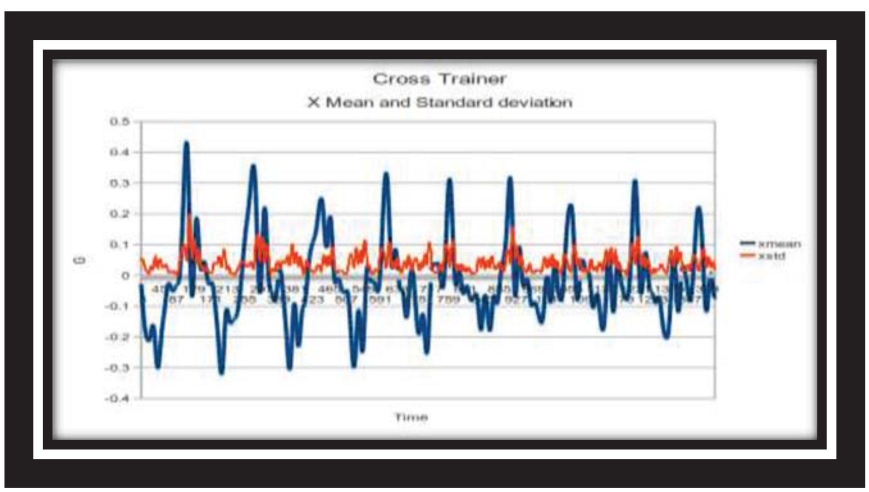

Cross Trainer
Sum total Mean and Standard Deviation
G
Time
xyzmean
xyzstd

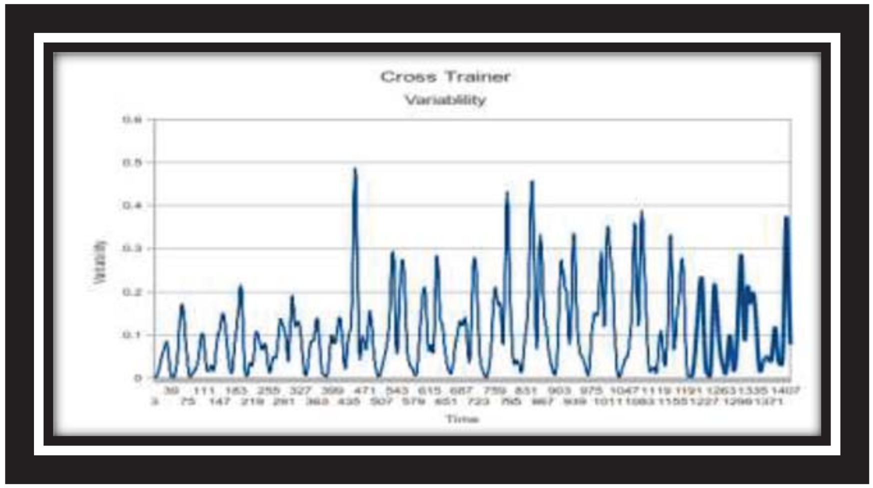

Cross Trainer
Y Mean and Standard deviation
G
Time
ymean
ystd

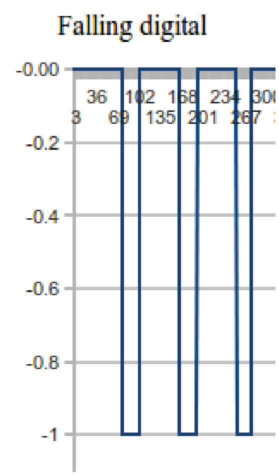

Cross Trainer
Digitzed Z and raw Z
Time
zmean
Digitized Z


Cross Trainer
Super imposed Digitized Y and Z
Time


Cross Trainer
Digitized X and raw X
xmean
Digitized X
Time


Cross Trainer
X Mean and Standard deviation
xmean
xstd
Time

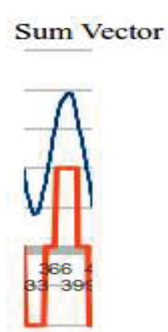




There are four tests to verify if a person is on the cross trainer.

11.2.1. Test 1

The falling digital would only register negative pulses at periodic rate. This is because when on the cross trainer, the user has sudden downward motion but that downward motion is not followed by a sudden impact unlike when running or when falling down.



11.2.2. Test 2

Test 2 is a combination of checking raw Sum Vector for an approximately sinusoidal periodic pattern as well as digitized sum vector. Digitized sum vector has negative pulse followed by the positive pulse. These patterns are periodic; therefore they continue to repeat themselves.

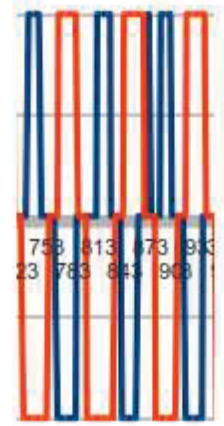
11.2.3. Test 3

Test 3 is very similar to test 2, except in this occasion the Y acceleration is tested for.

11.2.4. Test 4

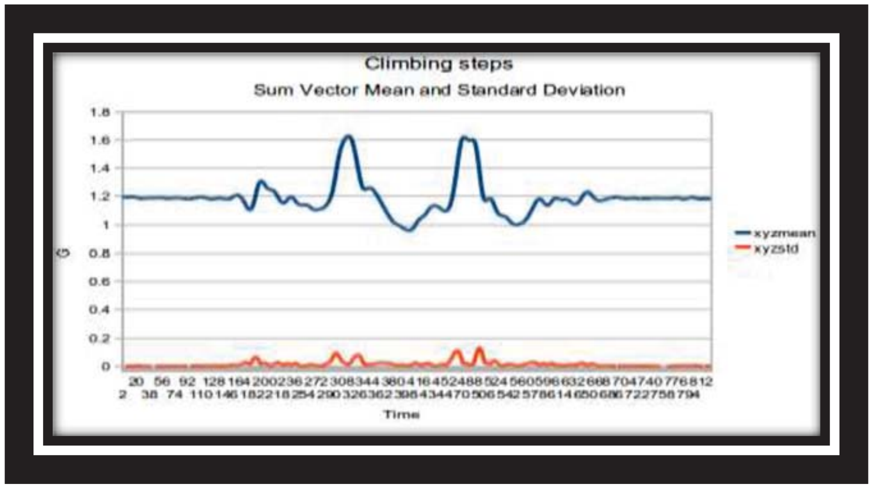
In the test 4, digitized Y and Z are super imposed to check for the positioning. When Y has positive pulse Z has negative pulse and when Z has negative pulse Y has positive pulse.

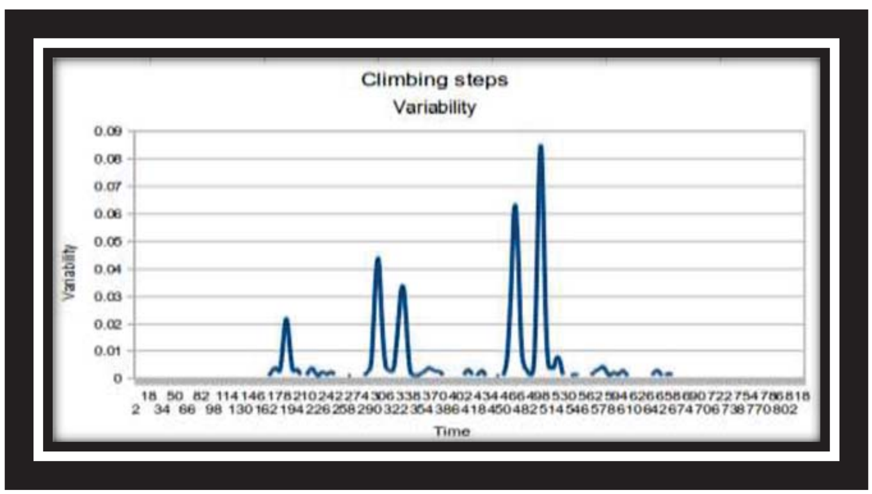
Inverted nature of Z and Y

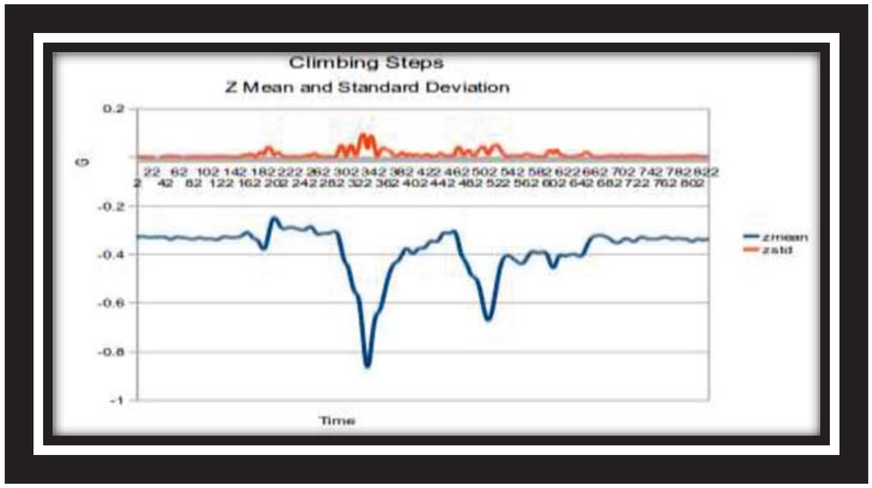


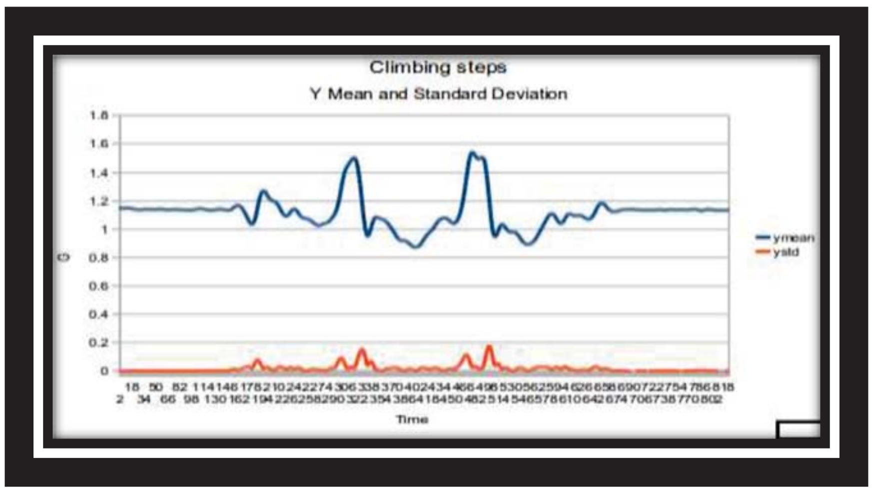
11.3. Climbing Steps

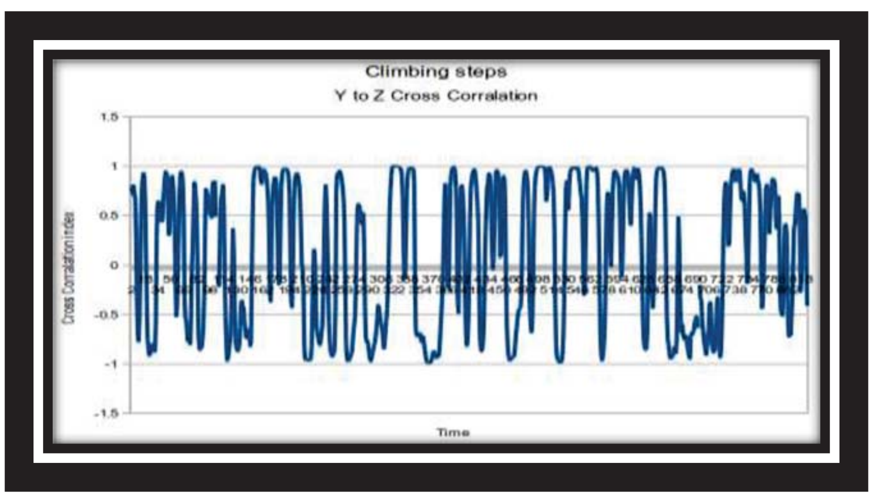
Climbing stacks of stair-cases is not a common daily activity of an elderly as above can be very strenuous. To climb stairs a person is working against the gravitational force and therefore requires increased blood flow to the periphery, which in return demands an increased workload of the cardiac output. Therefore strenuous activities like above is difficult to perform unless the person is in a good physical health [80]. In this experiment participants are asked to climb only two steps.

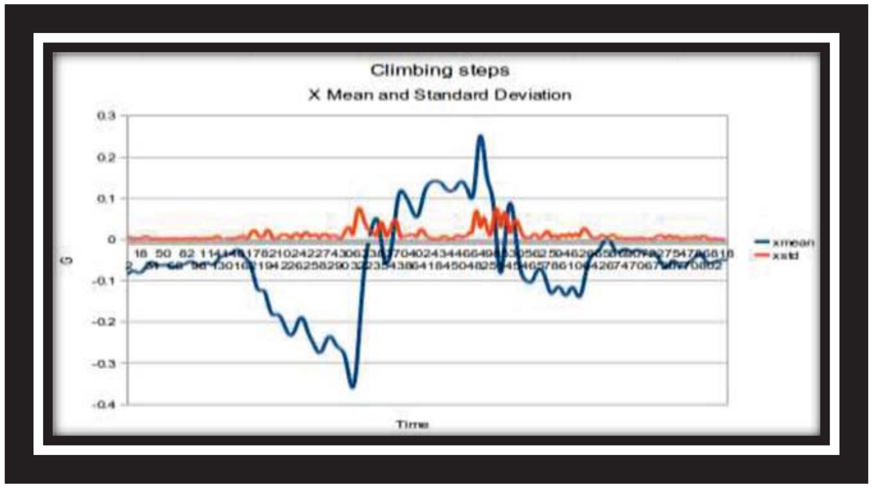


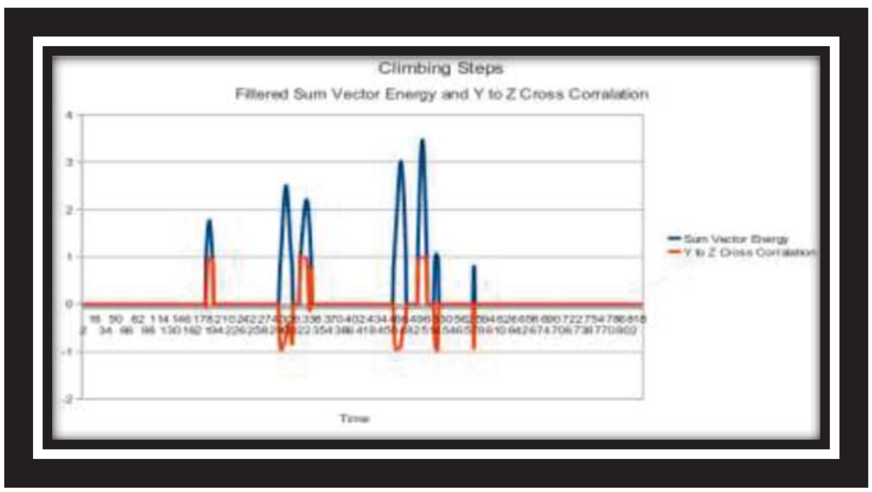


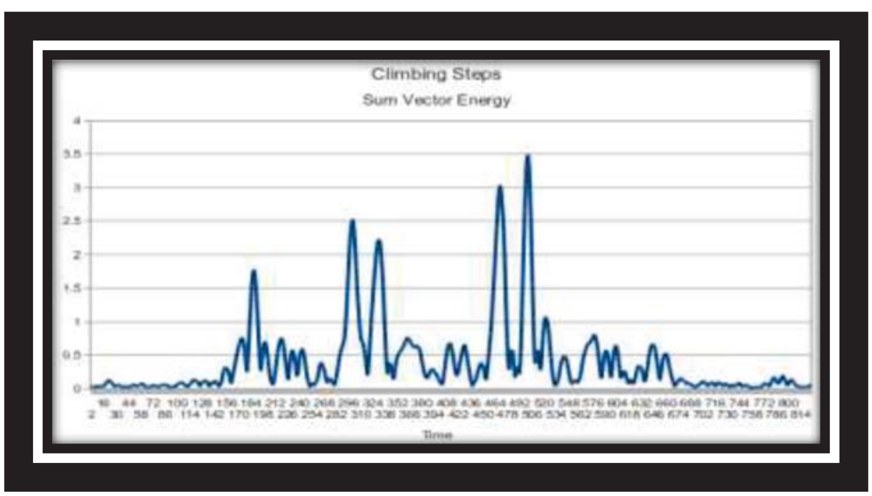

Climbing Steps
Z Mean and Standard Deviation
0.2
-0.2
-0.4
-0.6
-0.8
-1
G
Time
zmean
zstd

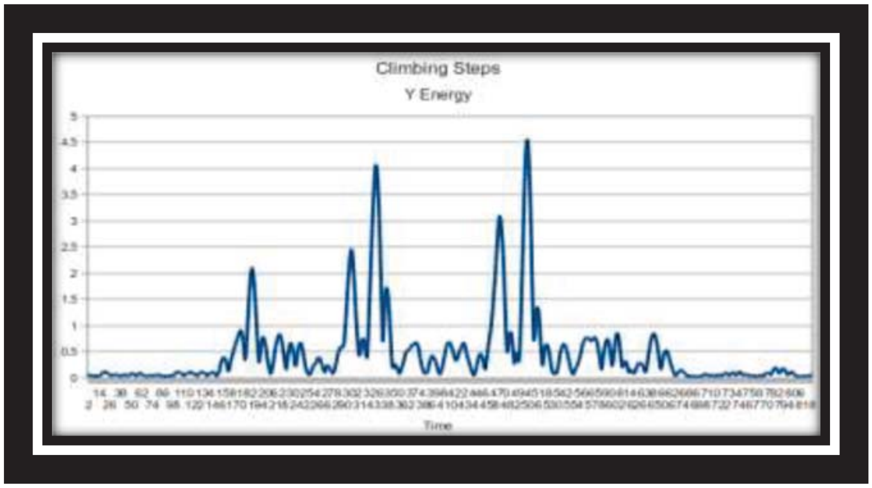

Climbing steps
Y Mean and Standard Deviation
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
G
Time
ymean
ystd

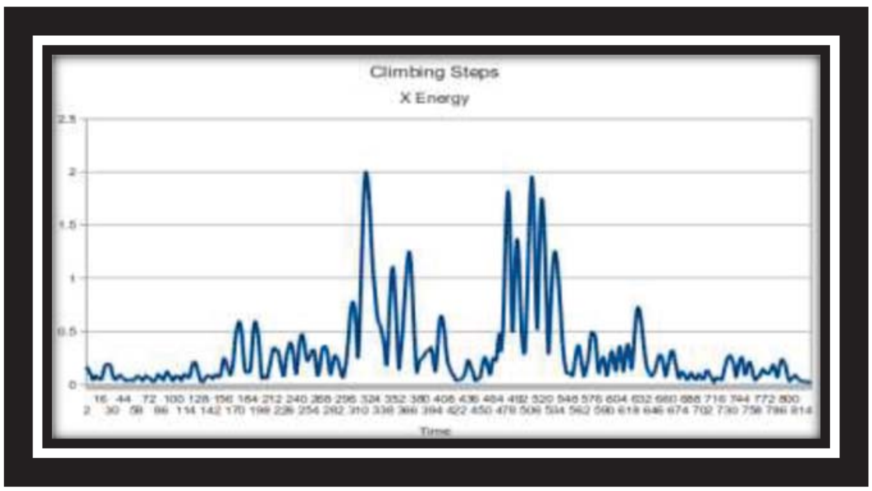

Climbing steps
Y to Z Cross Corralation
1.5
1
0.5
0
-0.5
-1
-1.5
Cross Corralation index
Time

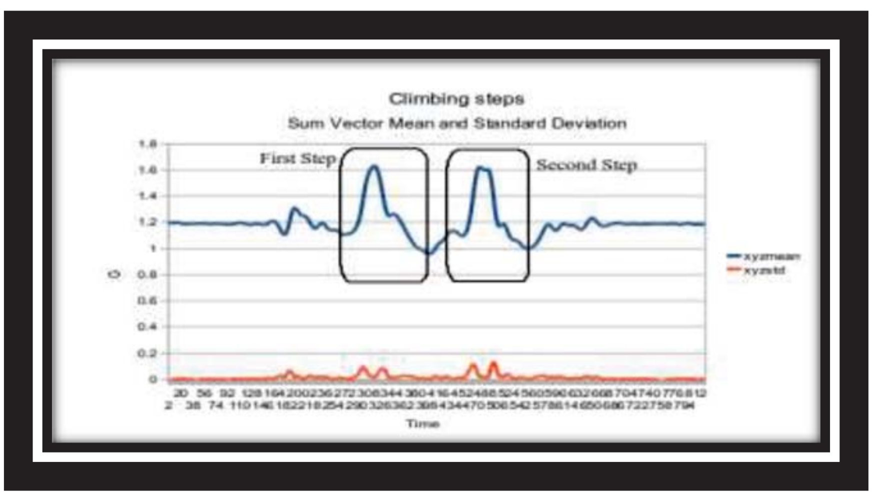

Climbing steps
X Mean and Standard Deviation
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
G
xmean
xstd
Time

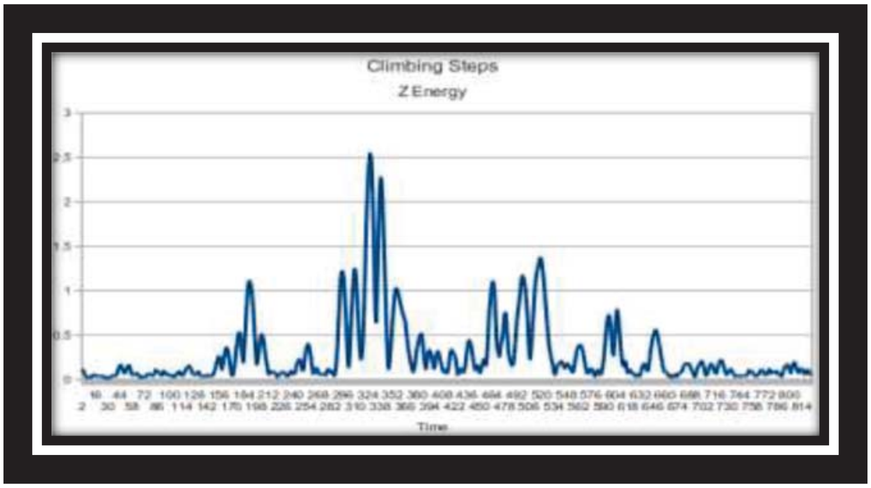

Climbing Steps
Filtered Sum Vector Energy and Y to Z Cross Correlation
Sum Vector Energy
Y to Z Cross Correlation
Time

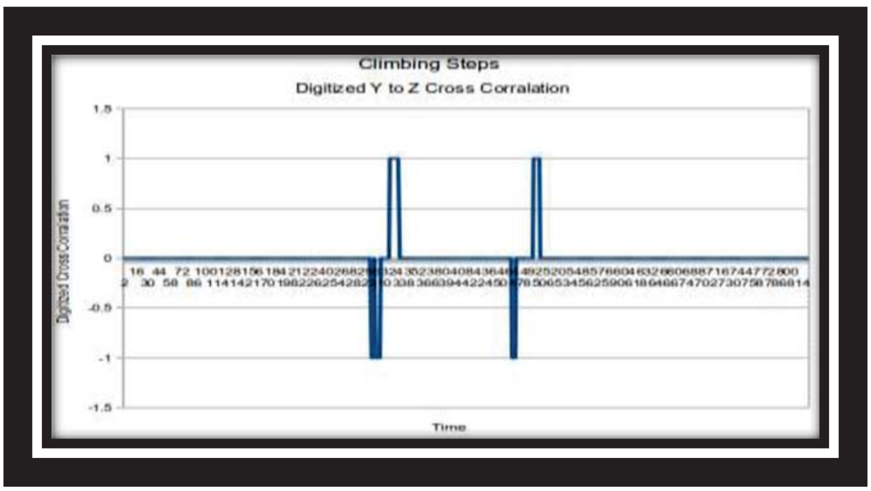

Climbing Steps
Sum Vector Energy
Time

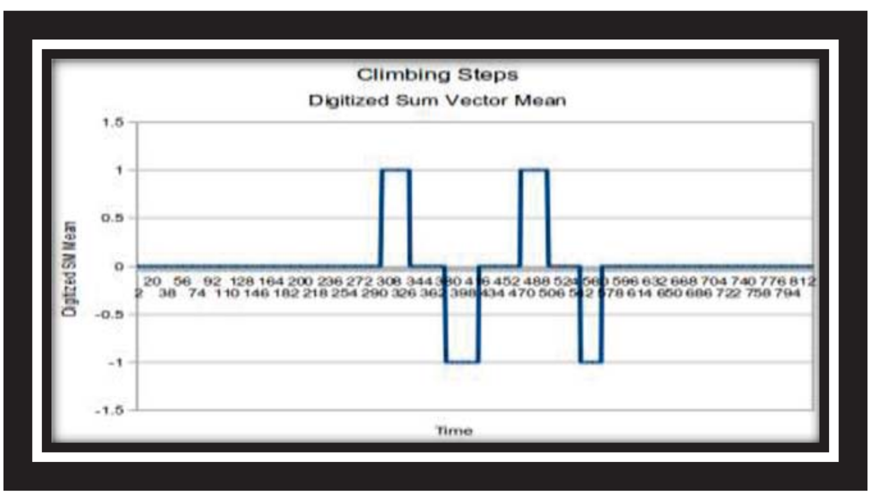

Climbing Steps
Y Energy
Time

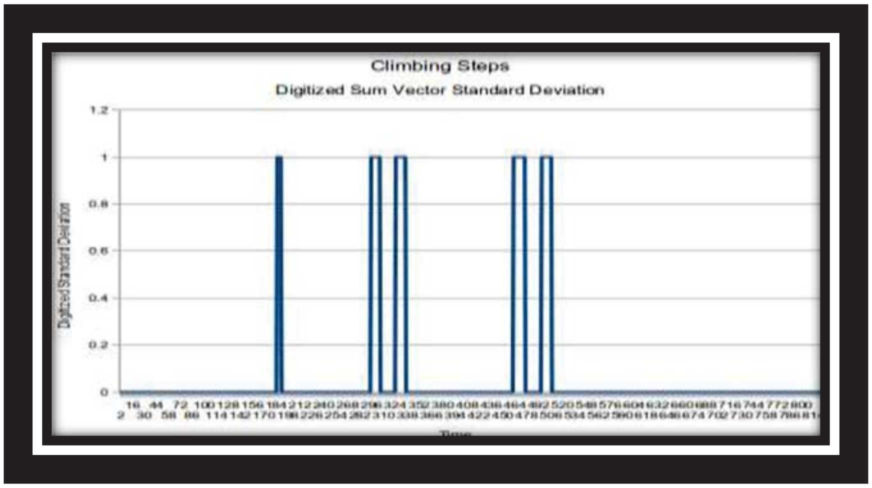

Climbing Steps
X Energy
Time

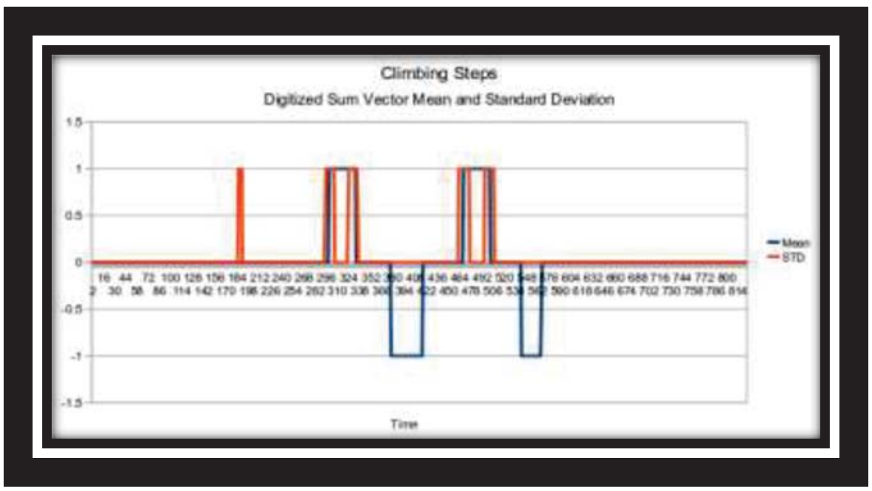

Climbing steps
Sum Vector Mean and Standard Deviation
First Step
Second Step
Time

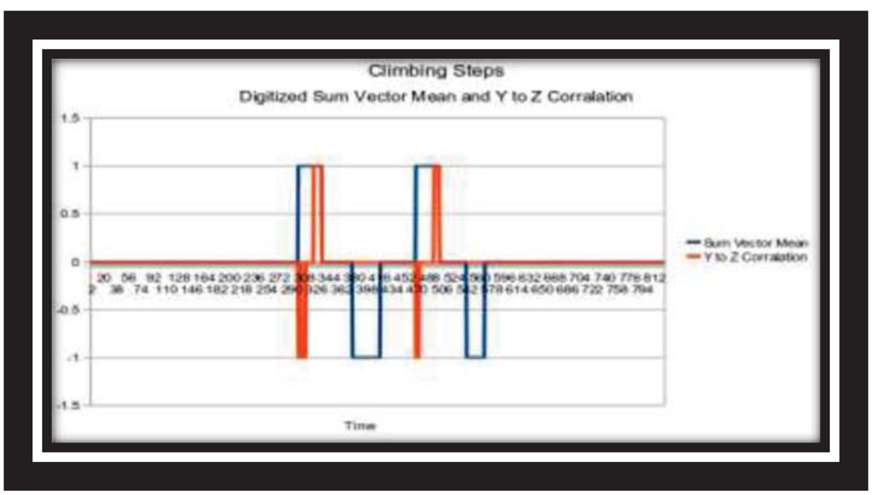

Climbing Steps
Z Energy
Time


Climbing Steps
Digitized Y to Z Cross Corralation
Digitized Cross Corralation
Time


Climbing Steps
Digitized Sum Vector Mean
Digitized SV Mean
Time

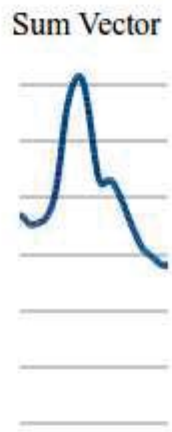

Climbing Steps
Digitized Sum Vector Standard Deviation
Digitized Standard Deviation


Climbing Steps
Digitized Sum Vector Mean and Standard Deviation
Time


Climbing Steps
Digitized Sum Vector Mean and Y to Z Corralation
Sum Vector Mean
Y to Z Corralation
Time

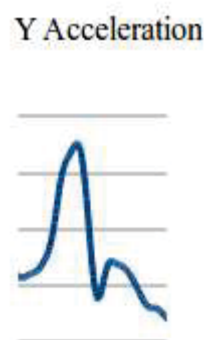
There are 12 tests to carry out in order to identify if a person is climbing a step.

11.3.1. Test 1



Look for the Sum Vector pattern which matches the following. This pattern is re-occurring when every time person is climbing another step. The width and peak point of this pattern are indicative of the person's health. Shorter width coupled with peak magnitude of over 2.5G is an indicative of a healthy person climbing steps fast. For a healthy individual, the average width is 108 time slots with average peak magnitude is 1.6G (Including the gravitational component), whereas having a well excess of 108 time slots in width and peak magnitude smaller than 1.6G is an indication of poor health.

11.3.2. Test 2



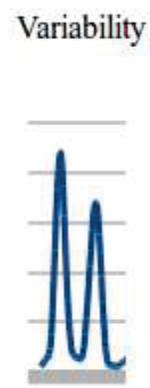
Look for the Y Acceleration pattern which matches the following.

11.3.3. Test 3

Look for Z Acceleration pattern which matches the following.

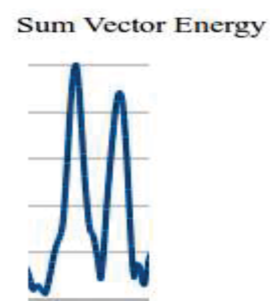
11.3.4. Test 4

Check for the following pattern in Variability. It has back to back peaks.



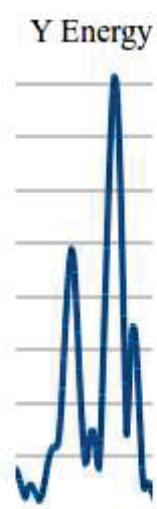
11.3.5. Test 5

Test for the pattern in Sum Vector Energy for the back to back peaks.

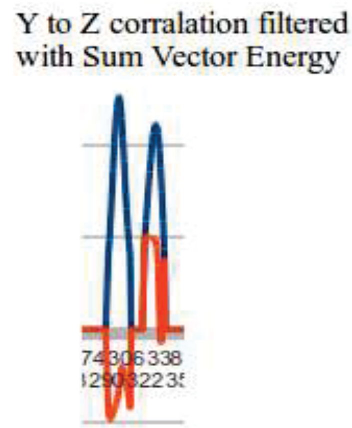


11.3.6. Test 6

Look for the following pattern in Y Energy. This time look for shorter peak followed by the longer peak.



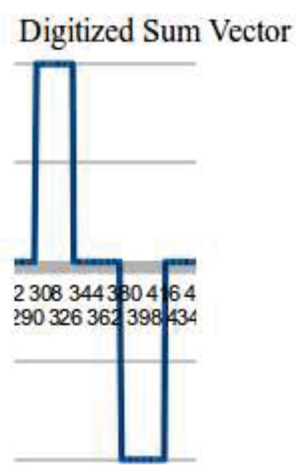
11.3.7. Test 7



Y to Z Correlation data in its original form looks clumsy and appears to give no vital information. But in reality it gives very important information about the relationship between the two axes. So to get rid of the clumsiness, the data are filtered using the Sum Vector Energy Calculations. The test is carried out to see when Sum Vector Energy has reached to its first peak, Y to Z cross correlation value should be closer to -1 and the Sum Vector Energy is at its second peak, Y to Z cross correlation value should be closer to +1.

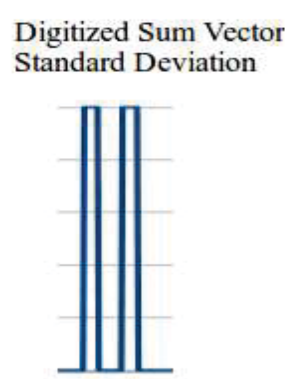
11.3.8. Test 8

Test for Digitized Sum Vector for the following pattern. Should have first positive pulse followed by the negative pulse.



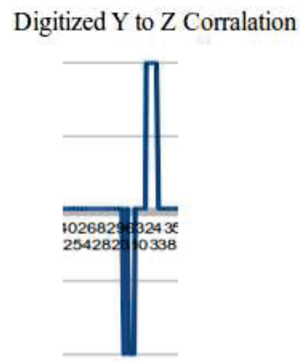
11.3.9. Test 9

Test for Digitized Sum Vector Standard Deviation for the following pattern. Should have back to back positive pulses.



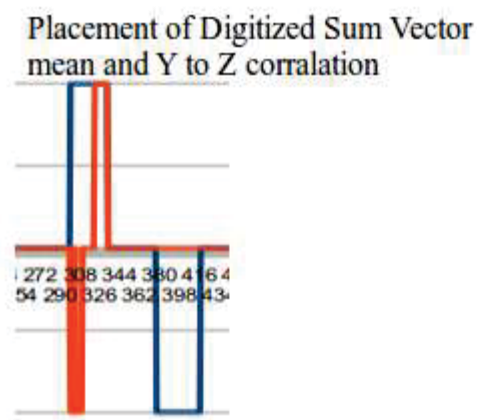
11.3.10. Test 10

Test for digitized Y to Z Correlation. Looking for negative pulse followed by the positive pulse.



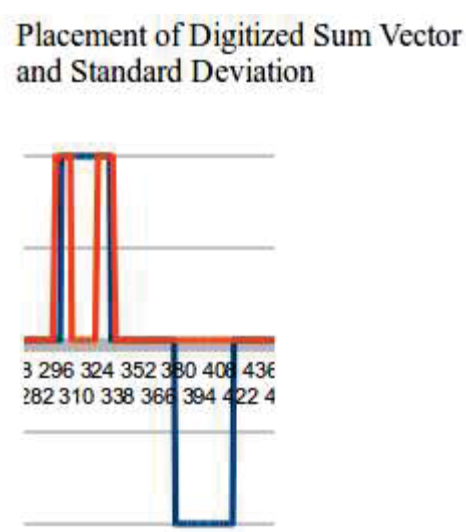
11.3.11. Test 11

This test is carried out only if Test 9 and Test 11 are passed. In this test, it is checked to see the placement of the pulses. At the beginning of the Sum Vector positive pulse the Y to Z cross correlation has negative pulse and at the end of the Sum Vector positive pulse the Y to Z cross correlation has positive pulse. During the Sum Vector negative pulse the Y to Z cross correlation shows inactivity.



11.3.12. Test 12

This test is carried out only if test 9 and test 10 are passed. In this test digitized Sum Vector is super imposed with digitized sum vector standard deviation. In the test 10, it is verified that the digitized standard deviation has two peaks. In this test, it is checked that at the beginning of the sum vector positive pulse, the first pulse of the standard deviation is present and the at the end of the sum vector positive pulse the second pulse of the standard deviation is present.

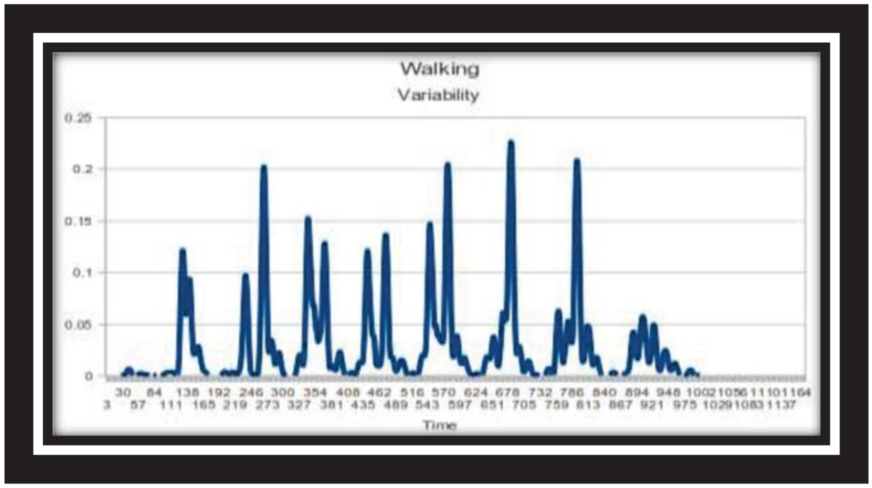


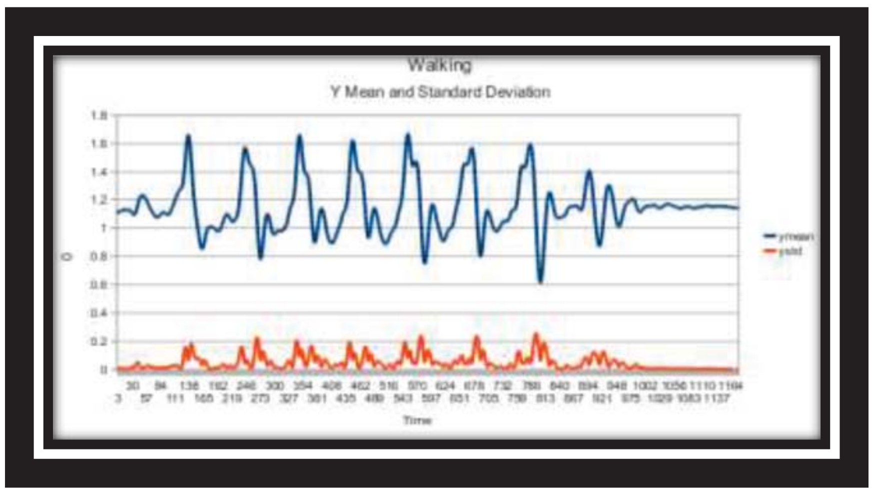
12. Low activity repetitive activity

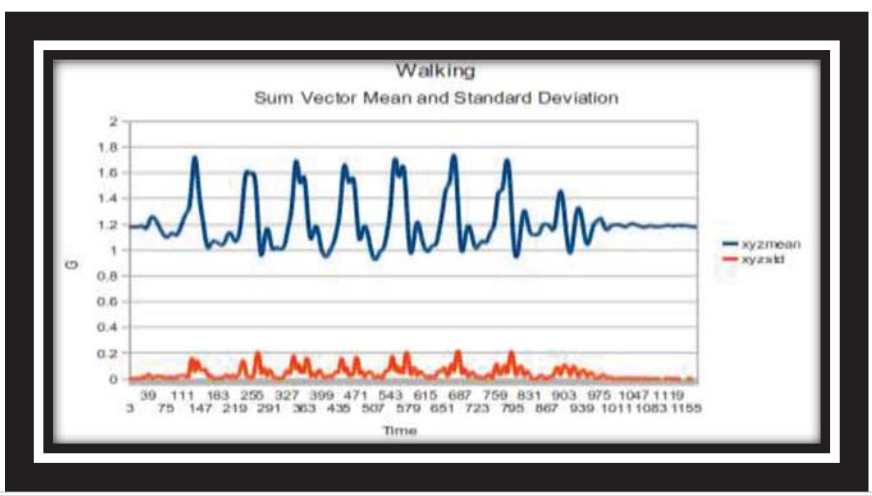
12.1. Walking

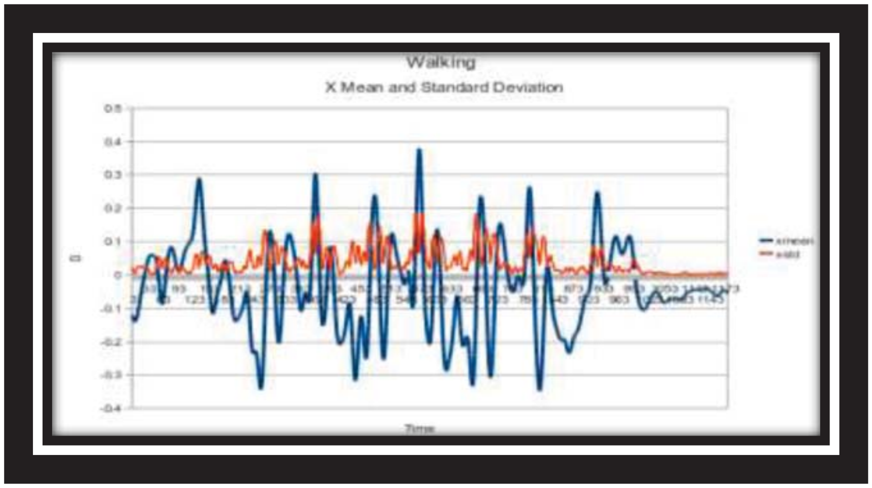
Walking is a low energy repetitive action. Unlike running, walking is a common daily activity of elderly, therefore its' analysis has far more significance when it comes to predicting the health status of the user. Strokes are a significant issue which limits the quality of life of many elderly individuals by causing paralysis (mainly partial) or otherwise balance impairments, speech impairment or cognitive dysfunction. Even though most of the stroke sufferers are taken by surprise of their first occurrence of stroke due to their negligence/lack of resources to take timely health checks, most of the stroke cases are preventable if the early warning signs are detected early on. The cause of a stroke is lack of blood flow to an area of the brain resulted from a blocked artery which in turn cuts off the oxygen supply to the brain cells in the affected area and gradually killing those affected brain cells. This type of stroke is a gradual process which can be detected by analysing the gait patterns (the way a person is walking). This analysis has to be done over a significant period of time in order to first get used to the normal gait pattern of the person and then to distinguish any abnormality. When blood flow to a certain part of the brain is reduced thus invalidating the brain cells in that area, the tasks which are controlled by those brain cells are hampered. Brain can be imagined as a large network of nodes which communicates with each other to pass data and control different activities of the body. Brains of different people are wired differently but the general bottom line is brain cells' communication does not use the shortest path instead use the most used path, so having malnourished brain cells would affects the entire brain function because of this selective nature of the communication path, if the damage of the brain cells are so severe and no alternative communication path is activated then the person starts to show the symptoms which in medical terms people consider as a disease. This understanding allows us to connect the dots between gait analysis and brain function. Usually pre-stroke individuals start to show increasingly bias gait pattern towards one side of the body. The tricky issue is sometimes this can be caused by other factors such as hip or knee injury. These kind of joint injuries show the changes in the gait pattern more quickly rather than as a gradual build up like in a brain disease. In more general terms, by tracking the daily walking pattern of a person can tell the overall health of the person, for example identifying flu like situation. This analysis gets complex due to the different preferences of the people such as some people prefer to stay in the bed for long hours when the weather is very cold and some people choose to get active to warm up their bodies to beat the cold winter blues. Bottom line is analysing the walking gait pattern and daily walking pattern can produce very important predictions of the persons' future health condition and also current health issues but this analysis has to be context aware to produce the accurate results.

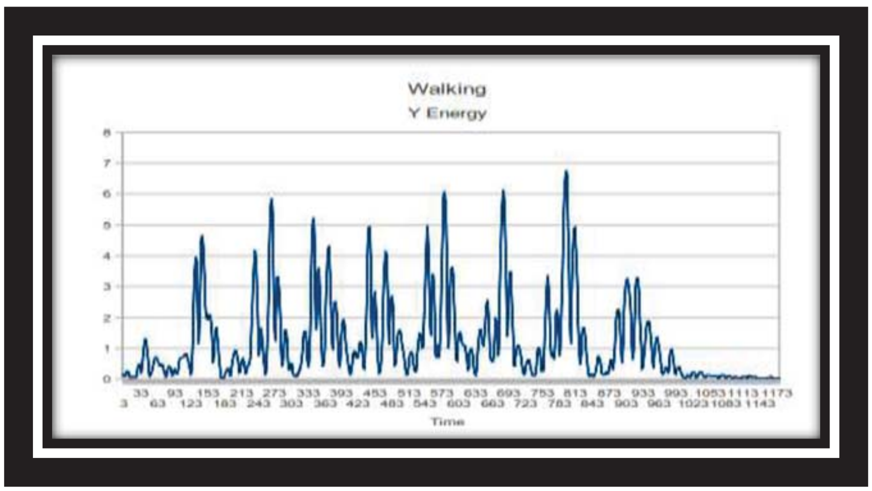
Identifying the walking event is very simple and it is very similar to identifying the running event, only major difference is falling digital (Falling digital is the digitization algorithm which is run on Sum Vector data to identify free fall like motion and significant impacts) produce a flat line when a person is walking. The reason for the above said flat line is, there is not much significant downward motion or high impact when a person is walking compared to the running.

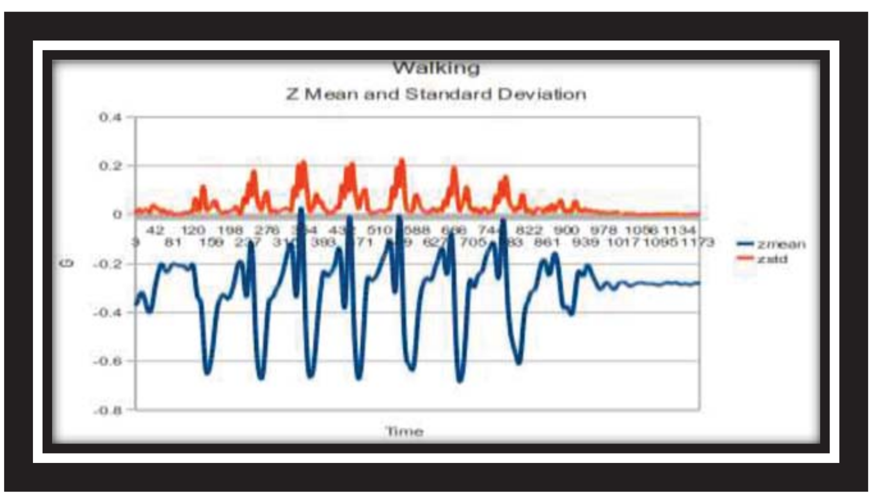


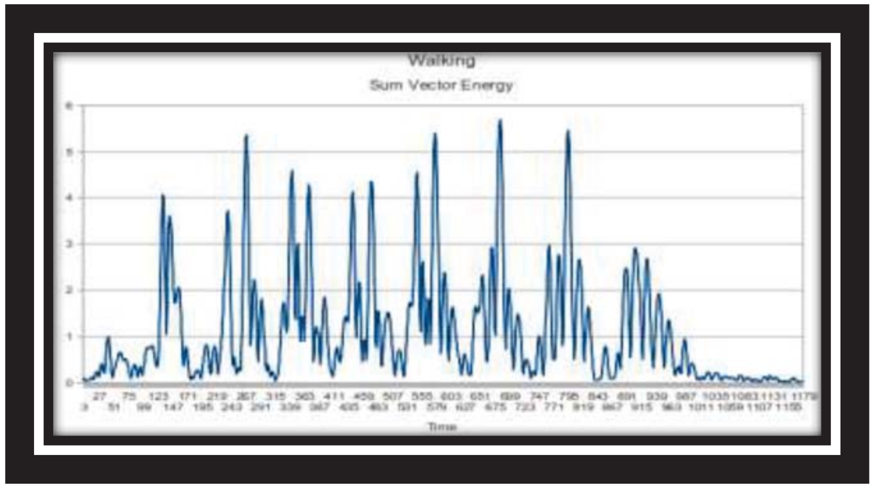


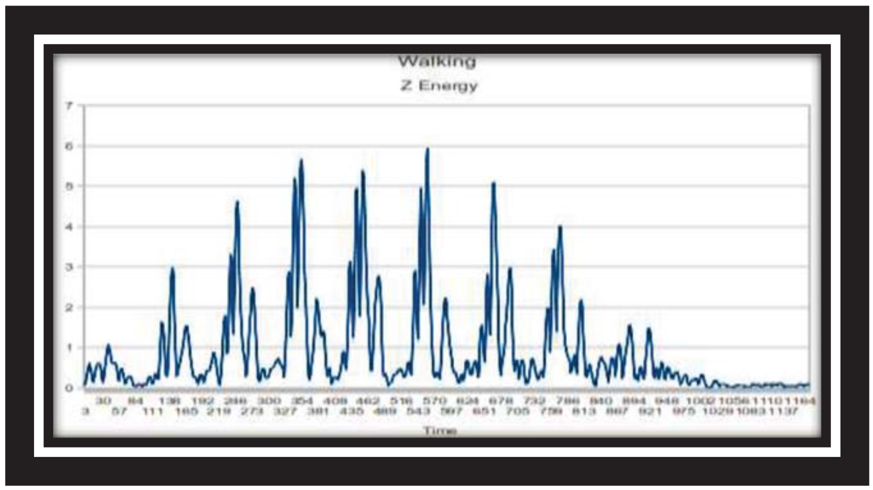


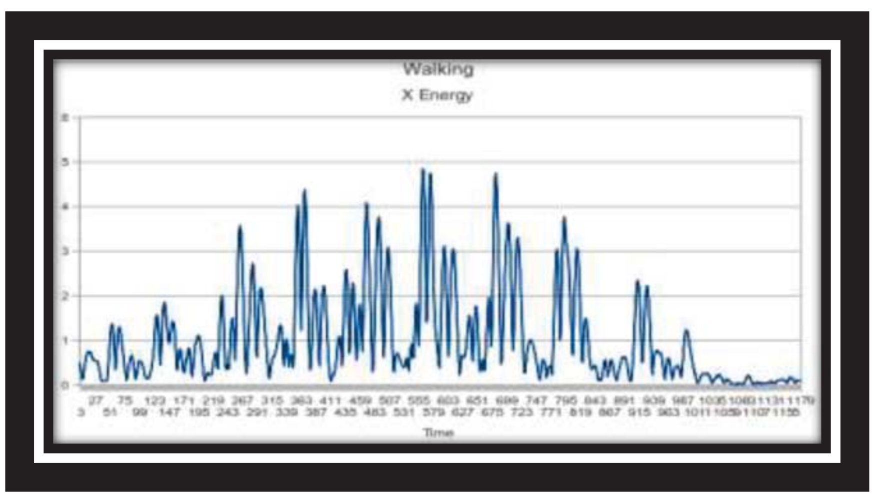

Walking
X Mean and Standard Deviation
Time

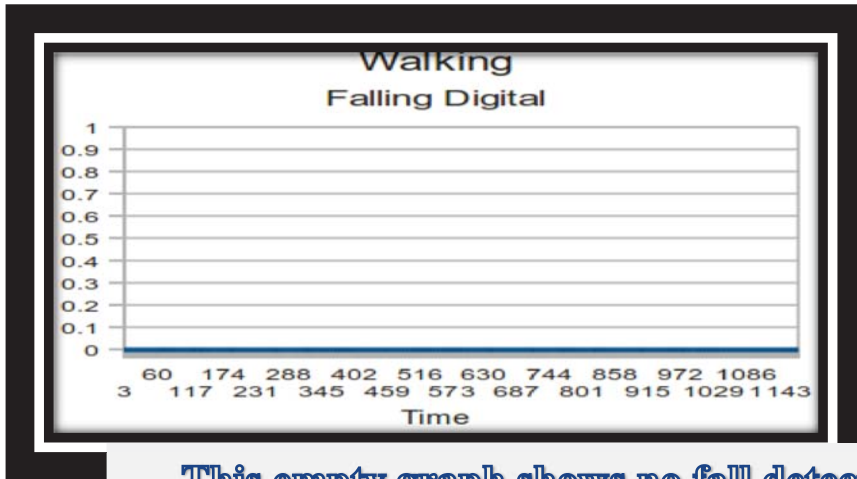

Walking
Y Energy
Time


Walking
Z Mean and Standard Deviation
zmean
zstd
Time


Walking
Sum Vector Energy
Time


Walking
Z Energy
Time


Walking
X Energy
Time



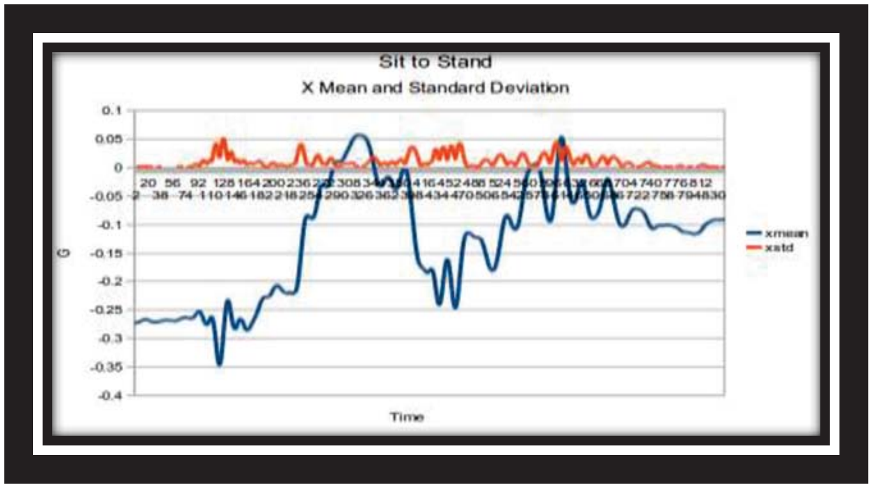
This empty graph shows no fall detection digitized signal presents

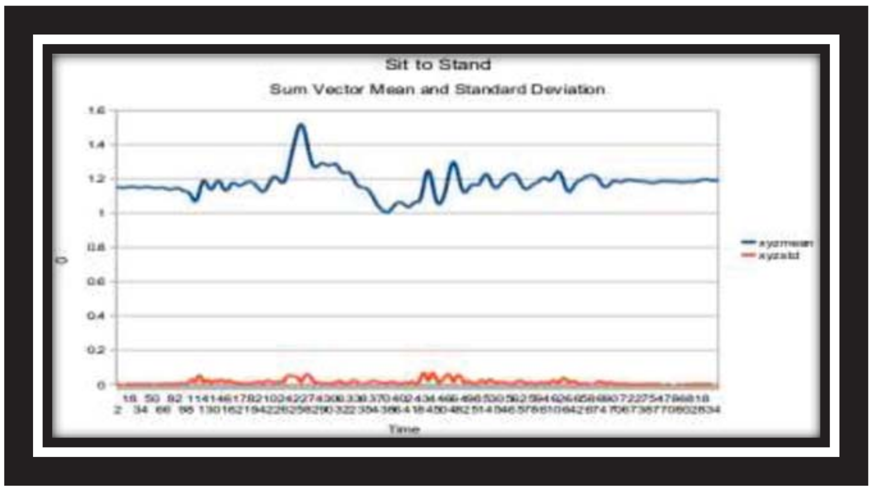
Testing for walking is very similar to testing for running except the fact the falling digital shows complete inactivity.

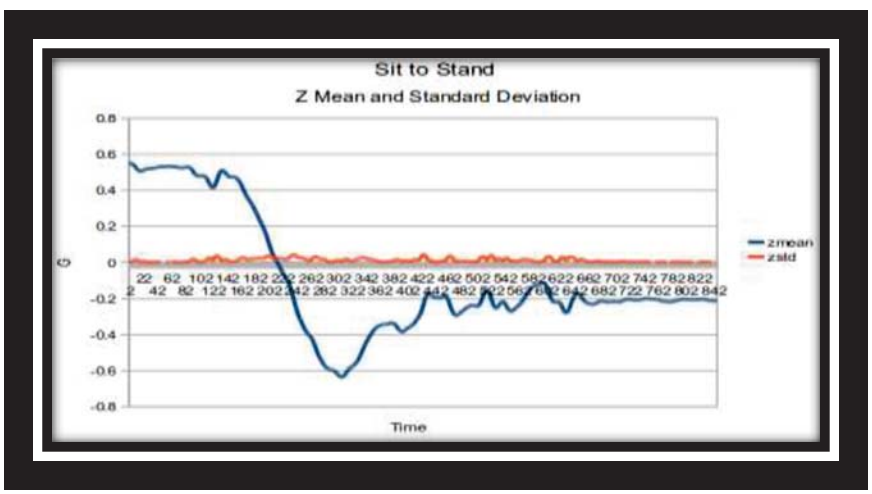
13. Transitional activity

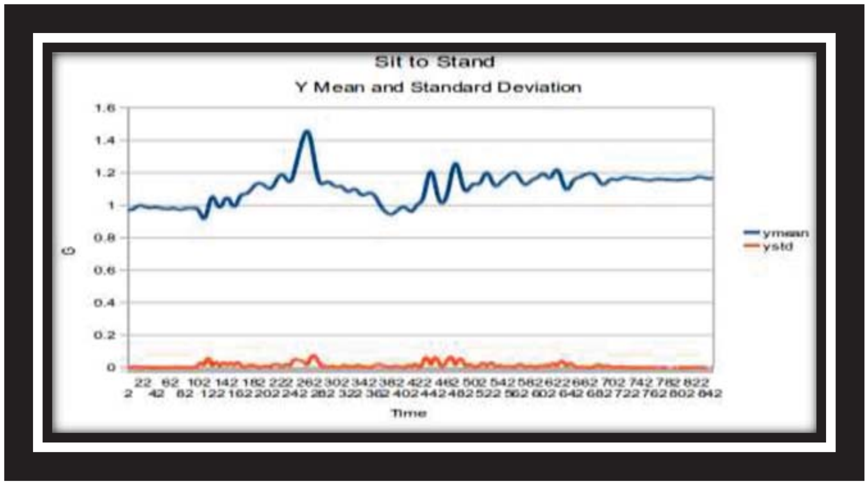
13.1. Sit To Stand

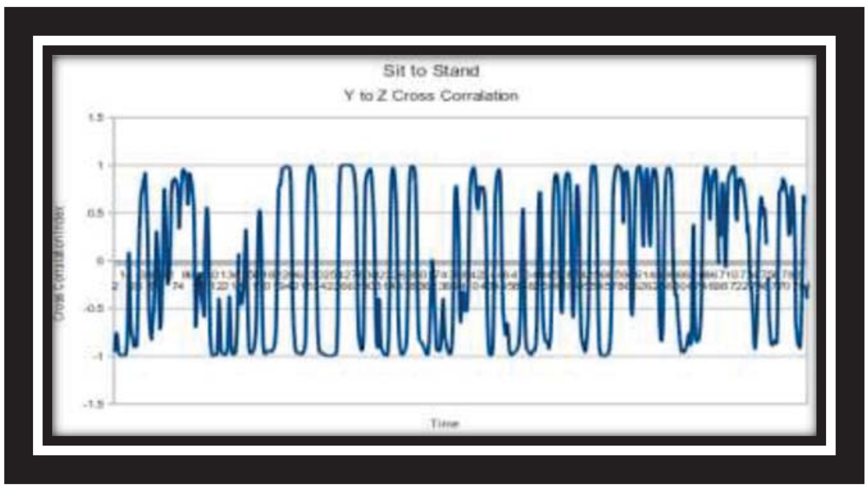
When a person is transitioning from seated position to standing position, a forward tilt of trunk is observed which is followed by the upward force. The amount of forward bending and the magnitude of the upward force vary from person to person, depending on the strength of the person, medical conditions, habits and seating arrangements [75]. Therefore using pre-determined threshold values would not be possible in this scenario. The other issue is even though it is common in all Sit to Stand transition to have forward tilt and then the upward force, the time gap between these two components change vastly from each Sit to Stand transition [76]. As a person gets older they tend to bend almost 50 degrees forward before exerting upward force to stand up but the time gap between the maximum bend position and the start of the upward force is very high compared with a young healthy subject. A young healthy subject would bend forward only about 10 to 15 degrees and the upward force would be applied almost simultaneously. But it has been observed that some young individuals do bend forward more than 20 degrees. In young healthy individuals the amount of forward motion mostly depends on the way they have been sitting prior to the transition. A young healthy individual who has been sitting with perfectly upright posture with erect spine would mostly bend forward less than 15 degree before exerting the upward force whereas a young healthy individual who is sitting with backward inclination where his/her back is resting on the chair would bend forward with more than 20 degrees. This is understandable because a healthy young individual when start to bend the trunk forward to get to the standing positing from seated back position, the momentum of the trunk would allow the trunk to bend more when compared to the erect spine position. But the elderly subjects, irrespective of their initial sitting posture, they tend to move the trunk forward in a comparatively large angle. The larger the bending forward angle of the elderly the lesser the upward force they exert afterward. The maximum forward bending angle, magnitude of the upward force and time gap between the maximum forward bending angle and the upward force are indicative of a person's physical health. Higher forward bending angle, followed by lower upward force and larger time gap suggest low physical activity.

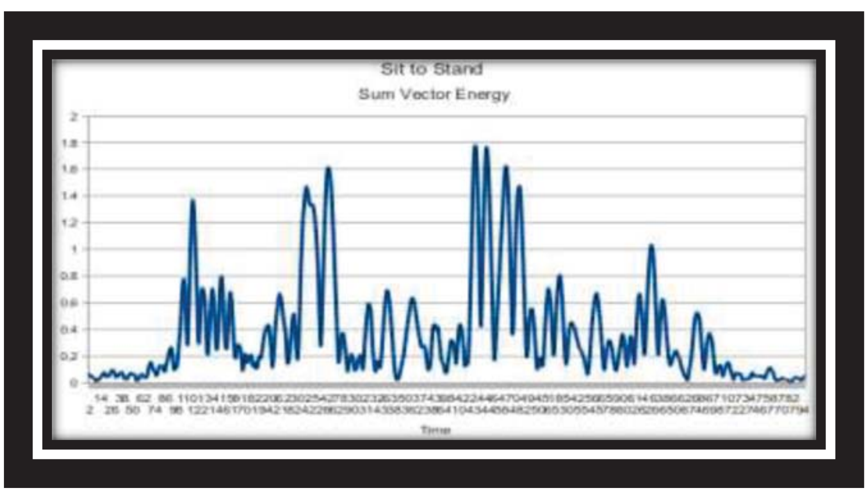

Sit to Stand
X Mean and Standard Deviation
G
Time
xmean
xstd

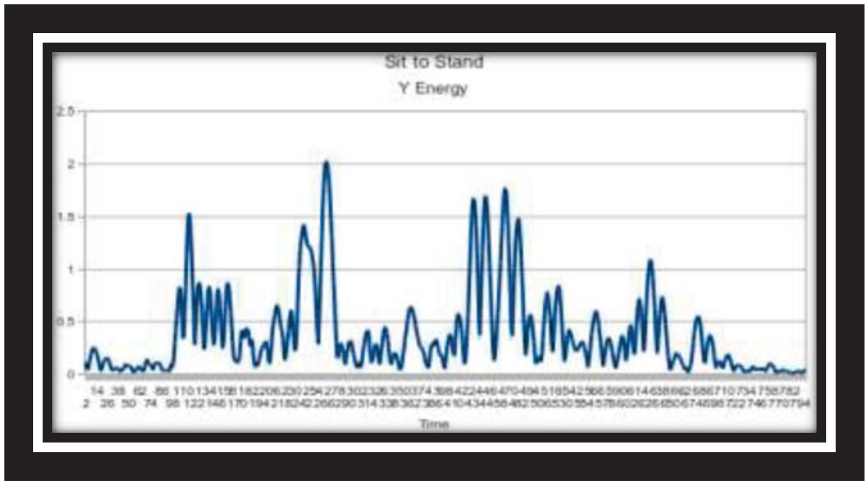

Sit to Stand
Sum Vector Mean and Standard Deviation
G
Time

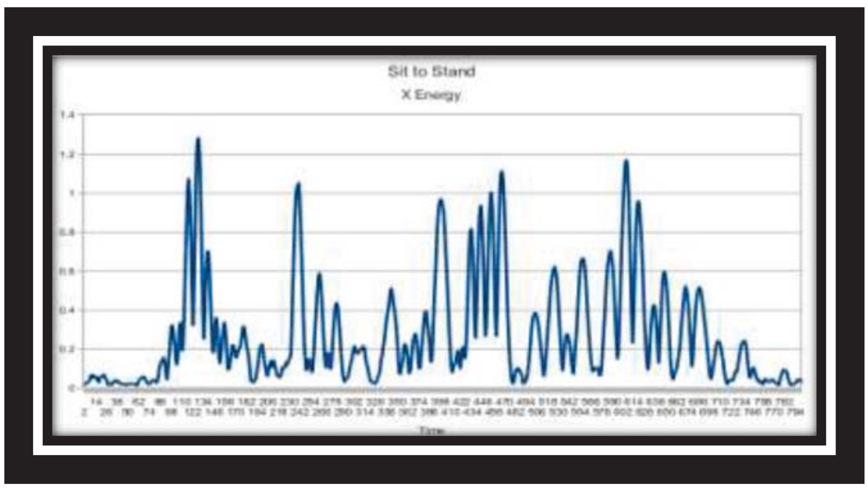

Sit to Stand
Z Mean and Standard Deviation
G
Time
zmean
zstd

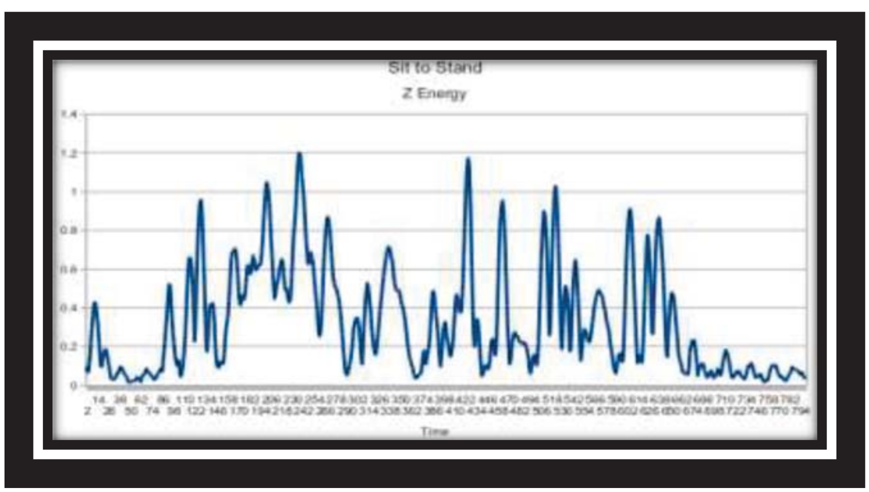

Sit to Stand
Y Mean and Standard Deviation
G
Time
ymean
ystd

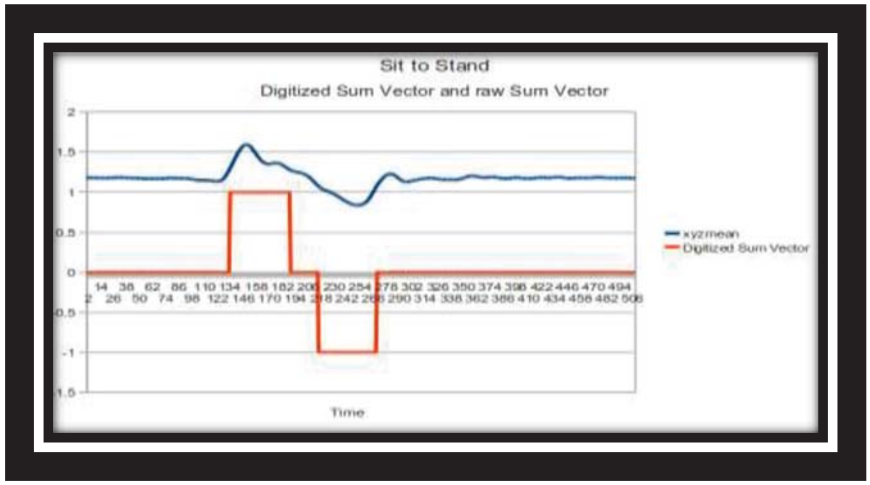

Sit to Stand
Y to Z Cross Corralation
Time

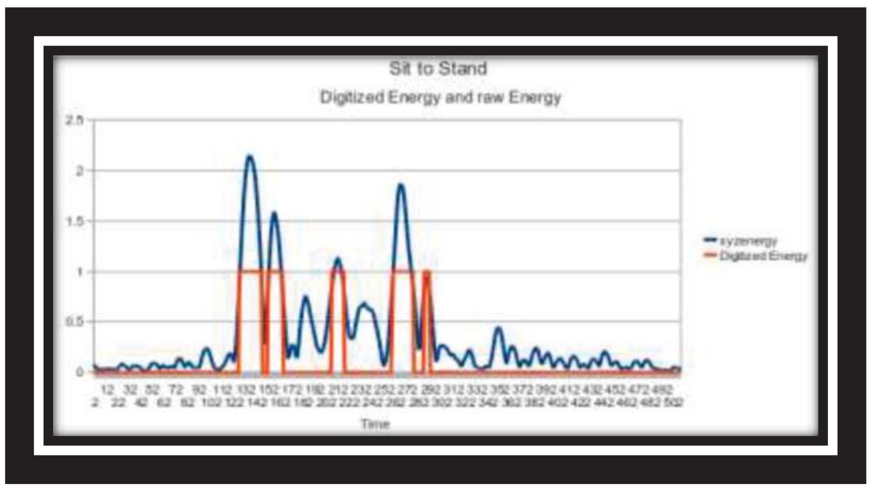

Sit to Stand
Sum Vector Energy
Time

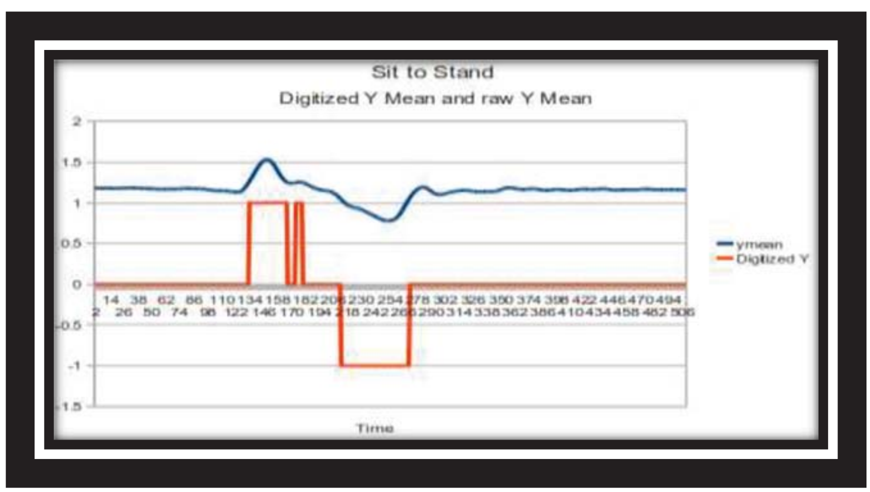

Sit to Stand
Y Energy
Time

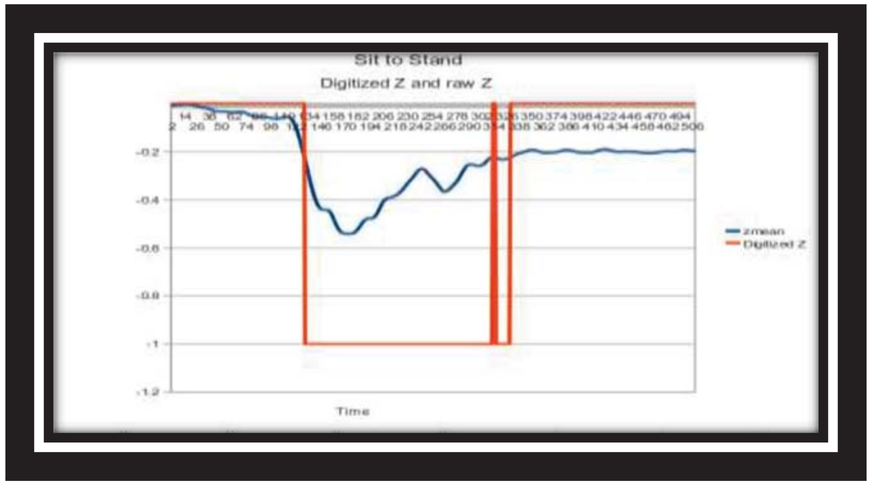

Sit to Stand
X Energy
Time


Sit to Stand
Z Energy
Time


Sit to Stand
Digitized Sum Vector and raw Sum Vector
xyzmean
Digitized Sum Vector
Time


Sit to Stand
Digitized Energy and raw Energy
xyzenergy
Digitized Energy
Time


Sit to Stand
Digitized Y Mean and raw Y Mean
ymean
Digitized Y
Time


Sit to Stand
Digitized Z and raw Z
zmean
Digitized Z
Time

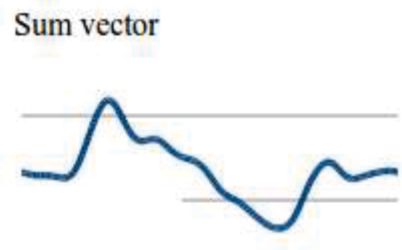

Sit to Stand
Digitized Y and Z
Digitized Y
Digitized Z
Time


Sit to Stand
Digitized Energy and Sum Vector
Digitized Energy
Digitized Sum Vector
Time

Sit to Stand test:

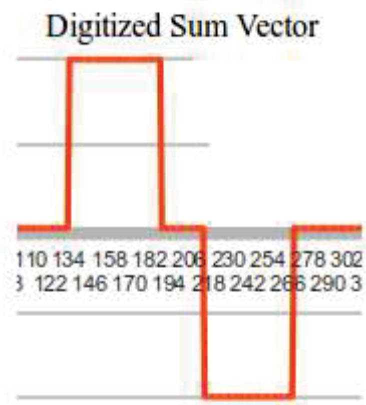
13.1.1. Test 1

Look for the following pattern in Sum Vector. This pattern should not be repeatable unless this pattern is followed by stand to sit pattern.



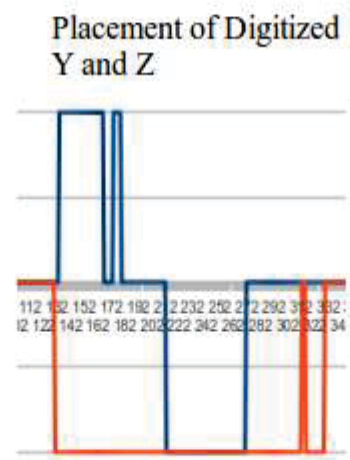
13.1.2. Test 2

In the Digitized Sum Vector look for the positive pulse followed by the negative pulse.



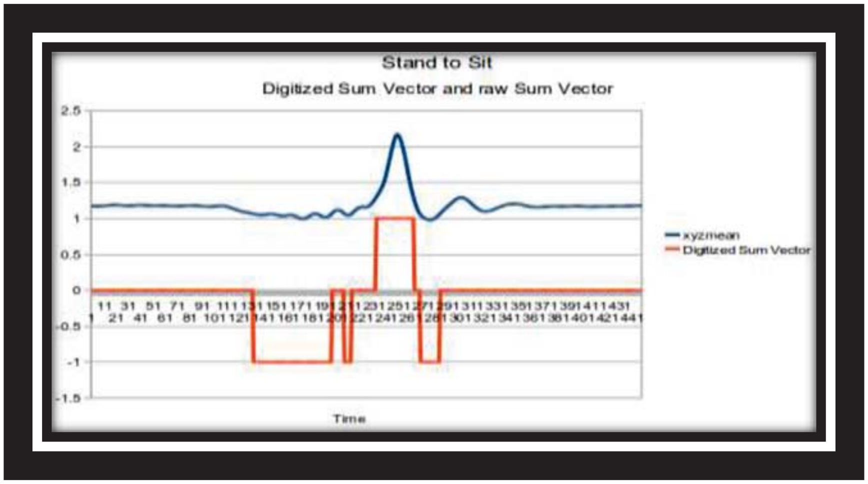
13.1.3. Test 3

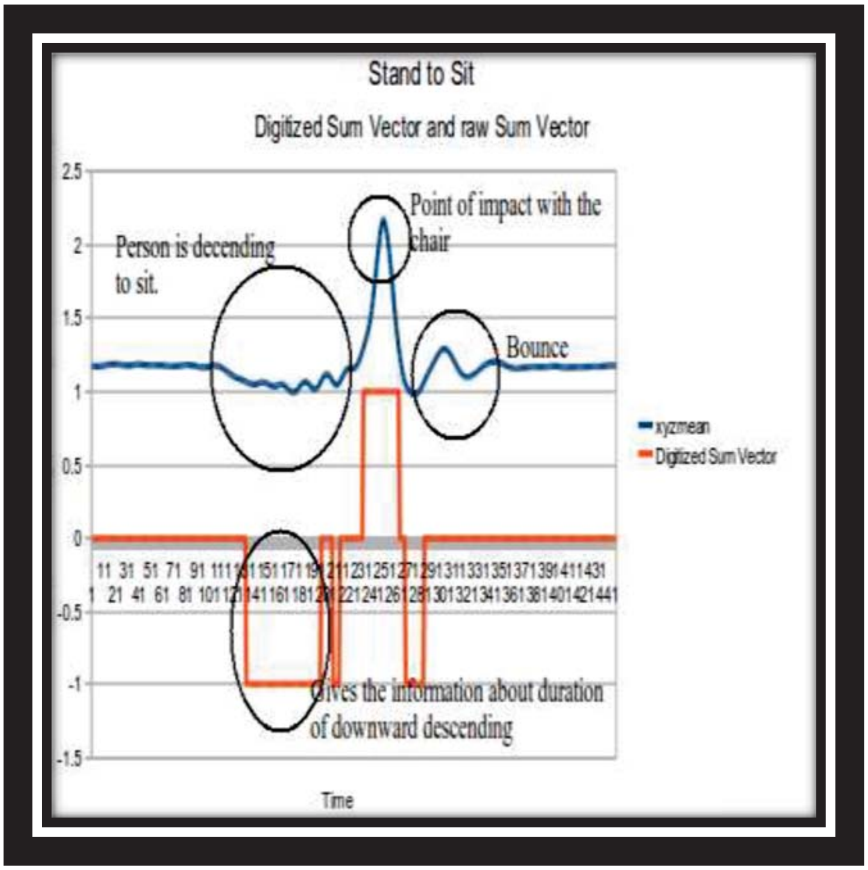
In this test 3 different components are tested. First it is checked that Digitized Y has a positive pulse followed by the negative pulse. (To be an acceptable pulse it should last at least the duration of 20 time ticks, therefore any narrow pulses with less than 20 ticks are ignored). Then it is checked that Digitized Z has a wide negative pulse. Then it is checked that, start of Digitized Y positive pulse and the start of the Digitized Z negative pulse overlaps within each other with 10 time ticks and Digitized Z negative pulse stays on until the Digitized Y ends it negative pulse phase as illustrated in the following mini-graph.



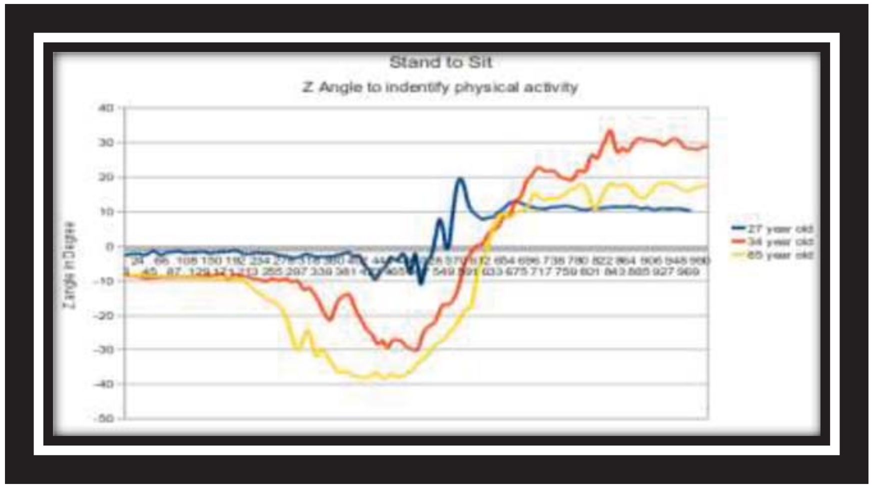
13.2. Stand to Sit

Transition from standing position to the seated position generally has 4 phases, which are, mild forward bending, downward motion, impact and low activity phase [81]. Amount of forward bending is an indication of a person's physical health (An example of this is given later in this chapter). Downward motion on its own does not convey much information about the person because an unhealthy person can get succumbed to the gravity and have a high downward velocity and also a very healthy individual also have the similar high downward velocity due to the fact if his/her athletic ability, in its essence downward motion has to be analysed with the context awareness along with other phases [82]. Magnitude of the Impact is a function of downward velocity, the weight of the person and also the materials of the chair is made of. The magnitude of the impact is proportional to the downward velocity, persons' weight and Hardness of the surface of the chair [81]. When it comes to the nature of the chair, a chair made out of cushioned surface along with springs would not register any detectable impact peak. This is due to the fact that cushion absorbs some portion of the energy and then pass that energy onto the spring which absorb those energy even further. The recoil of the springs does release energy back through the cushions but it is a very mild force and when factor in the time taken to the store the initial energy in the coil and then the releasing time, the impact Impulse is reduced. Generally when a person is sitting he/she shows low activity, so to verify Stand to Sit transition completion, the final restful low activity phase is important [81].

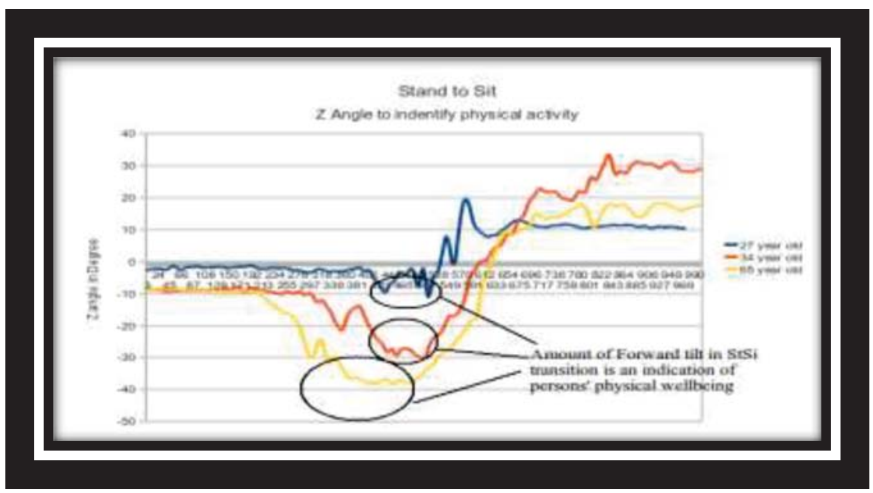


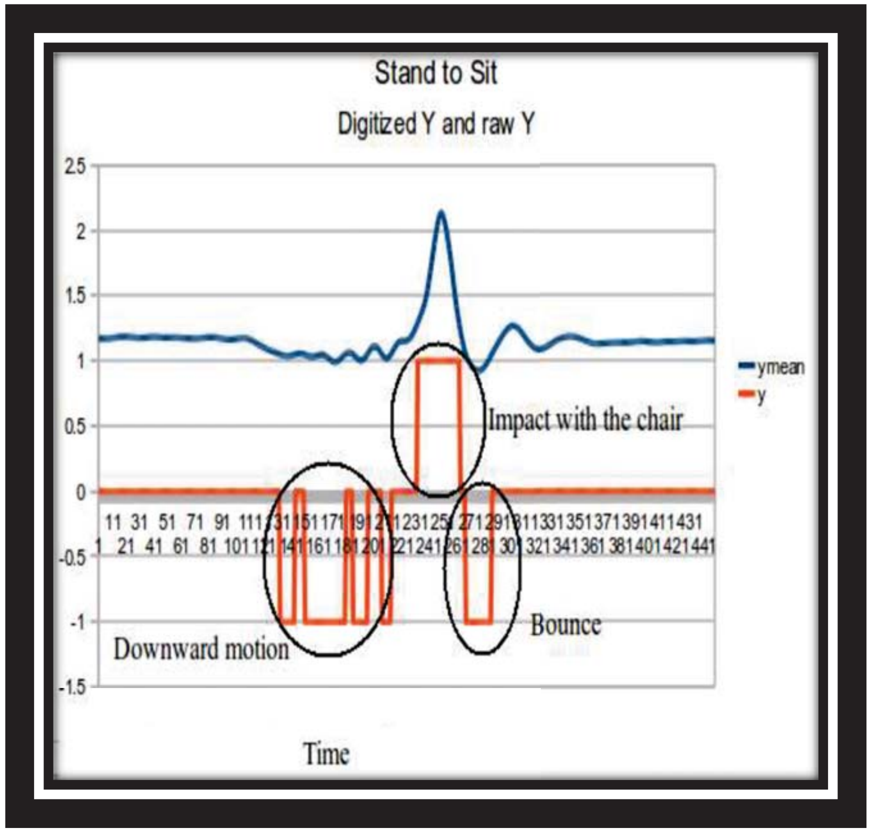


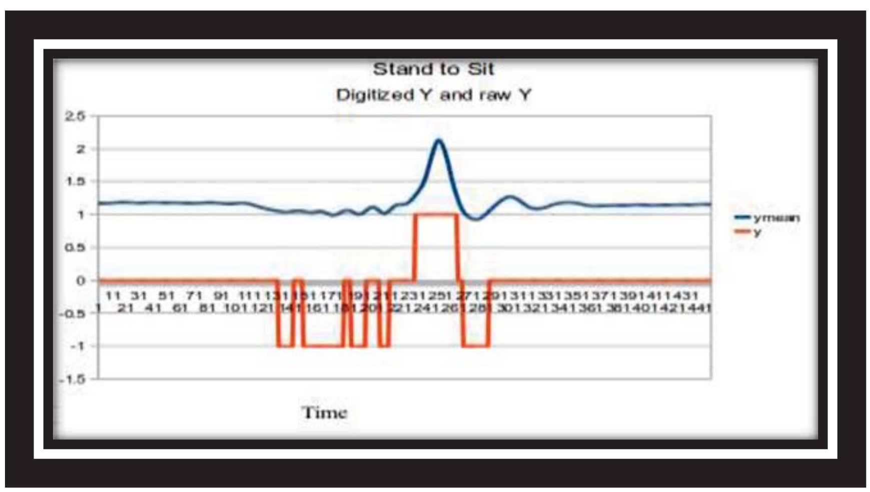
By correlating the damping factor of the bounce ripples one can identify the nature of the chair. If the bounce ripples have high damping that is an indicative of a hard surfaced chair. If the damping of the bounce ripples is low, it is an indicative of a cushion chair. The other vital piece of information is the duration of the descending. Duration of the descending can be found by the digitized Sum Vector's negative pulse.

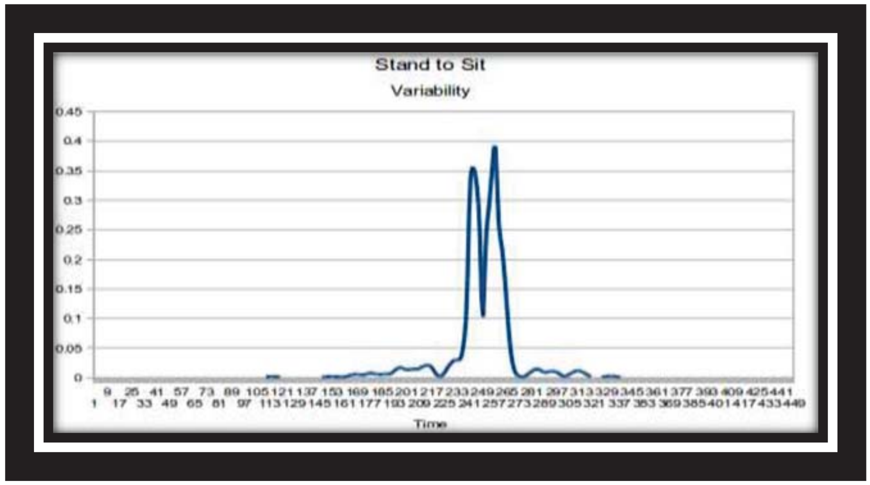


A person with very high physical activity would only have a very mild forward bending such as 5 to 15 degrees and normal healthy person has a mild forward bending around 20 to 30 degrees and healthy older individuals have a moderate forward bending of 35 to 45 degrees.



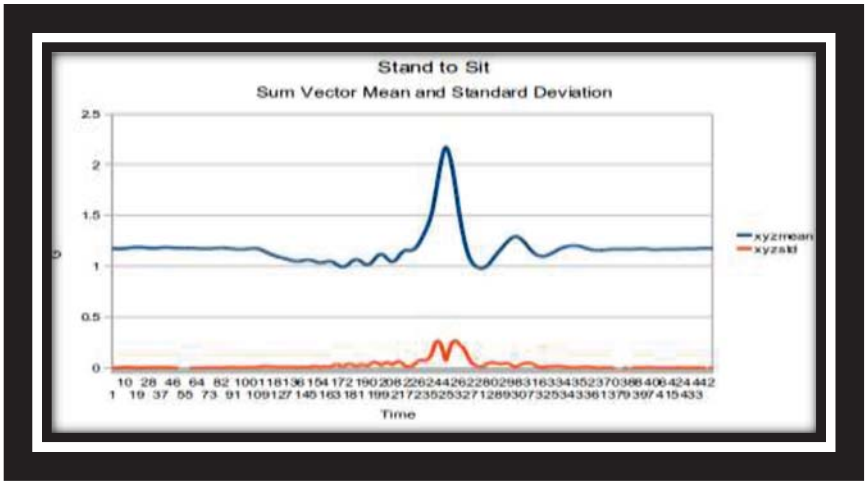

Stand to Sit
Digitized Y and raw Y
ymean
y
Impact with the chair
Downward motion
Bounce
Time

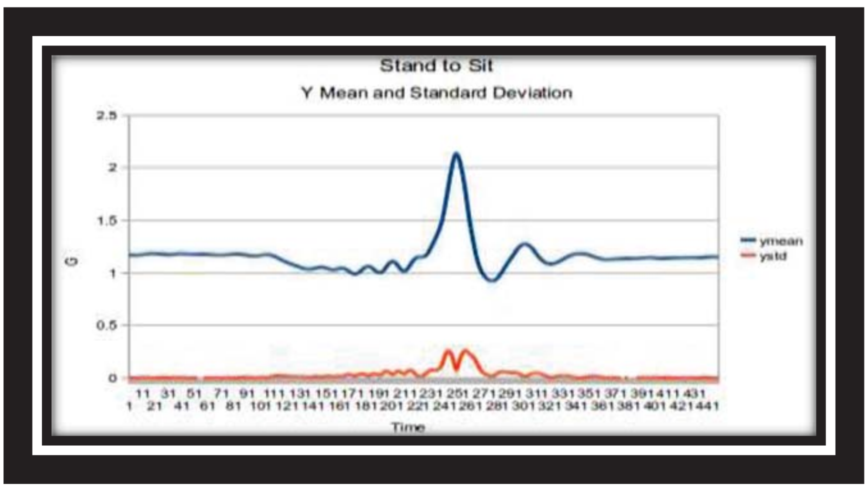

Stand to Sit
Digitized Y and raw Y
ymean
y
Time

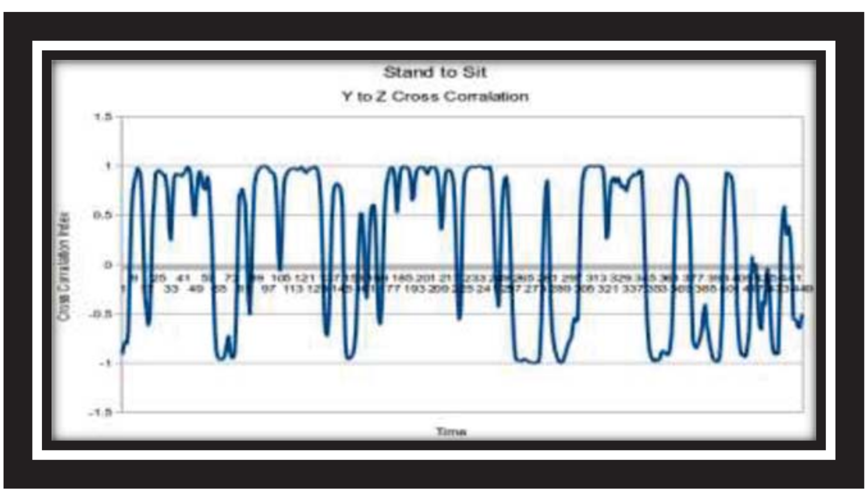

Stand to Sit
Variability
Time

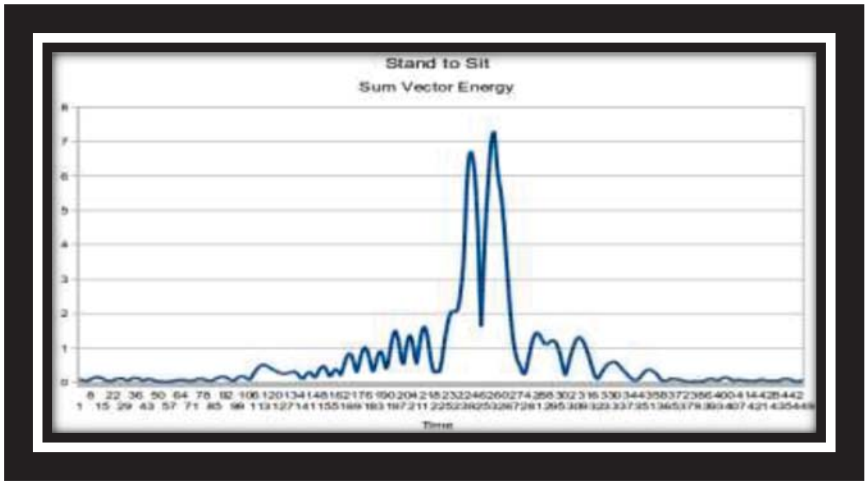

Stand to Sit
Digitized Y and Z
Time

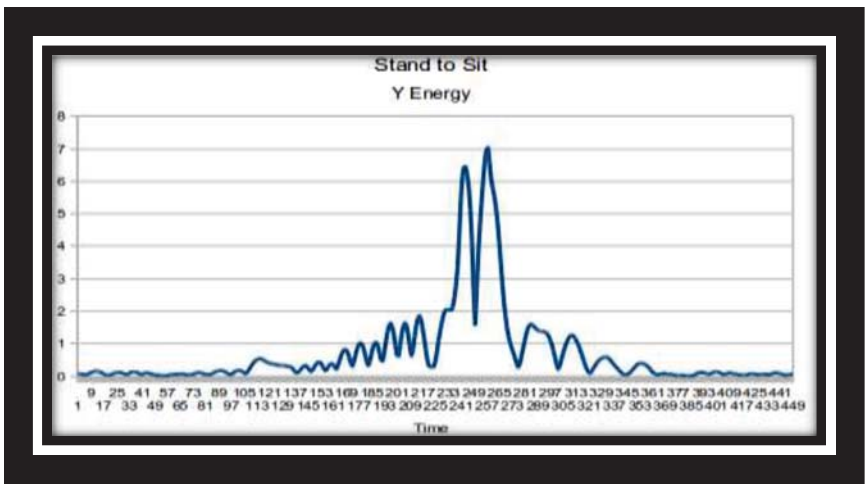

Stand to Sit
Digital falling
Time

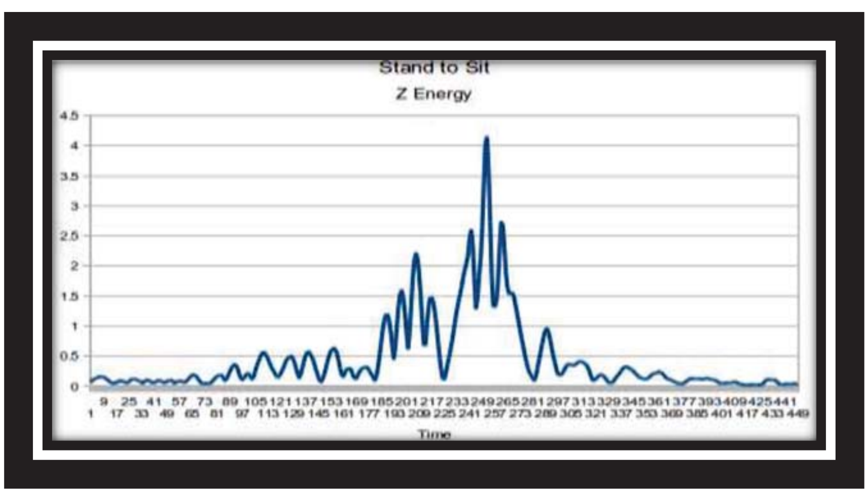

Stand to Sit
Sum Vector Mean and Standard Deviation
xyzmean
xyzstd
Time

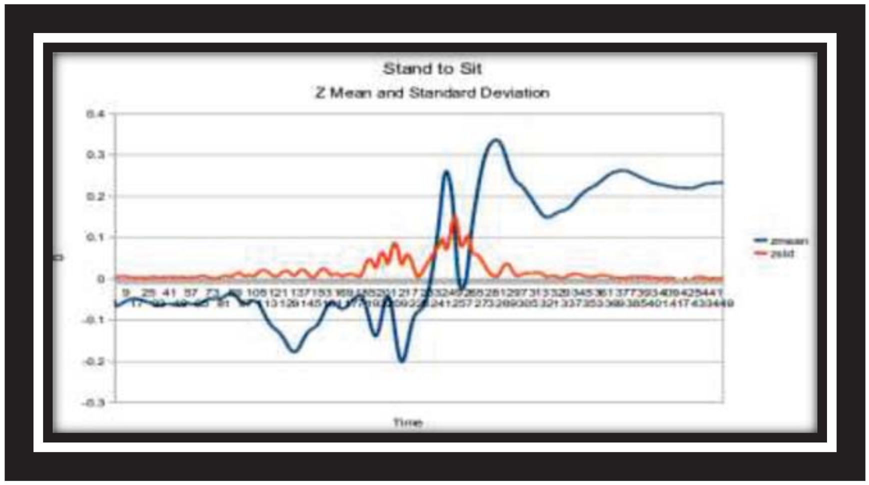

Stand to Sit
Y Mean and Standard Deviation
G
ymean
ystd
Time

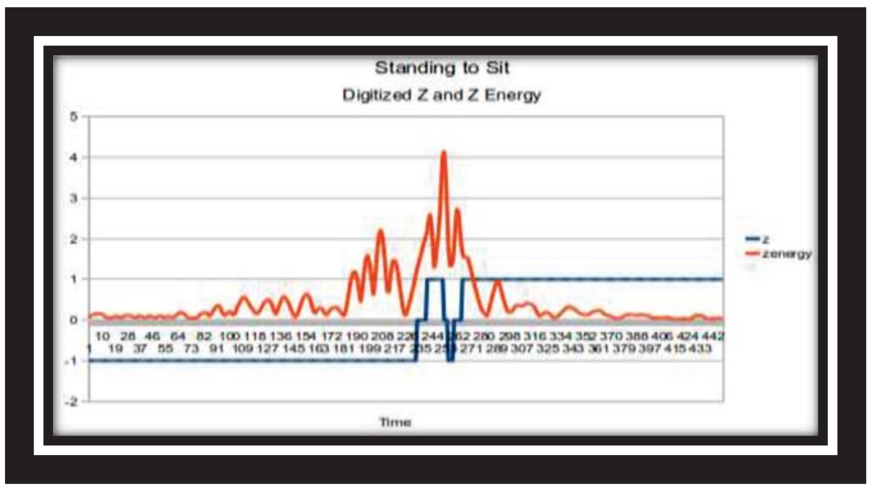

Stand to Sit
Y to Z Cross Corralation
Cross Correlation Index
Time

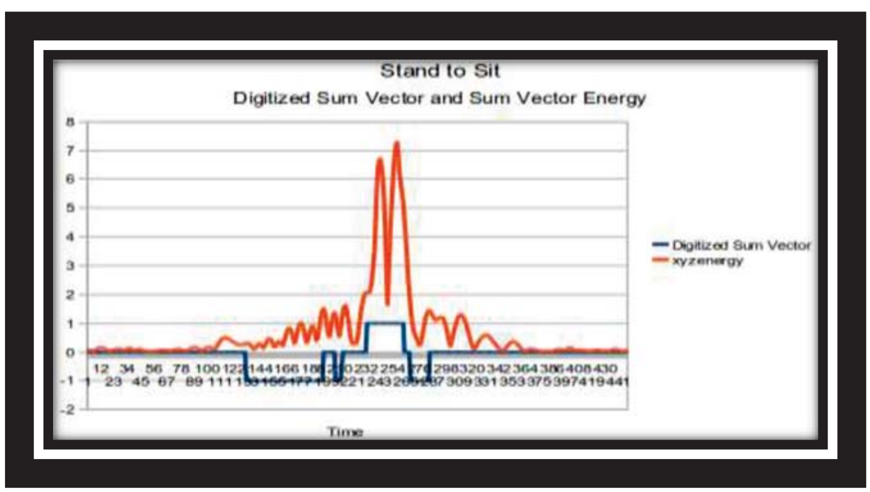

Stand to Sit
Sum Vector Energy
Time


Stand to Sit
Y Energy
Time

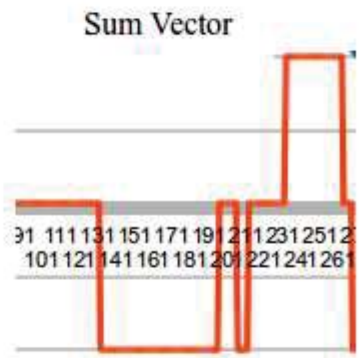

Stand to Sit
Z Energy
Time


Stand to Sit
Z Mean and Standard Deviation
zmean
zstd
Time


Standing to Sit
Digitized Z and Z Energy
z
zenergy
Time

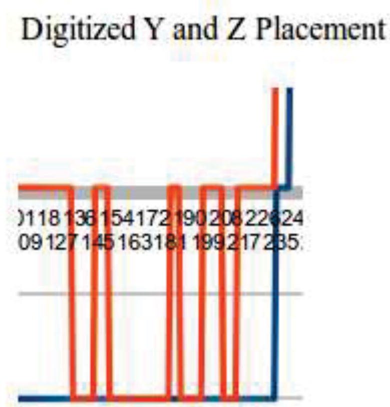

Stand to Sit
Digitized Sum Vector and Sum Vector Energy
Digitized Sum Vector
xyzenergy
Time

Stand to Sit test,



13.2.1. Test 1

In digital Sum Vector look for the negative pulse followed by the positive pulse. This is non-repetitive.



13.2.2. Test 2

In digitized Y and Z placement, when the negative Y pulse is found, the Z should have a negative Z pulse.
This is because during the normal stand to sit motion, people tilt forward during the descending phase.

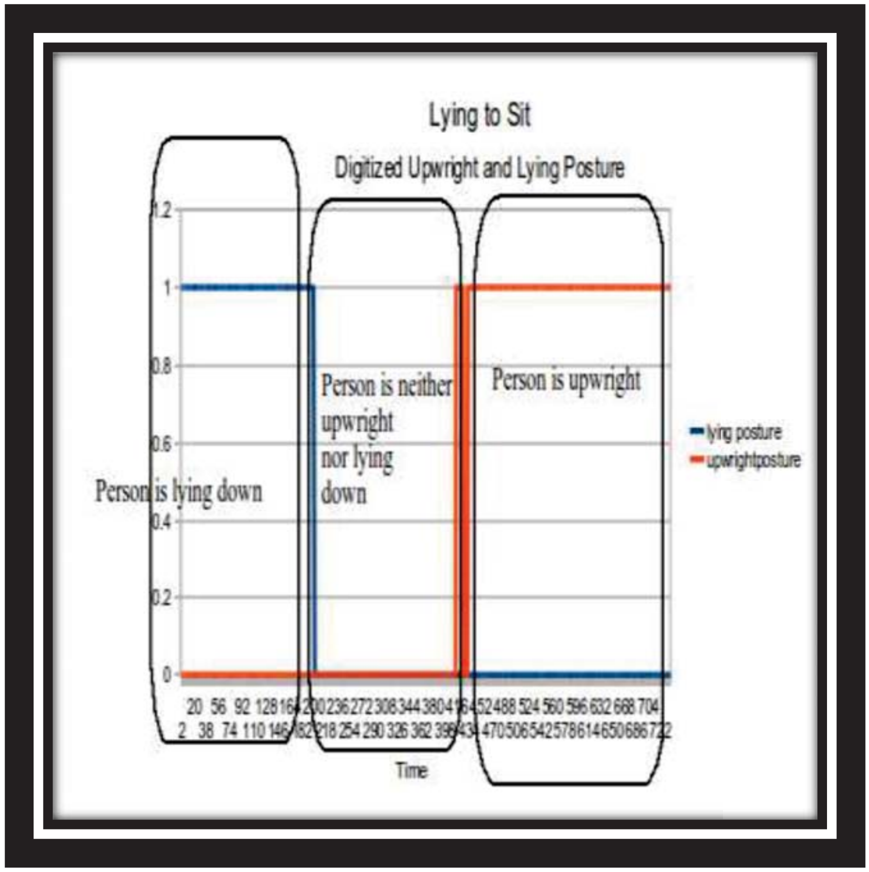
13.2.3. Test 3

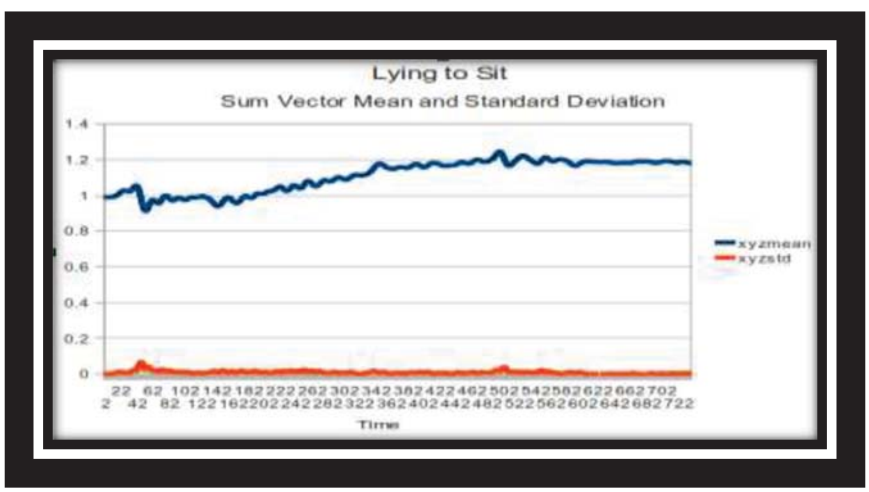
If the test 1 is passed, "falling digital" should be checked to see it is inactive. Because digitized sum vector shows similar negative pulse followed by the positive pulse for the falling , running, and jumping up and down but in all those occasions "falling digital" is active.

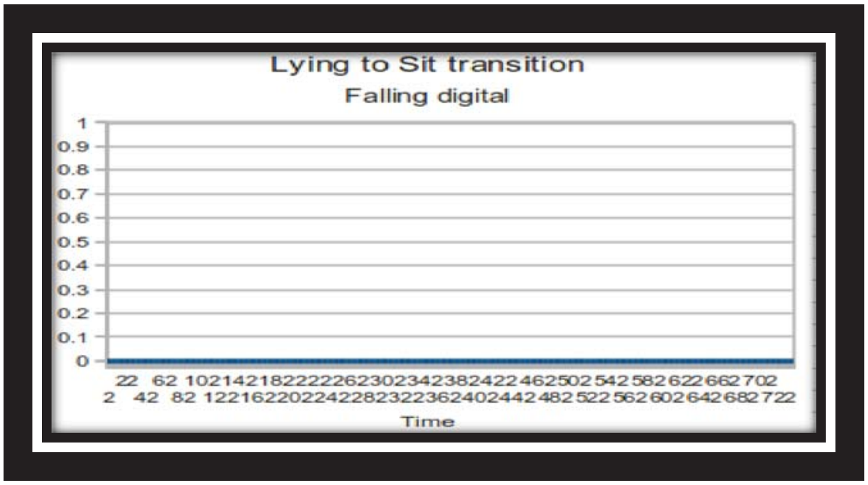
13.2.4 Test 4: After a time delay from the impact it is checked to see if the person has low energy signature.

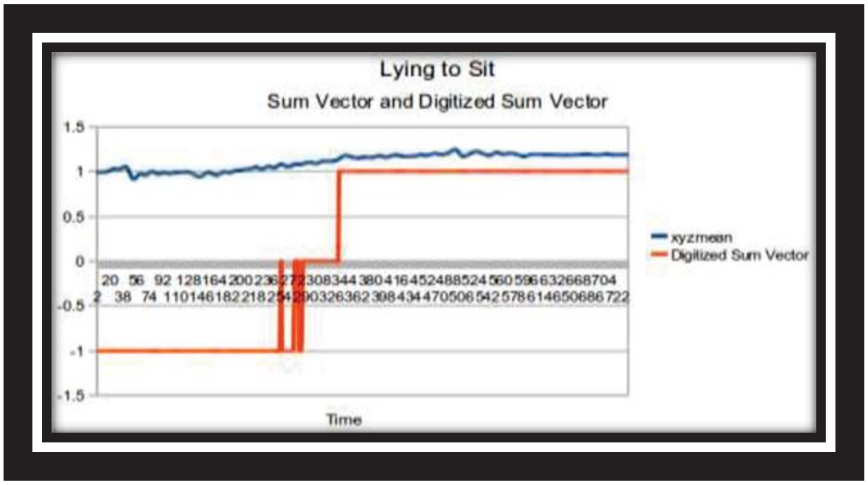
13.3. Lying to Sit

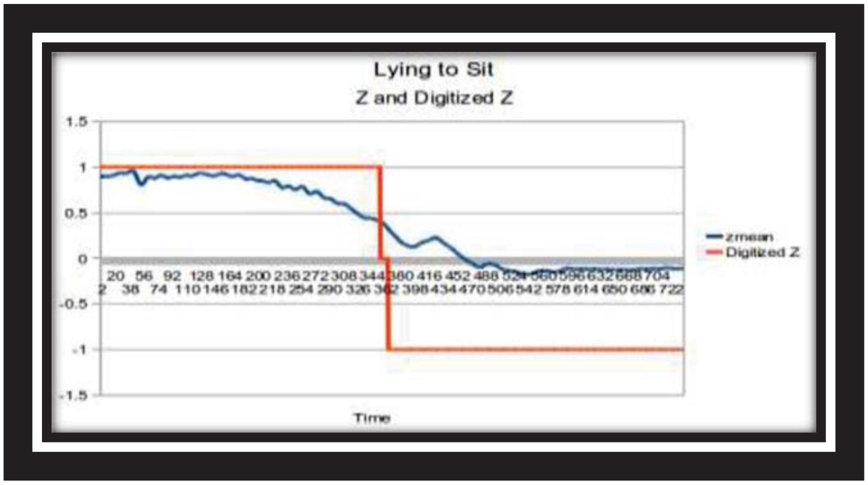
Lying to Sit is transition from the static lying posture to static sitting posture. Unlike Sit to Stand or Stand to Sit , Lying to Sit or Sit to Lying can be very easily identified due to change in the trunk angles is so significant.

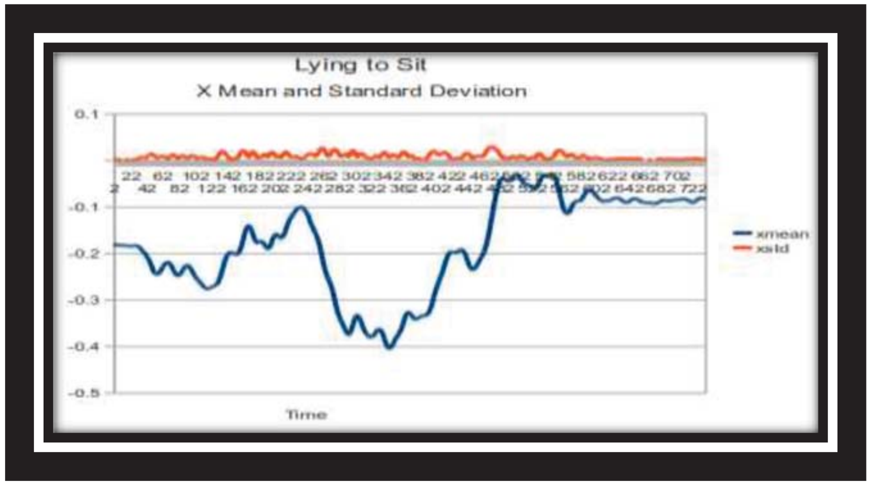


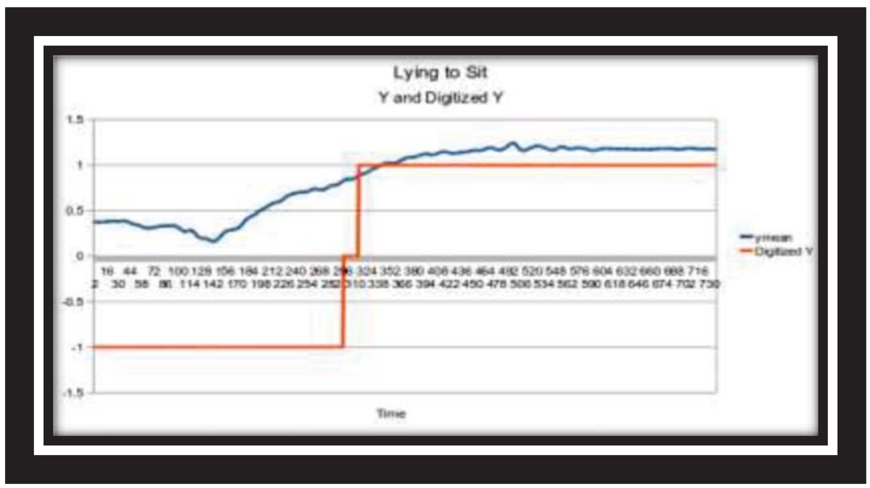


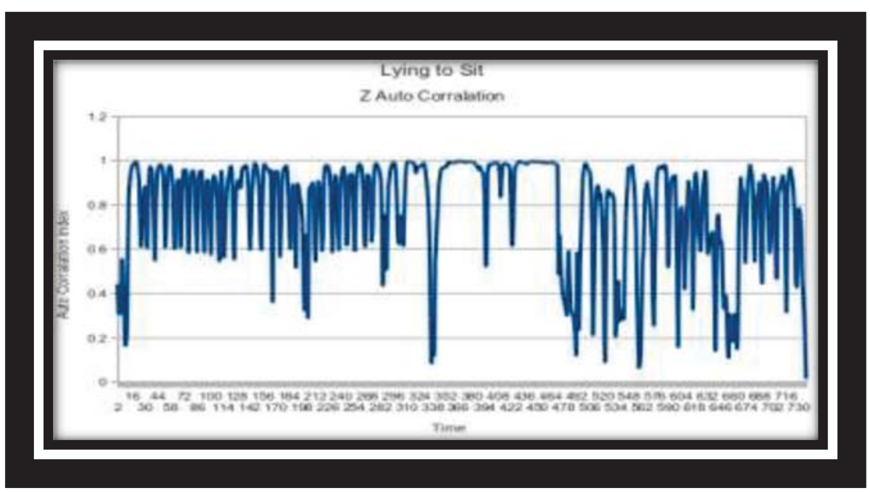

Lying to Sit transition
Falling digital
Time

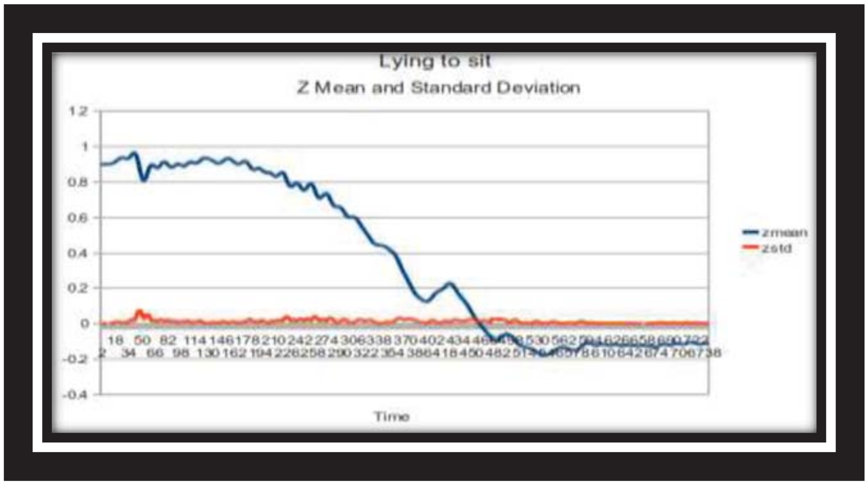

Lying to Sit
Sum Vector and Digitized Sum Vector
xyzmean
Digitized Sum Vector
Time

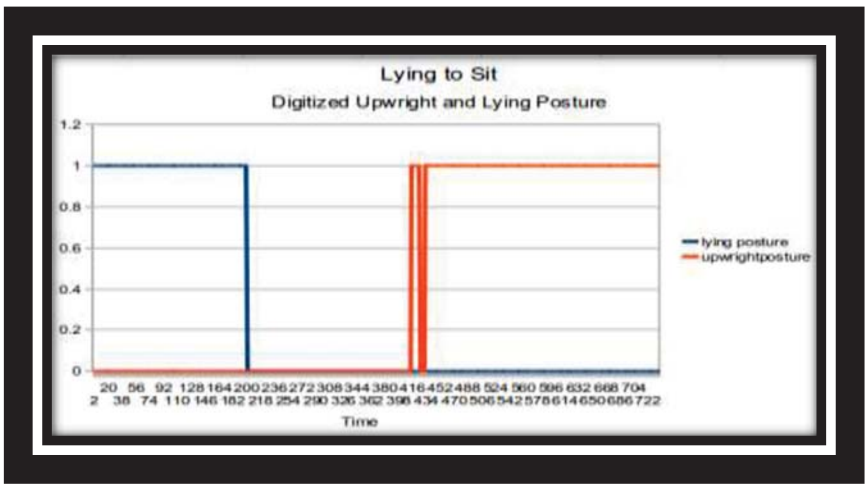

Lying to Sit
Z and Digitized Z
zmean
Digitized Z
Time

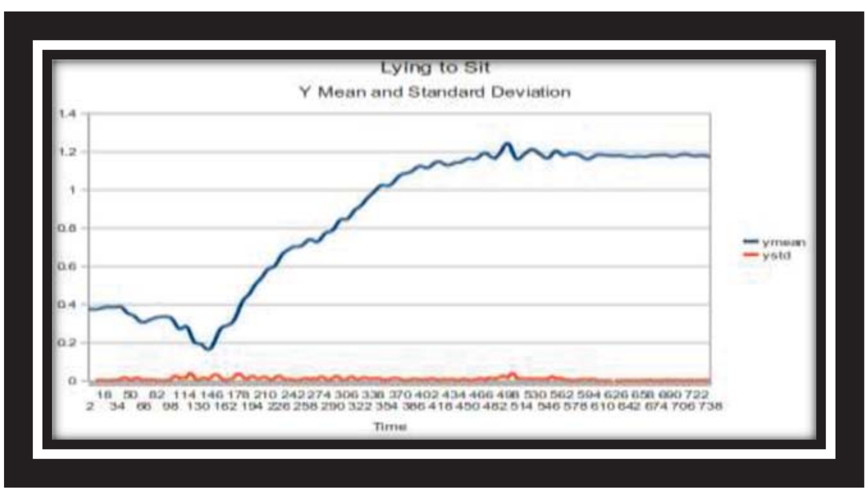

Lying to Sit
X Mean and Standard Deviation
xmean
xstd
Time

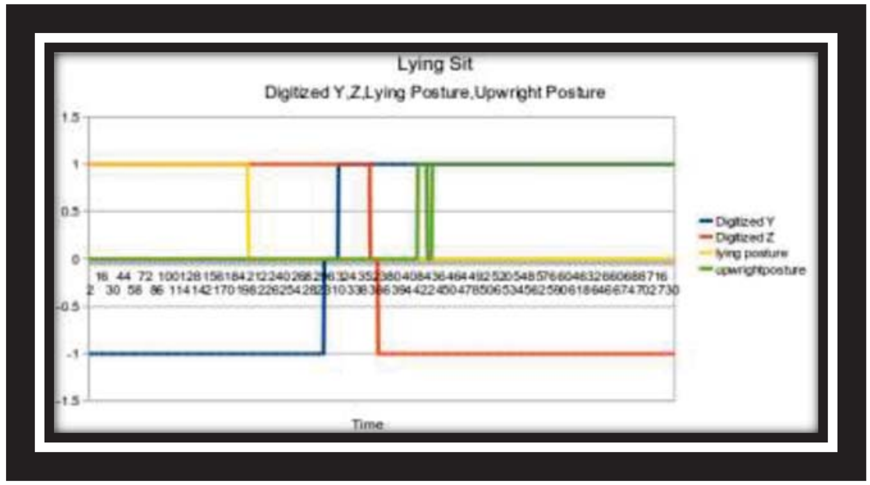

Lying to Sit
Y and Digitized Y
ymean
Digitized Y
Time

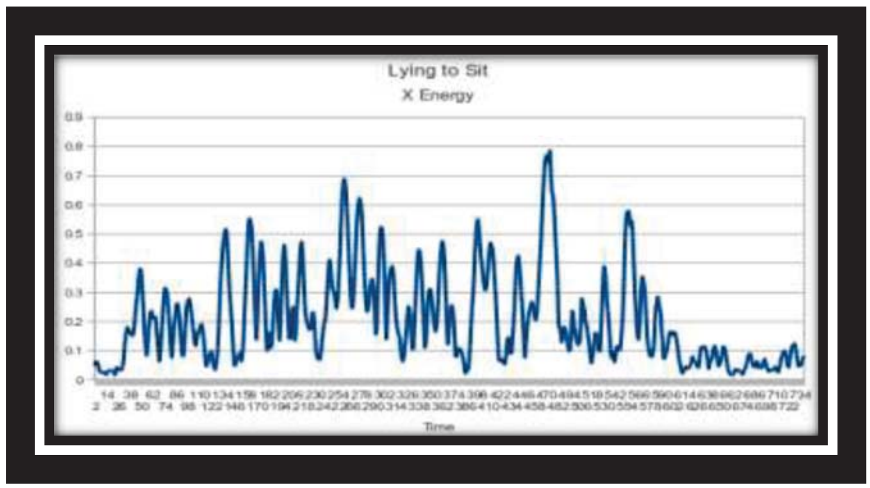

Lying to Sit
Z Auto Corralation
Time

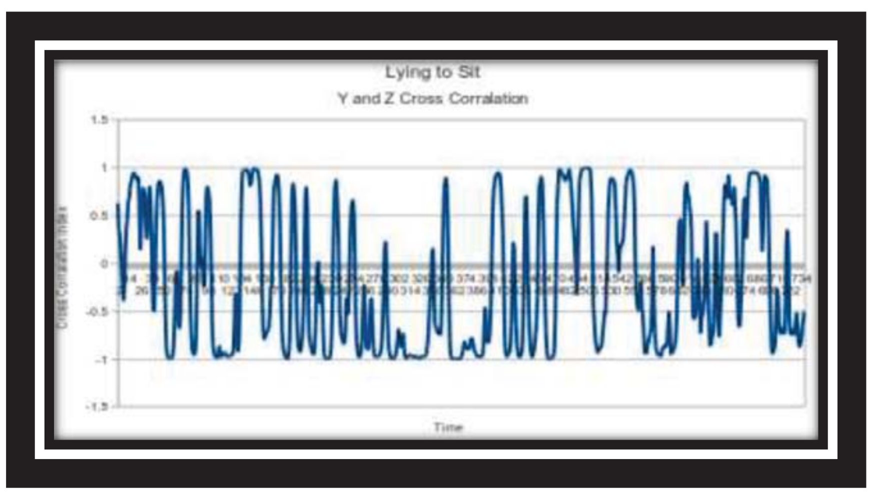

Lying to sit
Z Mean and Standard Deviation
zmean
zstd
Time

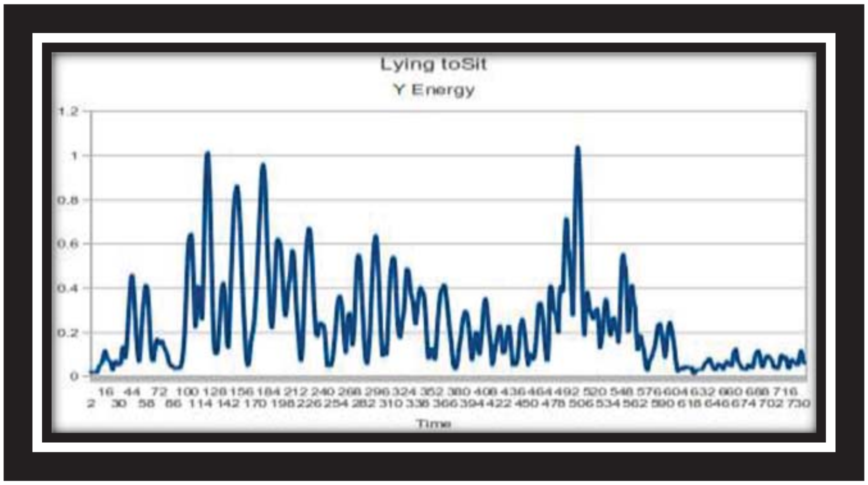

Lying to Sit
Digitized Upwright and Lying Posture
lying posture
upwrightposture
Time

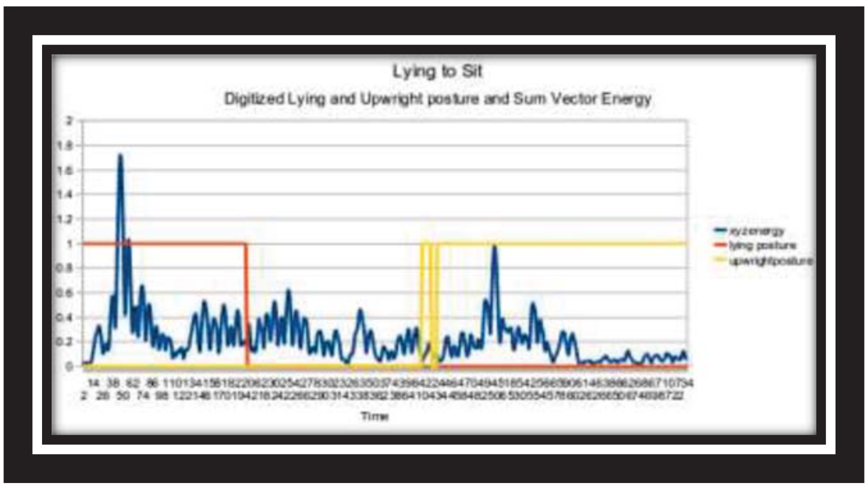

Lying to Sit
Y Mean and Standard Deviation
ymean
ystd
Time

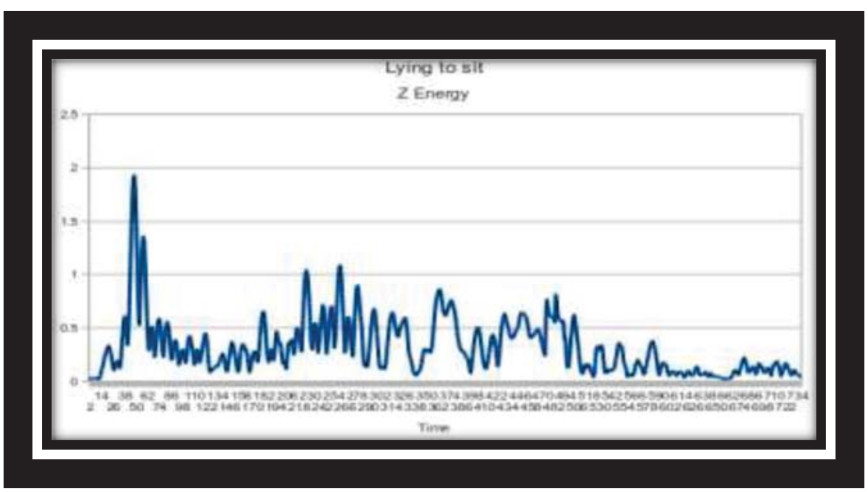

Lying Sit
Digitized Y,Z,Lying Posture,Upwright Posture
Digitized Y
Digitized Z
lying posture
upwrightposture
Time

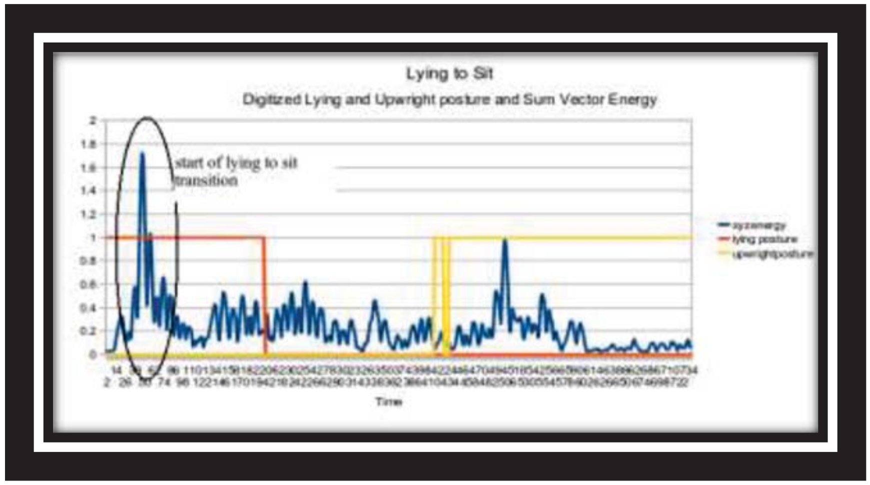

Lying to Sit
X Energy
Time

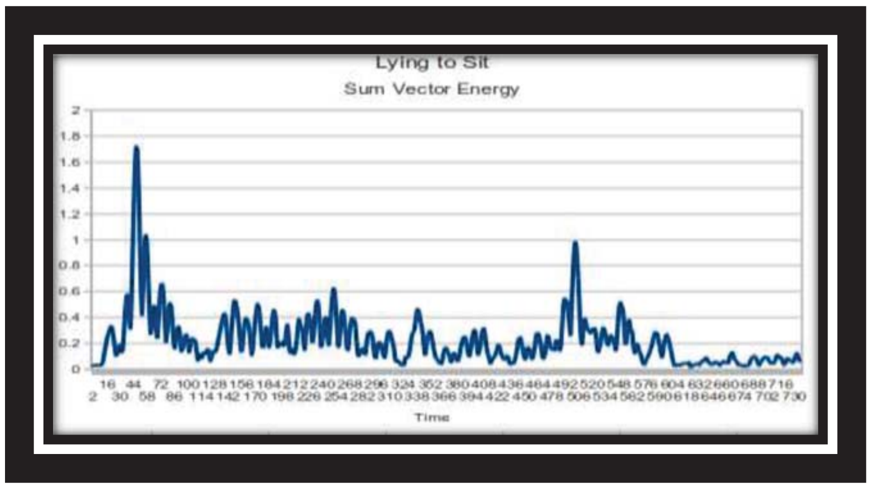

Lying to Sit
Y and Z Cross Corralation
Time


Lying toSit
Y Energy
Time


Lying to Sit
Digitized Lying and Upwright posture and Sum Vector Energy
xyzenergy
lying posture
upwrightposture
Time


Lying to sit
Z Energy
Time

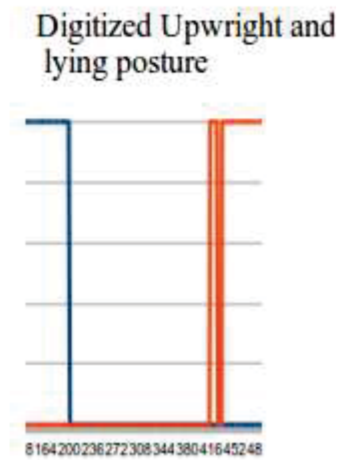

Lying to Sit
Digitized Lying and Upright posture and Sum Vector Energy
start of lying to sit
transition
Time


Lying to Sit
Sum Vector Energy
Time

<u>Testing for Lying to Sit:</u>

13.3.1. Test 1

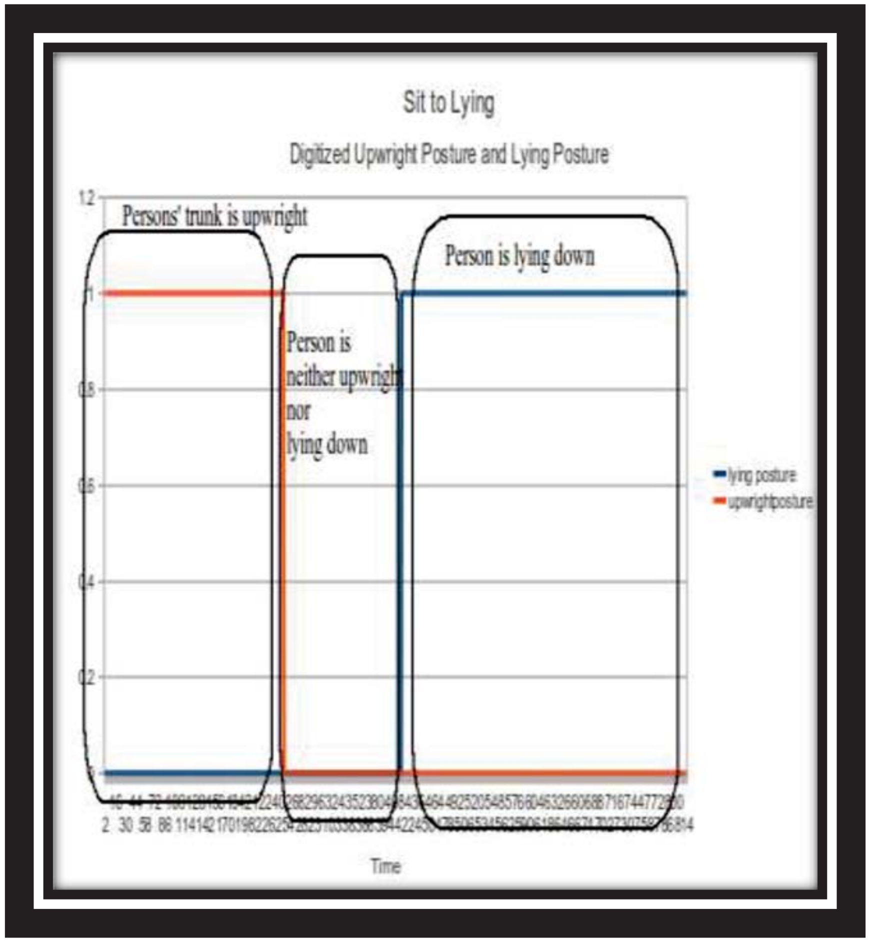
It is checked whether the digitized lying has prolonged positive state and once the positive state ends, it stays at zero state and after a time delay the digitized upright posture has a positive state which stays on.

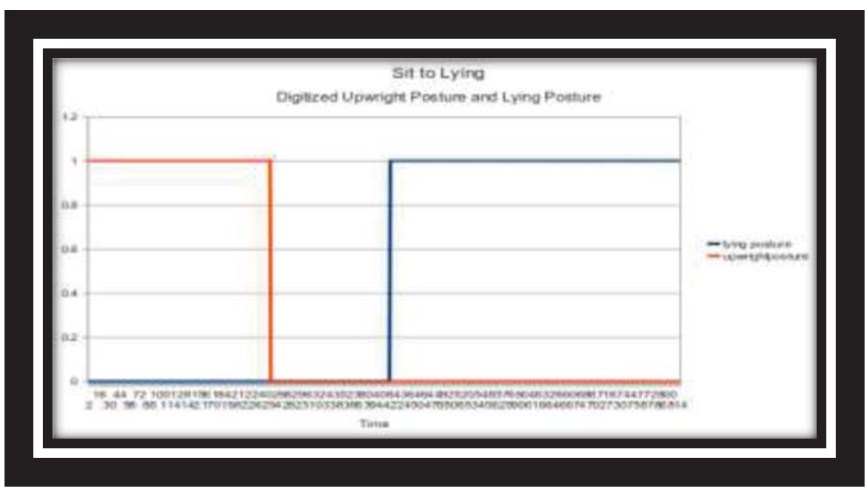


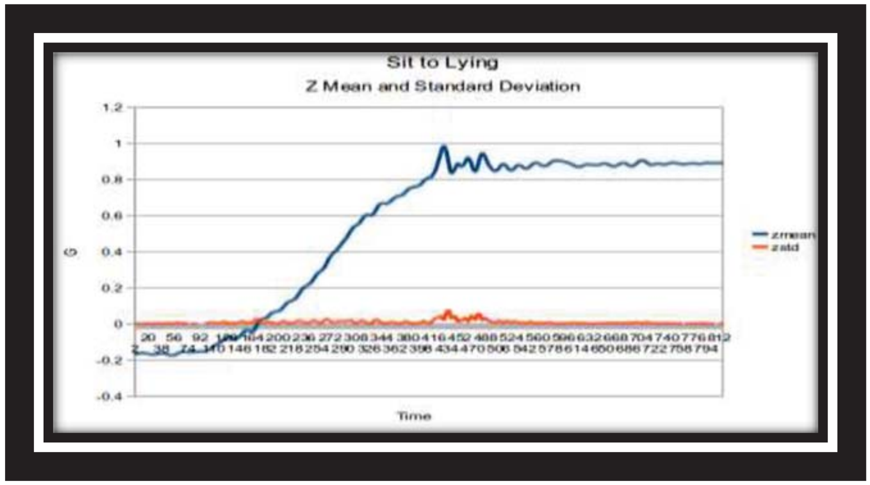
13.3.2. Test 2

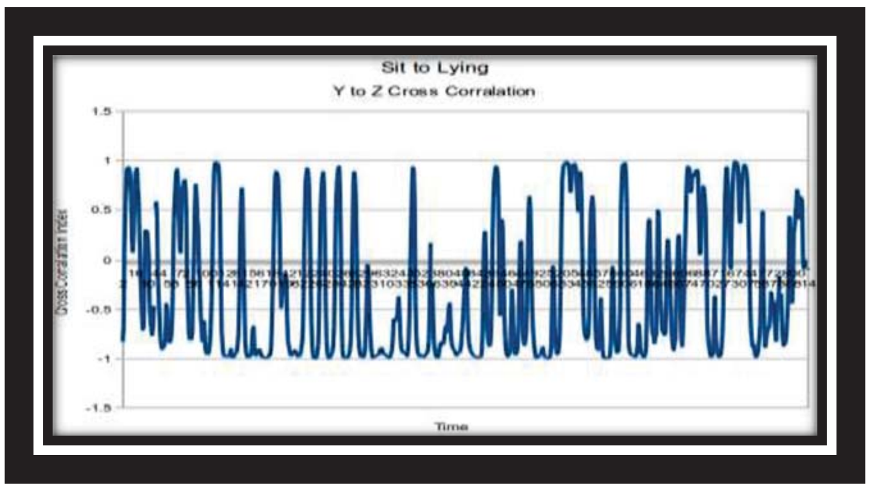
Start of lying to sit transition can be identified by the sum vector energy peak. This peak should be in the digitized lying posture positive state.

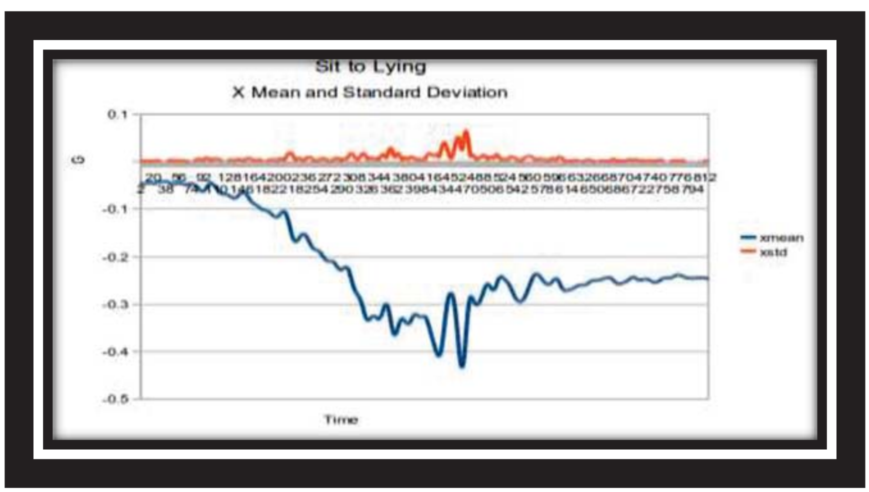
13.4. Sit to Lying

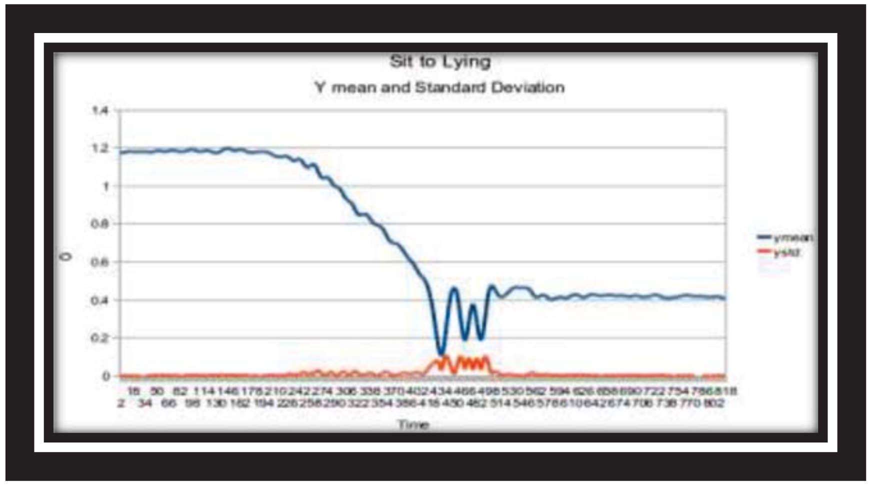


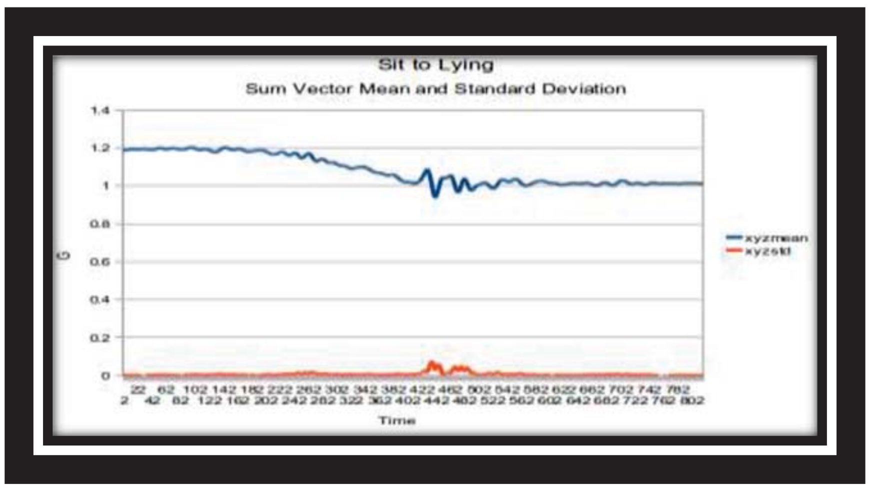


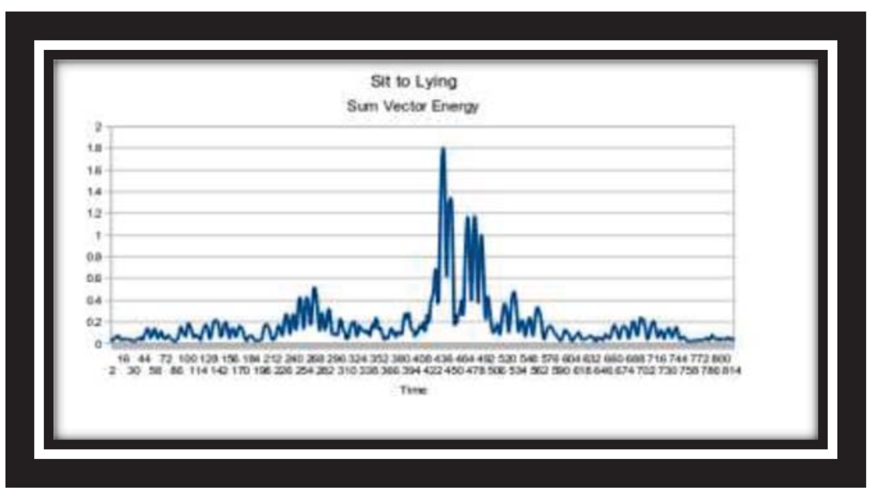

Sit to Lying
Z Mean and Standard Deviation
zmean
zstd
Time

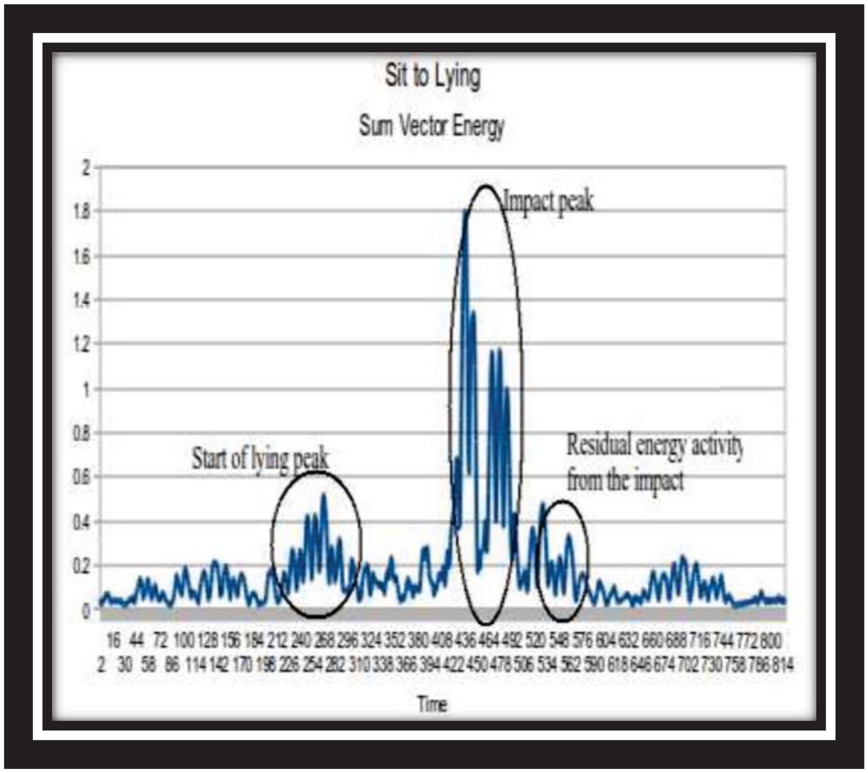

Sit to Lying
Y to Z Cross Corralation
Time

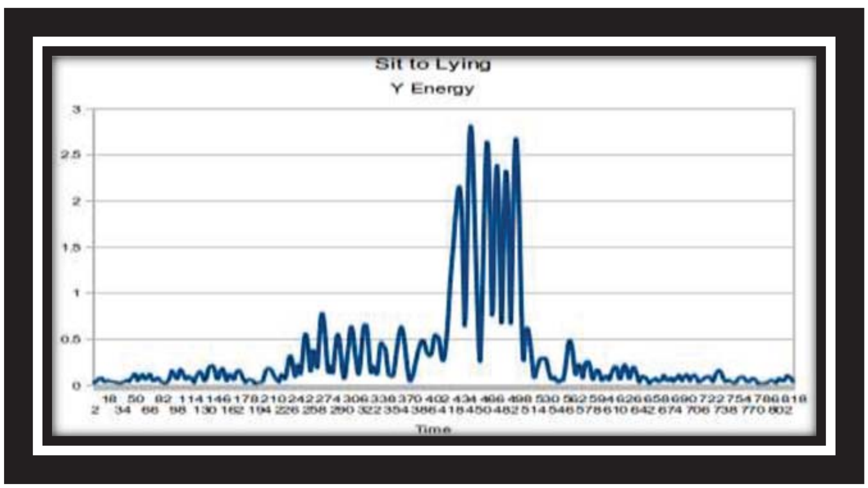

Sit to Lying
X Mean and Standard Deviation
xmean
xstd
Time

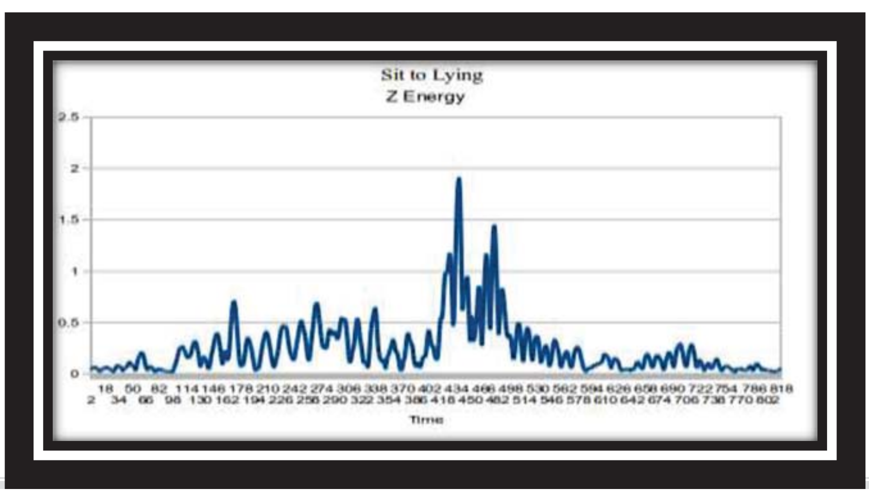

Sit to Lying
Y mean and Standard Deviation
Time

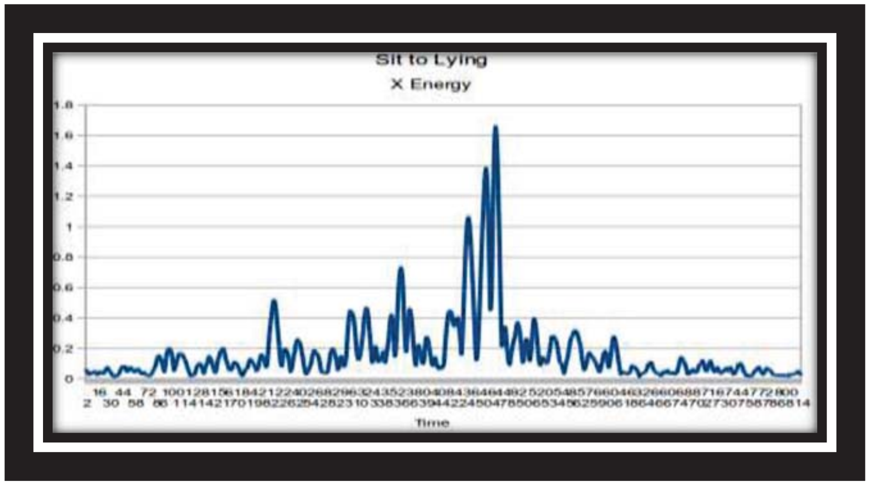

Sit to Lying
Sum Vector Mean and Standard Deviation
Time

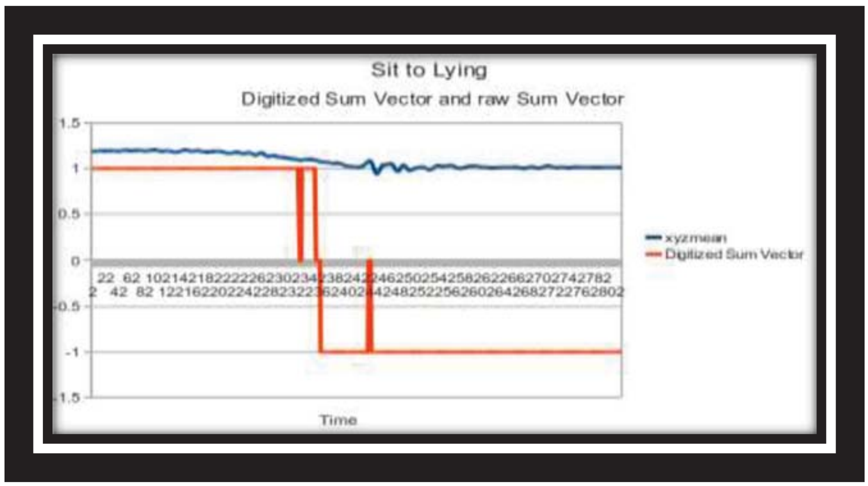

Sit to Lying
Sum Vector Energy
Time

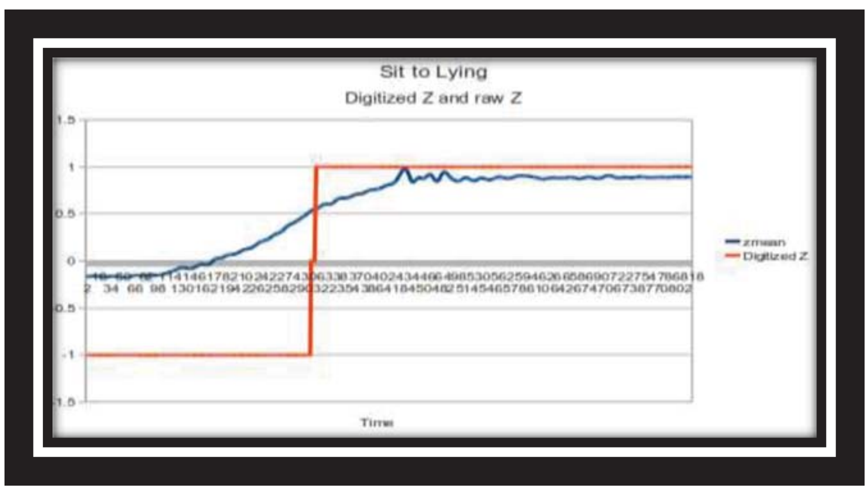

Sit to Lying
Sum Vector Energy
Impact peak
Start of lying peak
Residual energy activity from the impact
Time


Sit to Lying
Y Energy

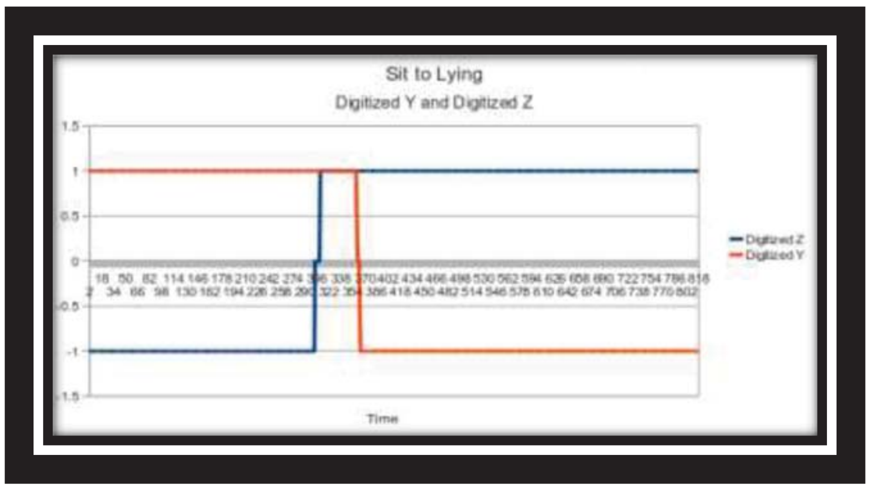

Sit to Lying
Z Energy
Time

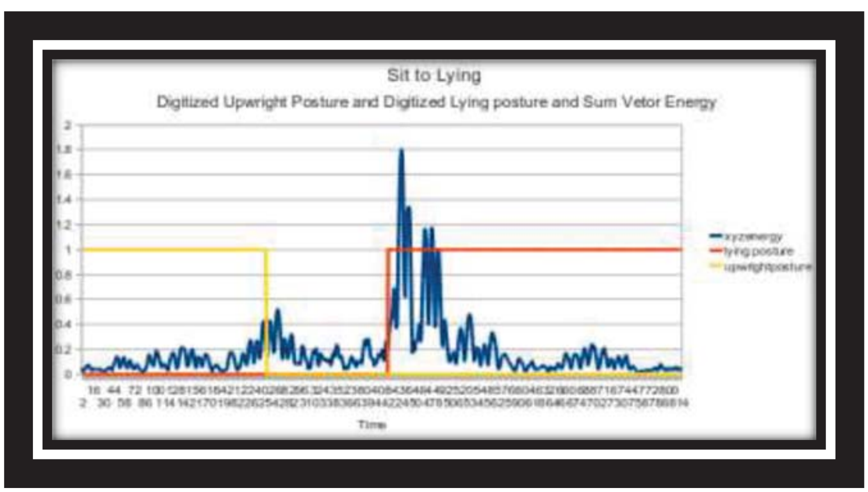

Sit to Lying
X Energy
Time

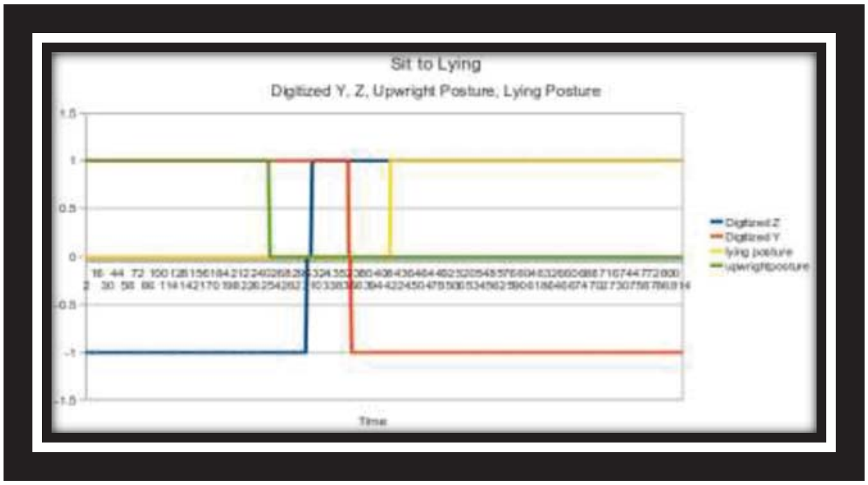

Sit to Lying
Digitized Sum Vector and raw Sum Vector
Time
xyzmean
Digitized Sum Vector

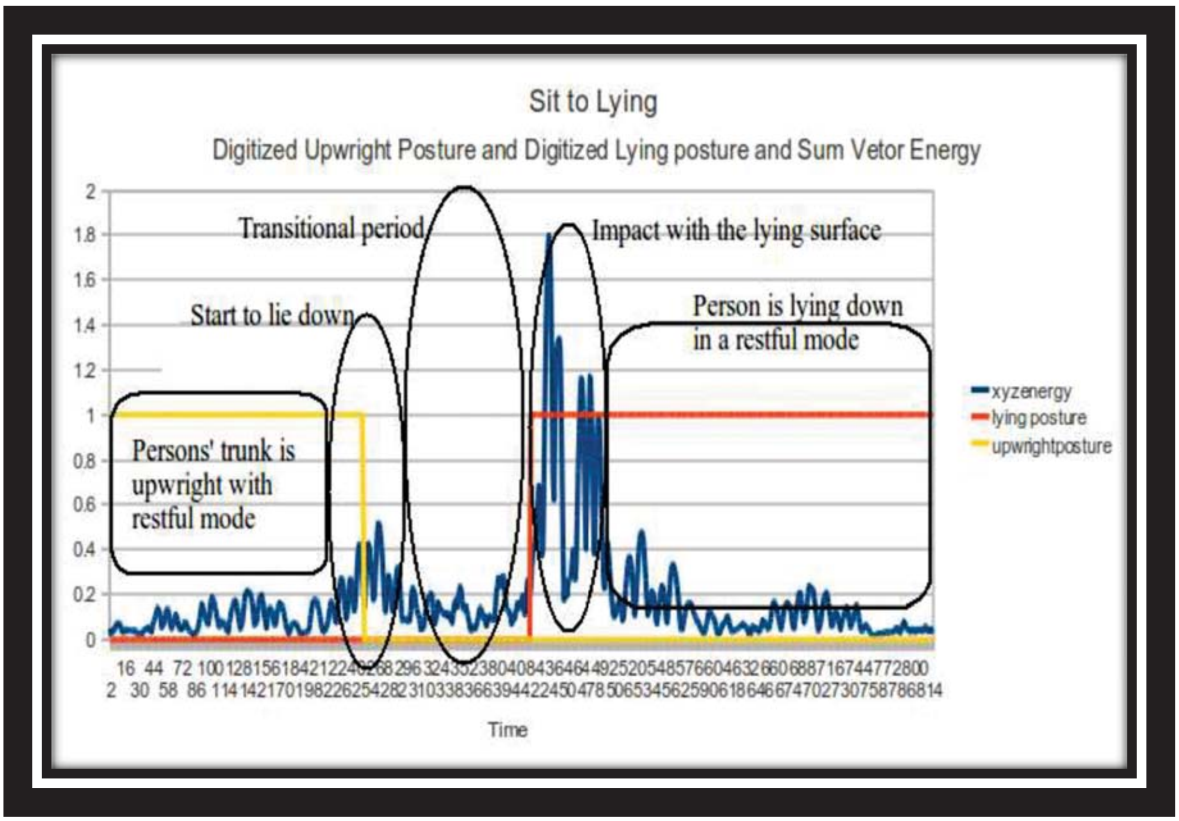

Sit to Lying
Digitized Z and raw Z
Time
zmean
Digitized Z


Sit to Lying
Digitized Y and raw Y
Time


Sit to Lying
Digitized Y and Digitized Z
Digitized Z
Digitized Y
Time


Sit to Lying
Digitized Upright Posture and Digitized Lying posture and Sum Vetor Energy
Time



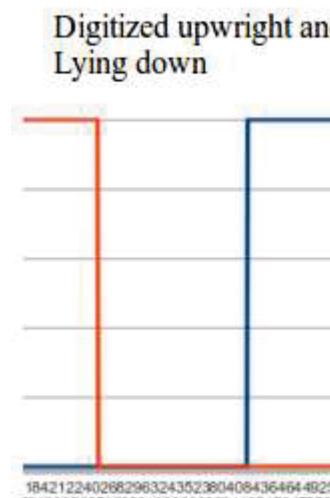


The energy emanates from the impact with lying surface indicates whether the lying action is a deliberate action or not. In the above illustration the impact energy is just lowly 1.8units, which means person is deliberately chosen to lie down. It is unwise to predict the persons' health condition based on the width of transitional period, because sit to lying transition involves core muscle usage, therefore a healthy individual in a restful state with core muscle strength would display a prolonged duration in the transitional period. Whereas an unhealthy person who might not be able to control the sit to lying motion might display the narrow transitional period. But this cannot be generalized because a healthy individual would choose to process with the lie down motion quickly, therefore predicting a persons' health condition based on the transitional period should be avoided. But having said that the energy emanated from the start of the lying is an excellent indication of persons' health excluding the fact of involuntary sit to lying transition in a sick individual where a sudden motion would display high energy for the start of lying, but this involuntary transitions can be recognized by the fact of very high impact energy where a healthy individual have a high start energy and their impact energy is higher than the start energy but only higher in few energy units. Identification of the position of start energy can be done by using the digitized upright posture. Identification of the position of the impact energy can be done by using the digitization of the lying posture.

Testing for Sit to Lying:

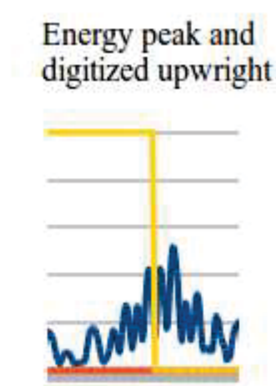
13.4.1. Test 1

In this test, it is checked that digitized upright posture has a positive prolonged pulse and at the end of the positive pulse it stays at zero level throughout. After the falling edge of the digitized upright, the digitized lying down starts the positive prolonged pulse which is continued throughout the duration of lying down.



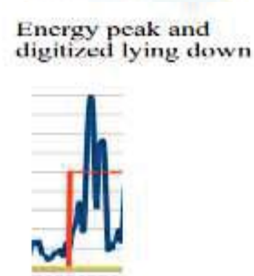
13.4.2. Test 2

If the test 1 is passed ,it is checked that in window of 20 time ticks at the falling edge of the digitized upright posture whether there is Sum Vector energy burst which signifies the start of the lying down.



13.4.3. Test 3

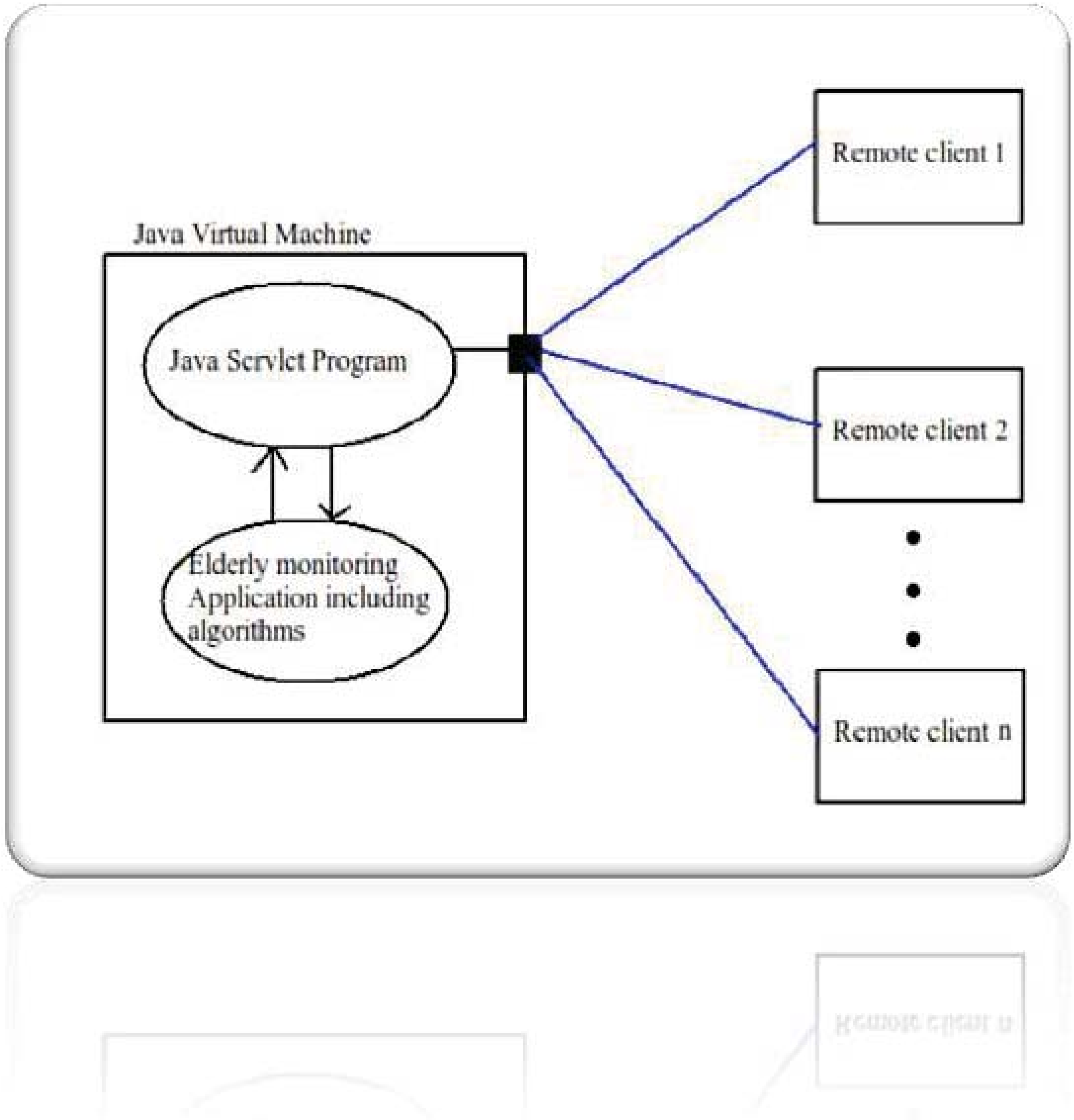
If the test 1 and test 2 are passed it is check that in a window of 20 time ticks at the rising edge of the digitized lying posture, a burst of Sum Vector Energy is detected.



14. Remote monitoring via Internet

Remote monitoring serves the purpose of monitoring the activities of an elderly person from a remote location via Internet. Therefore the person who is doing the remote monitoring can reside anywhere in the world as long as he/she has access to the Internet. This feature is developed due to the fact that modern societal fabric has been altered to a point which people are flocking to the cities for variety of reasons. The primary target group of this feature is busy people who are responsible for the wellbeing of the elderly but live seas apart from the elderly and due to their busy life schedule cannot phone their elderly relative regularly, especially if they live in a different time zone. But having this feature, they can easily monitor their elderly relatives' wellbeing just by using few mouse clicks. The secondary target group is the professional caretakers; this can be companies who provide rest homes for the elderly. One of the main issues these companies face is the shortage of skilled staff, and also the cost of the individual home visits. This feature allows them to monitor the wellbeing of their clients regularly from a remote location thus enabling them to reduce the cost of home visits and minimize the effect of skilled staff shortages.

The remote monitoring is done through apache tomcat server which runs in the data processing computer. The written Java servlet program invokes the elderly monitoring program when it first initiates itself. Then remote clients can talk to the Java servlet program through apache tomcat server and get continuous status update on the elderly activities. This process is depicted in the illustration below.


Java Virtual Machine
Java Servlet Program
Elderly monitoring Application including algorithms
Remote client 1
Remote client 2
Remote client n

15. System Testing

15.1. Results Table

Dynamic Activities

	TP	FP	TN	FN	Sensitivity (%)	Specificity (%)
Falling forward	100%	0%	100%	0%	100%	100%
Falling to Left	100%	0%	100%	0%	100%	100%
Falling to Right	100%	0%	100%	0%	100%	100%
Running	100%	0%	100%	0%	100%	100%
Walking Fast	100%	0%	100%	0%	100%	100%
Walking Slow	100%	0%	100%	0%	100%	100%
Lying to Sit	100%	0%	100%	0%	100%	100%
Sit to Lying	100%	0%	100%	0%	100%	100%
Stand to Sit	85%	0%	100%	15%	85%	100%
Sit to Stand	95%	5%	100%	5%	95%	95%

Static Postures

Very Mild Forward Bending	100%	0%	100%	0%	100%	100%
Mild Forward Bending	100%	0%	100%	0%	100%	100%
Medium Forward Bending	100%	0%	100%	0%	100%	100%
Large Forward Bending	100%	0%	100%	0%	100%	100%
Extreme Forward Bending (Lying face down)	100%	0%	100%	0%	100%	100%
Very Mild Backward Bending	100%	0%	100%	0%	100%	100%
Mild Backward Bending	100%	0%	100%	0%	100%	100%
Medium Backward Bending	100%	0%	100%	0%	100%	100%
Large Backward Bending	100%	0%	100%	0%	100%	100%
Extreme Backward Bending (Lying face up)	100%	0%	100%	0%	100%	100%
Very Mild Bending to Left	100%	0%	100%	0%	100%	100%
Mild Bending to Left	100%	0%	100%	0%	100%	100%
Medium Bending to Left	100%	0%	100%	0%	100%	100%
Large Bending to Left	100%	0%	100%	0%	100%	100%
Extreme Bending to Left (Lying on left side)	100%	0%	100%	0%	100%	100%
Very Mild Bending to Right	100%	0%	100%	0%	100%	100%
Mild Bending to Right	100%	0%	100%	0%	100%	100%
Medium Bending to Right	100%	0%	100%	0%	100%	100%
Large Bending to Right	100%	0%	100%	0%	100%	100%
Extreme Bending to Right (Lying on right side)	100%	0%	100%	0%	100%	100%

TP: TP which stands for True positive means, the system correctly detected the current activity/posture as it occurred.

FP:FP which stands for False positive means, the system incorrectly detected an activity/posture which actually did not happen.

TN:TN which stands for True Negative means, the device correctly identify that activity/posture did not happen.
FN:FN which stands for False Negative means, the device marked the activity/posture as did not happen when actually it did happen.
Sensitivity: The ability to detect the specific event accurately, Sensitivity=TP/TP+FN)
Specificity: The ability to correctly identify the event as not occurred, Specificity=TN/ (TN+FP)

15.2. Testing arrangements

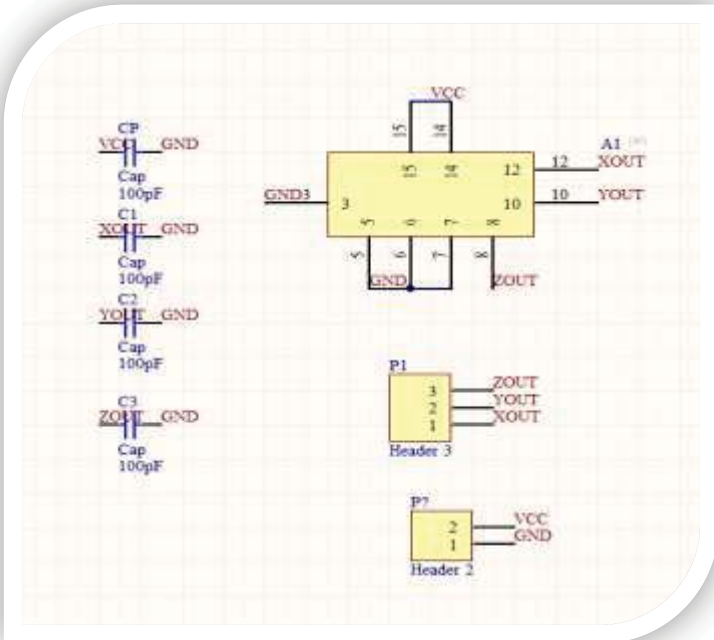
When testing for falls, volunteers were asked to fall on a cushion surface to avoid getting injured. Cushion surface with embedded springs was specifically avoided as the surface for the falling because; the springs act as a shock absorber which severely damps the shock impulse which is generated by the impact from the fall. Therefore falling on a spring laden cushion/bed is not a realistic falling method to test the developed system.
When testing for Stand to Sit, the volunteers were asked to stand in front of a chair and sit when requested.
When testing for Sit to Stand, the volunteers were asked to sit on a chair and stand up when requested.
When testing for Sit to Lying, the volunteers were asked to sit on a bed and lie down when requested.
When testing for Lying to Sit, the volunteers were asked to lie on a bed and sit up when requested.
When testing for walking, the volunteers were asked to walk inside the house and it was up to the volunteers to choose the walking path.
When testing for running, the volunteers were asked to run outside and prevented them from running indoors due to the safety reasons.
Testing for posture recognitions was split into two stages. In the first stage, volunteers were asked to bend (forward, backward, left and right) purposely in a pre-planned sequence (example: Asked to bend very mildly forward, then bend bit more in the same direction and keep on bending forward until the trunk is horizontal with the ground). In the next stage, the volunteers were asked to conduct random activities such as lying down, walking, yoga poses etc and while they were still doing those activities, the posture recognition was conducted and its accuracy was evaluated.
Due to ethical reasons, only young healthy adult volunteers were asked to carry out the falling and running tests.

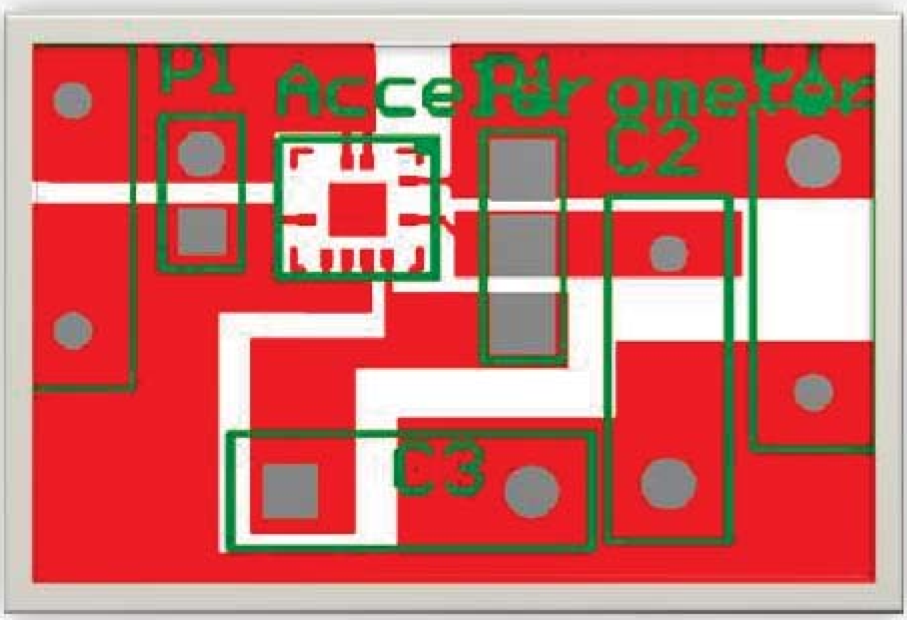
16. How the system is worn for testing

The volunteer depicted in the photo above is 65 years old.

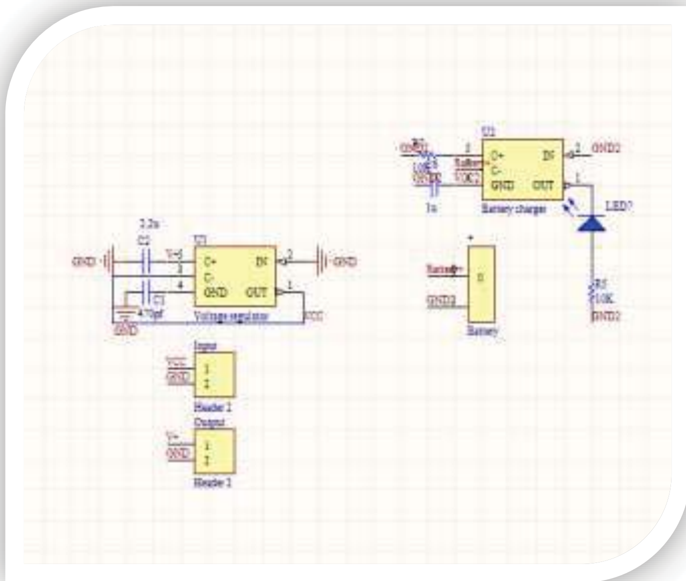
17. Electronic circuitry

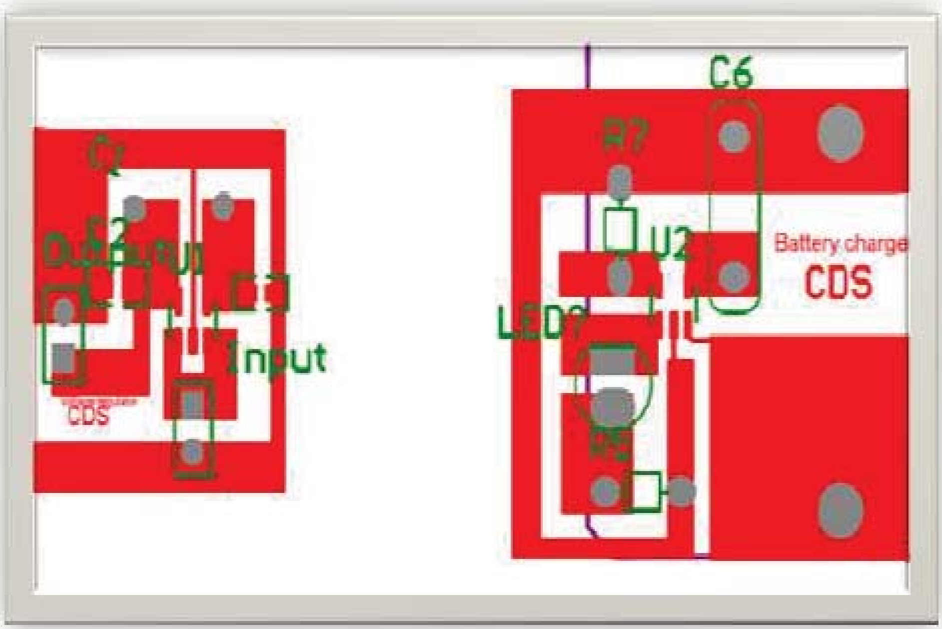
17.1. Accelerometer test board



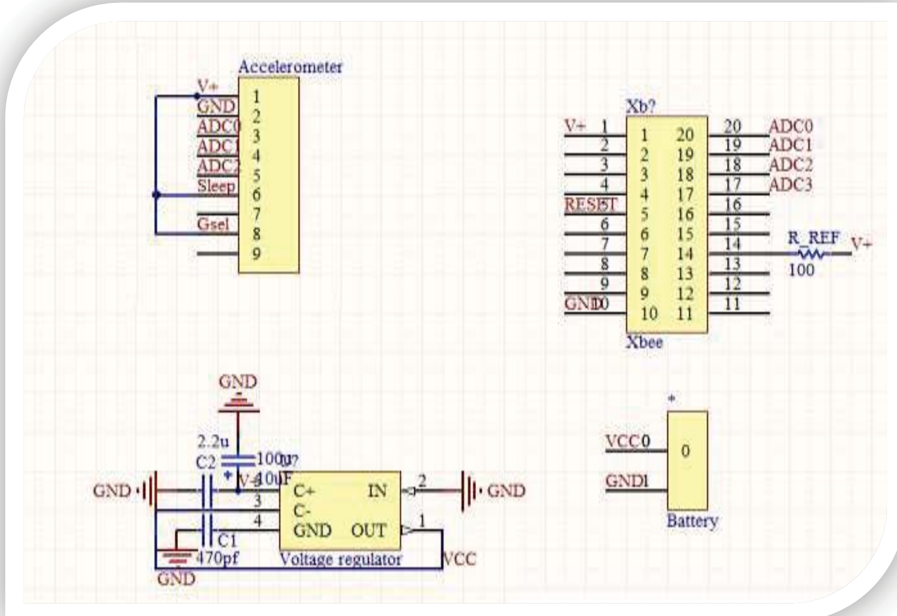


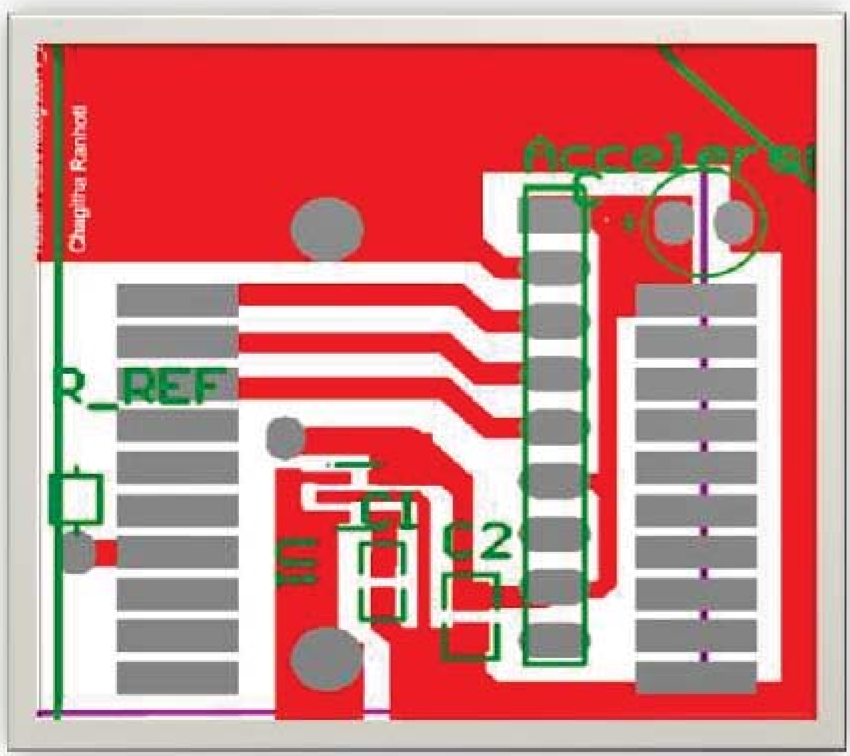
17.2. Voltage Regulator and Battery charger





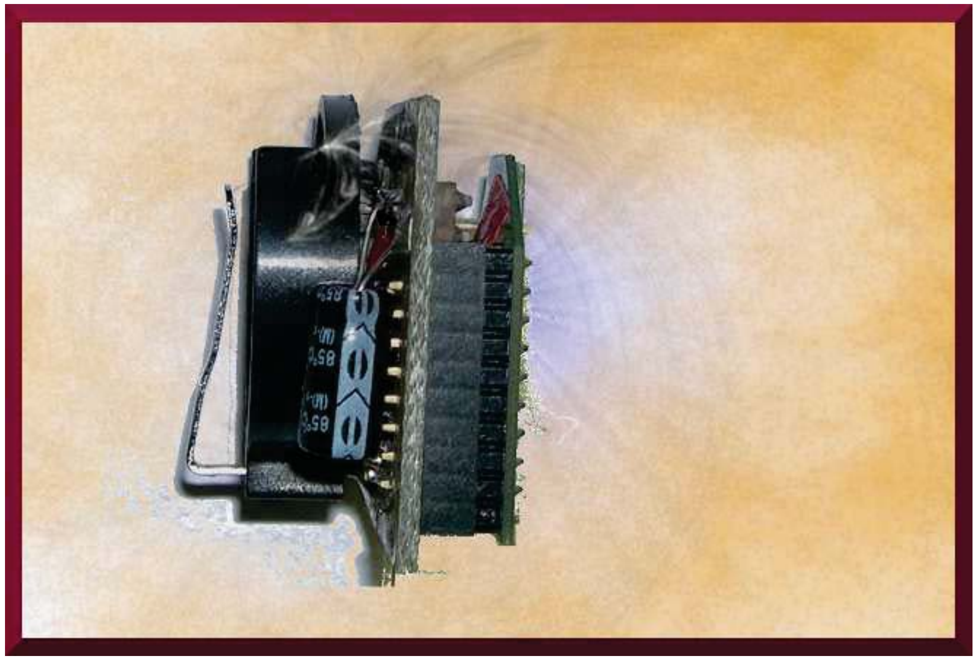
17.3. Putting it all together





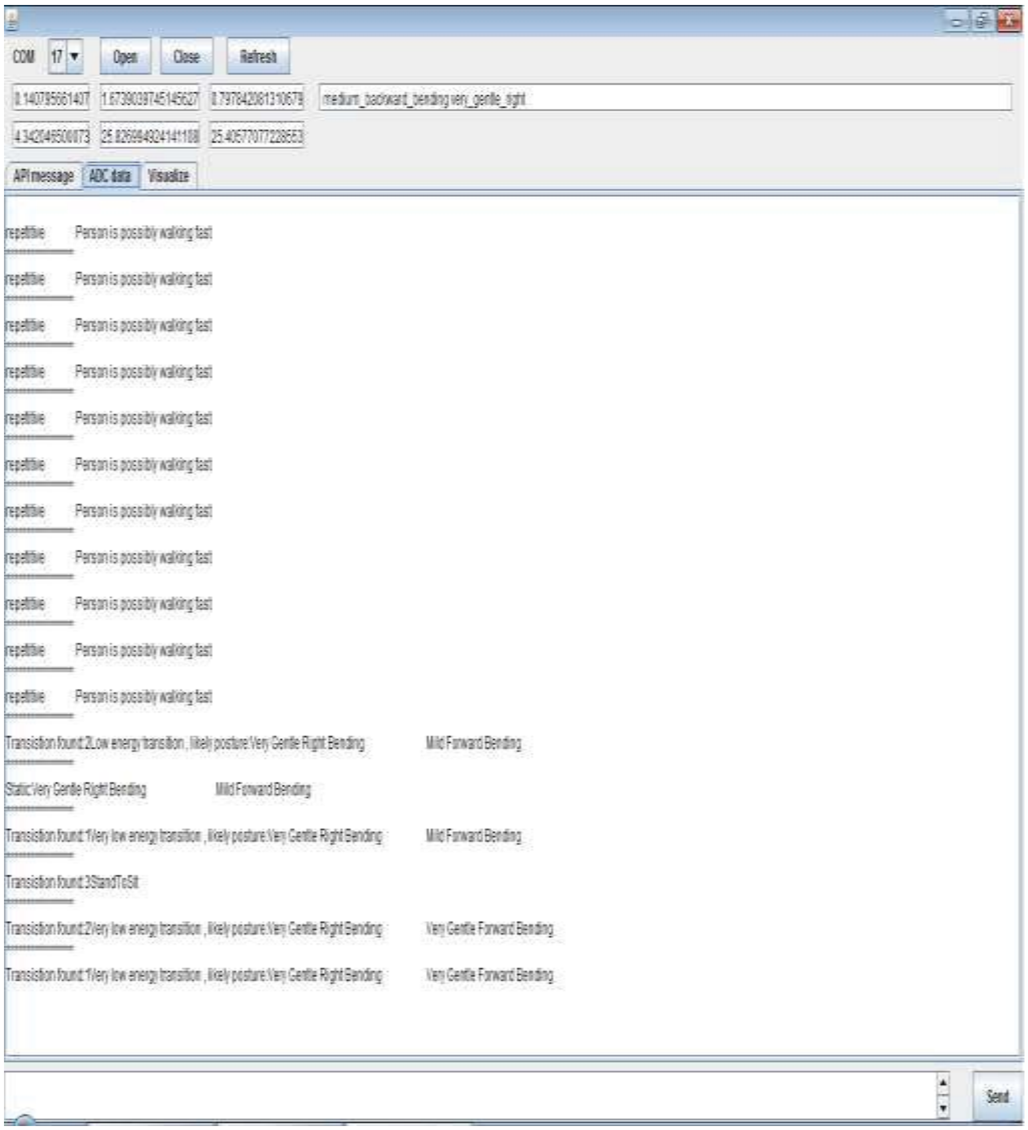
17.4. Prototypes used for testing

As shown in the images below, the size of the developed module is approximately 2cm x 2cm (width and length) and 1 cm in height including the coin cell batteries.

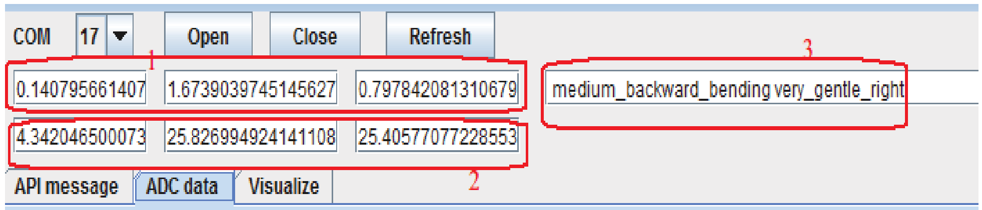


18. Computer- Graphical User Interface

The computer application is responsible for the real-time detection using the data received from the wireless accelerometer sensor module. Computer application runs the algorithm and displays the user activity information as well as posture using real-time detection in textual format.



18.1 Description of the user interface



Area 1: Instantaneous X, Y, Z axis acceleration in G
Area 2: Instantaneous X, Y, Z angles in degrees
Area 3: Interpretation of the angles
Larger white area: Commentary of the current activity/posture

19. Path to commercialization

The following improvements are needed if this developed product to be deployed to the commercial market.

- Improved battery life: The rechargeable coin cell battery used at the moment only lasts up to 2 hours. The battery should last minimum 24 hours after a full charge if this product is to be commercialized.

- Inductive wireless battery charging module needs to be made, which allows the user to place this wearable device on the inductive charging bay to charge up the battery. This would improves the usability of the product.

- Proper casing for the wearable device needs to be fashioned and should be made with low cost, durable and water proof material.

- Currently graphical user interface provides text based information, for example when it directs a person is walking fast it displays "Person is walking fast" or when a person is walking slowly, it displays "Person is walking slowly". To improve the usability along with the textual information a graphical real time animation which gives more illustrative information would be desirable in a commercial product.

- SMS based alert system should be introduced to inform any falling.

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