Gait Analysis and Automatic Gait Event Identification Using Accelerometers

George I. Zdragkas, John N. Avaritsiotis

***Abstract*— In this paper a method for footstep detection and gait event identification is presented. A three-axis accelerometer can be mounted on someone's foot to record the acceleration signals produced by their gait. The data can be analysed in real time or after a period of time to identify the gait events and their respective acceleration values. Data analysis consists of signal processing in order to point out some characteristics of the signals. Furthermore an algorithm is proposed for the automatic gait event identification based on these signals.**

I. INTRODUCTION

GAIT analysis has found many useful applications in modern medicine. Clinical gait analysis can be performed in a specialized laboratory with optical and force sensors, control and analysing equipment or in a doctor's office with visual observations. The first method produces very accurate results but is expensive. The second one is based on the doctor's knowledge and experience, gives results generally unreliable, subjective and valueless over extended periods of time.

With the development of accelerometers, small and low power sensor systems can be constructed, able to be mounted on a patient's shoe or in every other place of the body possible. They can produce qualitative results without the use of expensive equipment and laboratories. Furthermore they can be used without the presence of a doctor and acquire motion data of the user over long periods of time. The data can be analysed later by a doctor or a computer that executes a specific algorithm. These systems can be used for diagnosis, treatment and prevention of motion problems.

One of the uses of accelerometers for gait event identification is found in functional electrical stimulation (FES) assisted walking for spinal injured persons, stroke patients and hemiplegics. The accelerometers provide feedback information to a system that produces electrical stimulus to the foot in order to aid the walking of the patient. These real time systems must accurately identify the gait events with small delay. Therefore simple and fast algorithms must be used. A recearch shows how the heel contact event can be identified by the negative-positive changes in acceleration of the trunk [1]. It also shows how a simple algorithm can identify the heel contact of both feet with a delay of 150ms. The optimum accelerometer placement is a difficult problem that can be analysed with visual sensors [2]. We have chosen to place our sensor on the foot for many reasons. First of all we can receive more information for the gait cycle, identify more easily the gait events of the body and more accurate results can be acquired. Second of all, the sensor can be integrated to the shoe with minimal discomfort to the user. Lastly, the magnitude of foot acceleration is greater than any other place of the body. The trunk plays an important role in attenuating accelerations to the upper body and especially to the head produced by gait. This helps in the stability of the walking person [3].

It is known that elderly people suffer from injuries caused by falling accidents that can, in many cases, be lethal. A real time system can monitor a person, detect when a fall occurs and send the information to a nearby health center [4]. This research also shows the method for identifying the accident in frequency domain and proposes that the gait cycle also includes information for an upcoming fall.

Researches have shown that every person has a unique way of walking pattern that feels comfortable with. Once his gait varies from this pattern, instability problems may occur. These systems can analyse their motion in real time and warn them for the danger based on their data base. Stability research has been conducted with the use of accelerometers [5][6] and observed that the head has to be stable for total system stability [7]. Furthermore, another research has been able to identify the slipperiness of a surface based on the acceleration signal when the food strikes the ground [8]. Researchers have also created a shoe-integrated sensor system that can send acceleration and force data wirelessly to a base computer [9]. Activity recognition can also be performed with accelerometers. We can use accelerometers placed in different parts of someone's body to identify his activity i.e. walking, bicycling and typing [10][11]. Some other researchers managed with a tree-axis accelerometer placed on the waist to identify whether a person walks on level ground, up stairs or down stairs [12].

The accelerometer systems can also be used for long term monitoring of patients with Parkinson's disease [13][14] and in general for physical activity patterns [15] for better health

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recommendations. These methods can be implemented with the use of accelerometer systems and can contribute to a healthier population. However, it is very important for the system to be able to identify the gait events of the user. Automatic footstep detection has been researched in the past [16] with accelerometers placed on the ankles [17].

In this paper we present a method for gait event identification. First we acquire two orthogonal acceleration signals. Then we process these signals to better identify the footsteps and highlight some important gait events. After the isolation of each footstep we search in each one of them for the gait events. With this method we can obtain very useful information with only one accelerometer placed on someone's foot and with algorithms that can easily and efficiently be implemented.

II. METHOD

Our design utilizes MMA7260QT, a three-axis accelerometer that is capable of measuring acceleration values from -6g to +6g and a microcontroller (LPC2148) for collecting the data. The accelerometer is mounted on the user's foot as it is shown in figure 1. The microcontroller reads the data from a 12-bit ADC (MAX1247) and stores them in RAM. Then the algorithms of signal processing are executed. The data can also be transferred to a computer for more advanced processing through the serial port although the purpose of this paper is to demonstrate a method for real time gait event identification. Therefore simple yet efficient algorithms are used that decrease the need for high computer power. This helps in applications where fast footstep detection is required with low power consumption and long term monitoring capabilities. The sampling frequency of the system is set to 200Hz which is sufficient for the study of human motion. We use Y and Z accelerations and we manipulated these signals in order to achieve another set of signals for more efficient gait event identification.

For our research we acquired acceleration data from four people. The signals from the participants had the same waveforms but with different amplitudes. We have placed the sensor on the right foot of the volunteers. The gait event sequence is: First the left foot strike event occurs. Then the toe off event of the right foot takes place. Once the foot is in the air, it begins to move forward in a swinging motion. We can identify two events in this movement. The initial swing and the terminal swing event. After the terminal swing, the right foot hits the ground and we have the foot strike event. Finally the foot relaxes as it begins the preparation for another gait sequence. This last event is the begin stance phase.

III. DESCRIPTION OF THE SIGNALS

A. Y-Acceleration signal

Figure 1 shows the signal acquired from the sensor. Y-Acceleration starts with a relatively steady amplitude. As soon as the opposite foot strike event occurs there is a small rise on the acceleration. Afterwards when the right foot prepares to rise from the ground there is a sudden increase in the acceleration because it generates a massive force against the ground in order to move forward. The maximum peak of this increase is the toe off event of the right foot.

Immediately after the toe off, the foot is on the air and starts to swing forward. The initial swing event is spotted with a minimum value right after the toe off. When the foot starts to move forward the acceleration increases. At first the rate of increase is stronger but when the foot comes close to its final destination the rate decreases. When the foot covers the desired range, the terminal swing event occurs. It is usually at the top of the swing peak and can be found at the maximum value or at a local maximum. In either case, it is followed by a rapid change in acceleration. The acceleration drops to its nominal value because the foot has reached its destination and no further force is applied. Then the foot hits the ground and a large peak of acceleration is created. The foot strike event is identified on the top of this peak. After the foot strike event, the foot stays still, stabilized since it has entered the begin stance phase and the acceleration has returned to its nominal value.

Fig. 1. The accelerometer sensor mounted on a shoe and the acceleration axes orientation.

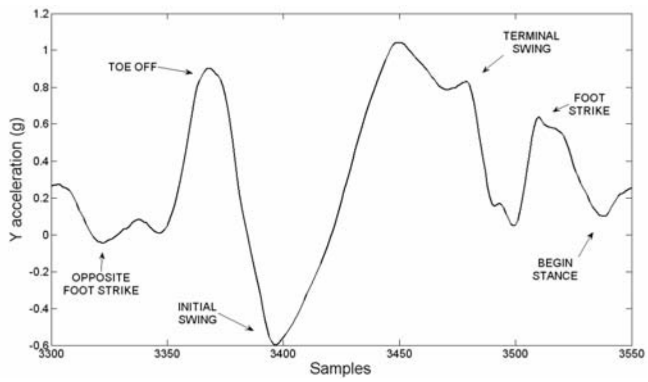

Fig. 2. Y acceleration signal.

B. Z-Acceleration signal

Z-Acceleration signal is presented in figure 3. The left foot strike event occurs when the acceleration is at its nominal value which means that nearly no acceleration is observed on the right foot. Soon after the opposite foot strike event, the acceleration decreases as the foot is pressed downwards. The minimal value is the toe off event. After that, the acceleration rises as the foot lifts up. At the top of this peak we can identify the initial swing event. Then the acceleration forms a V shaped curve. At the top of the second peak it is found the terminal swing event. Once the right foot has reached the desired location it starts to fall downwards. A sudden decrease in acceleration is observed. At the minimum of this decrease we can find the foot strike event. Finally the gait cycle ends with the stabilization of the right foot on the ground and the return of the acceleration to its nominal value.

IV. Signal Processing

In Y and Z acceleration figures we can see that gait events can be easily identified by visual inspection but for computerized identification further signal manipulation is required. Therefore we can create some new signals that amplify some gait events, narrow gait event peaks, create maximum and minimum extrema in gait events and remove the irrelevant events. This greatly helps in automatic gait event identification using algorithms. The new signals are energy and product.

A. *Energy signal*

The energy signal is the sum of the squared Y and Z accelerations. Figure 4 shows the energy signal. This new signal is positive making the developing process of an algorithm easier. It also helps in the isolation of the footstep waveform. We can clearly see in Y and Z accelerations that in the start and end of the footstep signal, the signal varies without the presence of a gait event. In energy signal this variability is reduced to zero. Moreover the energy signal starts with a rapid increase that highlights the toe off event at the top of this peak. The same happens at the end of the energy signal as the last peak corresponds to the foot strike event.

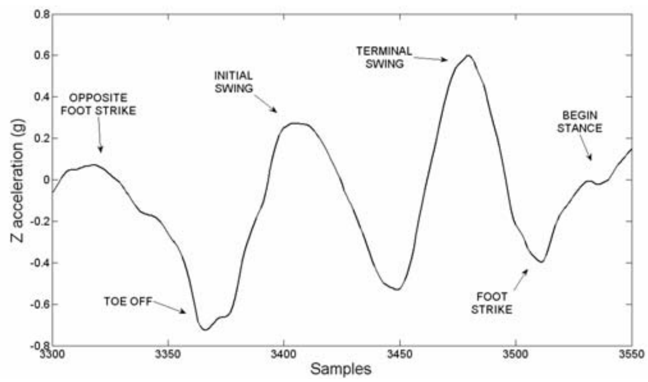

Fig. 3. Z acceleration signal.

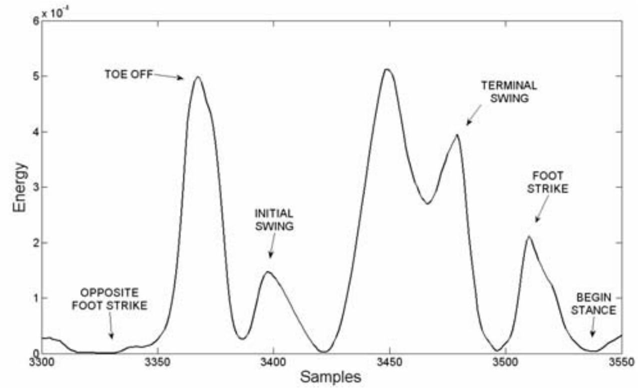

Fig. 4. Energy signal.

B. *Product signal*

The product signal is the product of Y and Z accelerations. Figure 5 shows the product signal we created from the original signals. The product signal helps us identify events that have opposite signs in Y and Z accelerations. First of all we can easily see that a nominal value of zero is set in the start and end of the product signals in contrast to the variability of the Y and Z acceleration signals. Furthermore we can clearly identify the terminal swing event as it has the maximum value of the product signal. This greatly helps in the identification algorithm as in Y and Z accelerations there are similar peaks of equal magnitudes near the terminal swing event, making it more difficult to identify this event in these signals. We can also see that in product signals the gait event sequence follows a pattern of positive and negative peaks and valleys of a rapidly alternate signal. This also helps in the development of an automatic identification algorithm.

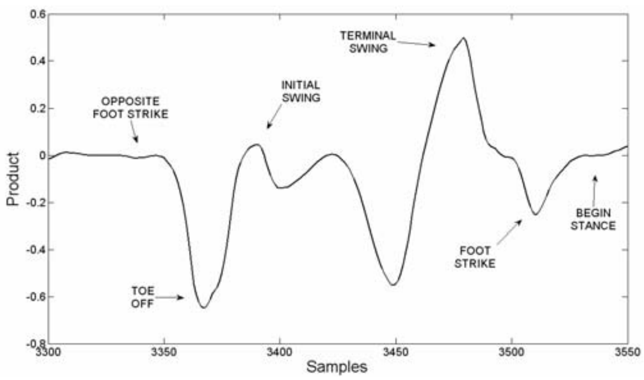

Fig. 5. Product signal.

V. Footstep Detection

A. *Thresholds*

After the acquisition of the acceleration signals we detect the footsteps that the user made. With this information we can calculate the cadence (steps/min) of the user. Furthermore footstep detection is needed in order to identify the gait events in each step.

A simple method for footstep detection is with the use of threshold values. Once the signal is obtained we can search for every time it rises above a certain value. However a threshold value that is set for a medium walk, can never be reached if the person walks slower or it can also trigger wrong footstep detections if the person walks with a stronger pace. Everyone can have more than one threshold values and each person walking style is different. Therefore threshold values constitute an unreliable method for footstep detection. Figures 6, 7, 8 and 9 show the difficulty in setting a specific threshold for identification of eight steps.

B. *Variance thresholds*

A solution to this problem can be found in the use of variance. Variance can be used for event detection where the signal changes suddenly like toe off and foot strike events.

$$S_{n_j}{}^2 = \frac{1}{n}\sum_{i=j}^{i=j+n}\left(x_i - \overline{x}_j\right)^2 \qquad (1)$$

$$\overline{x}_j = \frac{1}{n}\sum_{i=j}^{i=j+n} x_i \qquad (2)$$

The choice of sample size “n” that is used in the computation of variance affects the event detection. When we are using few samples, variance detects sharp changes in the signal with great amplitude. With a larger number of samples, variance is more sensitive to slower changes. We must carefully choose the sample size in order to detect gait events for many walking speeds. Figure 10 show the energy variance, with n=100 samples we can easily set a threshold value. Finally, in variance signals we can not only set a threshold value but also detect the rapid increase or decrease of the signal in order to identify the footsteps.

C. *Irrelevant event cancellation*

In figures 6 and 7 we can see a walking sample of a user that made four steps, encounter an obstacle and he was forced to turn and then he continued his walk for four more steps. The acceleration magnitude of his turn is comparable to his footstep acceleration value. This could trigger wrong footstep detections.

However we can see that in energy and product signals this event was diminished and it also has different waveform than the footsteps. Furthermore in variance signals, this turn event is reduced and a threshold value can be easily set above this event’s maximum value in order to correctly detect only the footsteps of the user. This further contributes to the effectiveness of this method to identify the desired events.

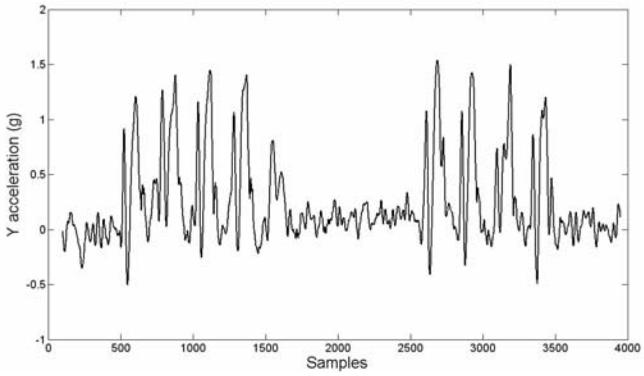

Fig. 6. Y acceleration signal of eight steps. A threshold value is difficult to be set.

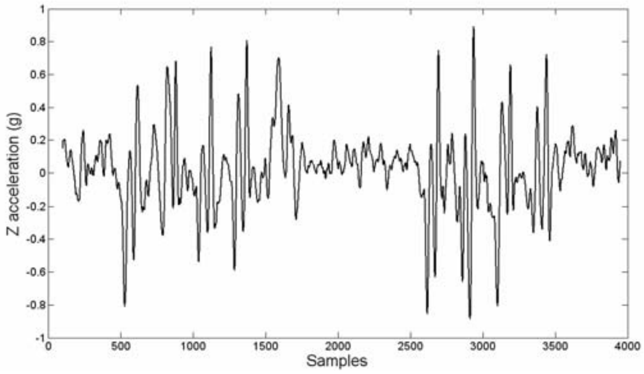

Fig. 7. Z acceleration signal of eight steps. A threshold value is difficult to be set.

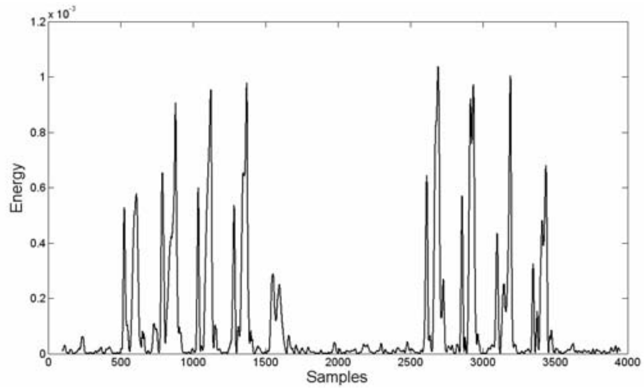

Fig. 8. Energy signal of eight steps. A threshold value is difficult to be set.

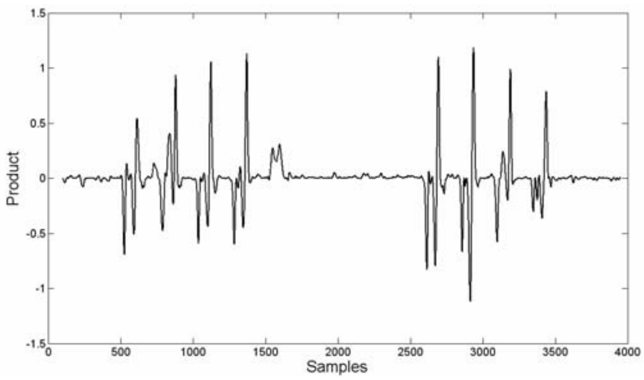

Fig. 9. Product signal of eight steps. A threshold value is difficult to be set.

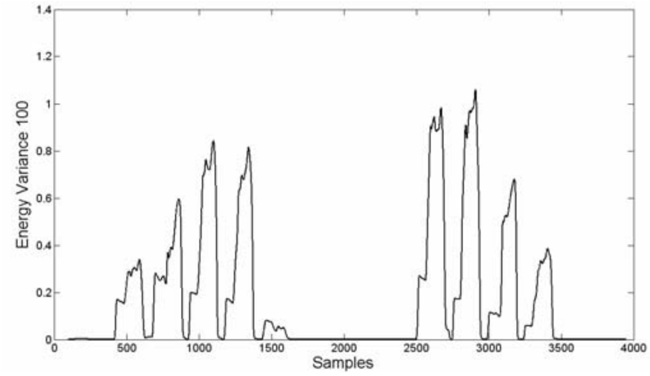

Fig. 10. Variance of an eight step energy signal. A threshold value can be set.

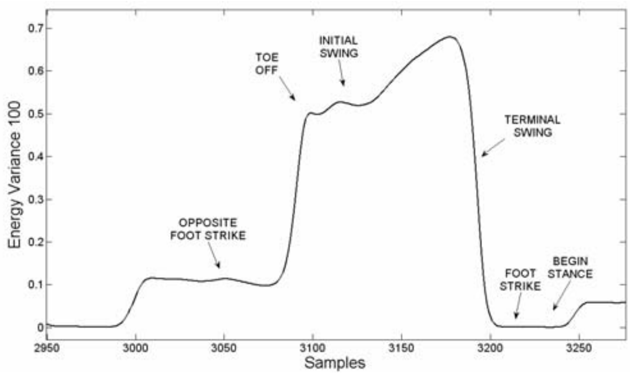

Fig. 11. Energy variance of one footstep.

VI. GAIT EVENT IDENTIFICATION PROCESS

A gait identification method can make use of the signal processing we have described, variance thresholds, extrema and the gait event sequence in order to identify the gait events.

First of all we use variance to isolate footsteps. With a carefully selected threshold value we can detect when the variance signal rises up and falls below the selected value. Alternatively we can search where there are rapid changes in variance signal. In energy variance signal in figure 11 we can see that the moment the signal drops rapidly the terminal swing event occurs. Furthermore at the end of the drop, we can identify the foot-strike event. Similarly, the rapid increase above the threshold value in energy variance signal, locates the toe off event.

Having located all the footsteps, we can now search in each one of them to identify the gait events. In product signal we can easily identify the terminal swing event as it has the maximum value. After the terminal swing event we can search for the first valley bellow zero and locate the minimum. This corresponds to the foot strike event. The begin stance event is now easily identified. We can search after the foot-strike event where the energy or product signal returns to zero.

In energy variance signal we have identified the general position of the toe off event. We use this information and we search before this event in the energy signal to find where the signal becomes zero. This spots the opposite foot strike event. For more accuracy we search in the energy signal for the first peak or in the product signal for the first minimum value below zero. This identifies the toe off event. In product signal, after the toe off event the signal rises rapidly. On the top of this rapid increase is the initial swing event.

VII. CADENCE COMPUTATION

Since we know the sampling frequency we can also calculate the user's cadence. We can select a time period, for example from sample s_1 to sample s_2. Since we know the sampling frequency we can calculate the time difference form s1 to s2. The cadence is the number of steps detected form s1 to s2 divided with this time difference. Then multiplying by 60 we calculate the cadence (steps/min).

VIII. FOOTSTEP DETECTION AGAINST OTHER MOVEMENT TYPES

For evaluating the performance of the system we examined footstep detection against other movement types. We took measurements of the following types of movements: running, running on the toes of the feet, shuffling the feet while slowly walking, walking with a strong pace and finally walking with a weight placed on the ankle of the foot. Figures 12, 13, 14, 15 and 16 show the energy variance of these measurements. We can see that the footstep detection algorithm can successfully detect the footsteps

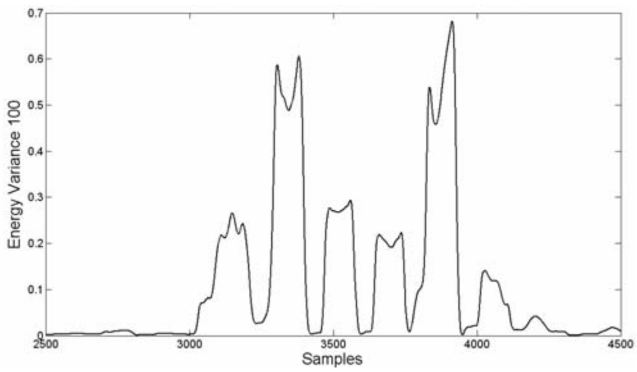

Fig. 12. Energy variance when running.

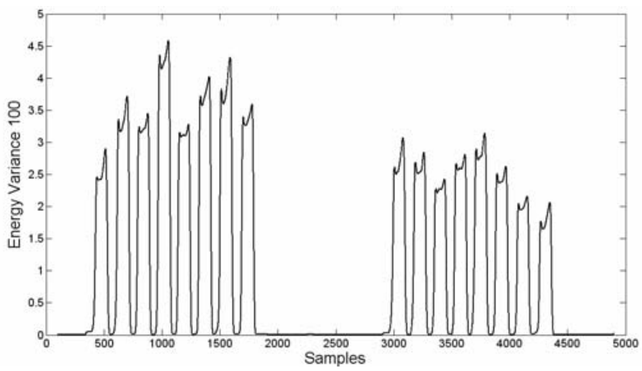

Fig. 13. Energy variance when running on the toes of the feet.

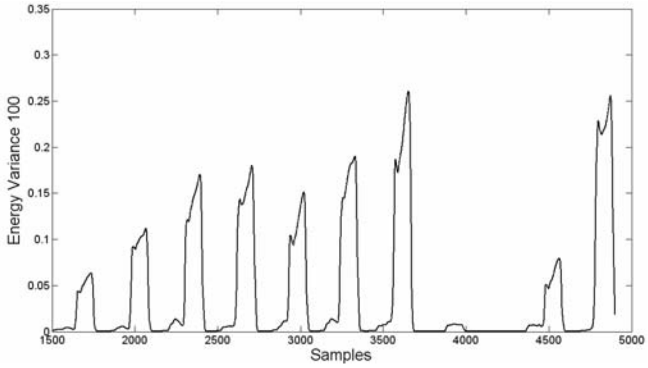

Fig. 14. Energy variance when walking with shuffling feet.

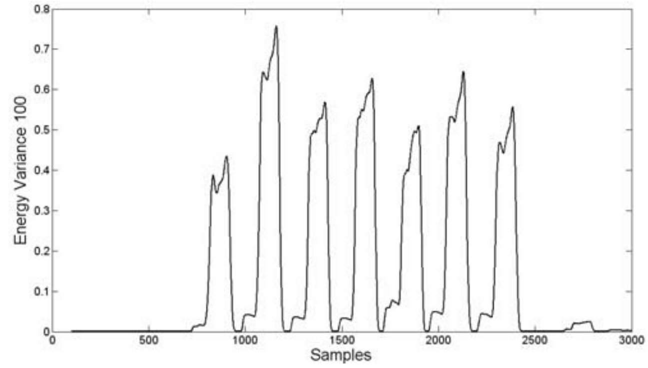

Fig. 15. Energy variance of a strong pace.

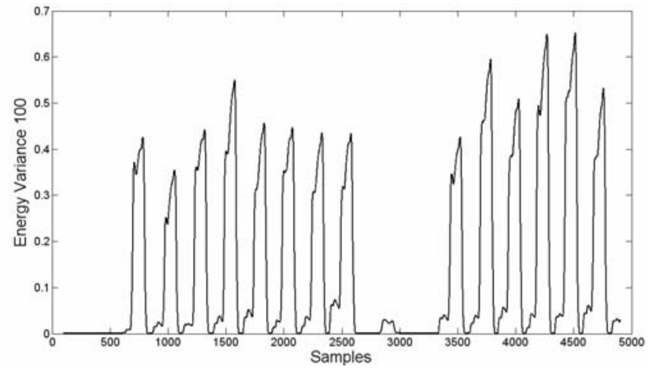

Fig. 16. Energy variance when a weight is placed on foot.

IX. CONCLUSIONS

Our system can successfully acquire and analyse in real time acceleration data. It can also detect footsteps in different types of movement and many different gait events. Due to the simple algorithms implemented there is no need for high computing power. The system is very small in size, energy efficient in order to operate for extended periods of time and without producing any discomfort. It can be placed in many places on the body including feet, joints, hands, head and waist. Finally, more algorithms can be implemented for the identification of more characteristics and features of the gait.

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