34th Annual International Conference of the IEEE EMBS
San Diego, California USA, 28 August - 1 September, 2012

Proof of concept of a shoe based human activity monitor

Ali Shad and Esther Rodriguez-Villegas, *Senior Member, IEEE*

Abstract— **This paper presents the proof of concept of a low power, low cost, wearable activity monitor. The functionality of the system is based on accurate stride detection from signals generated by two force sensing resistors integrated within a normal shoe. A novel algorithm is proposed that is able to differentiate between walking and non-walking activities with high accuracy. The performance of the proof of concept system was validated in five subjects who underwent five repetitions of three different speed walking tests, and five repetitions of five non-walking artefact generating tests. The system achieved a total sensitivity of 96% with 98% specificity and an overall accuracy of 94%.**

Keywords: *Activity monitor, walking, force sensing resistors, gait, wearable.*

I. INTRODUCTION

It is widely acknowledged that levels of physical activity can have a direct impact on human health. Lack of physical activity can, amongst others, significantly increase the risk of some of the most common causes of mortality in the developed world, such as cardiovascular diseases or cancer; as well as other conditions like diabetes or hypertension. Levels of activity can be quantified in different ways, with number of steps being one of the most commonly accepted ones [1].

In recent years sensors technologies developed for different applications within different fields have increasingly become smaller and cheaper. Many of these sensors are suitable and used for step detection. These include: foot switches [2], pressure mats [3], gyroscopes [4], inclinometers [5], global positioning satellites (GPS) [6], accelerometers [7] and force sensing resistors (FSR) [8]. Foot switches based systems have poor detection reliability, not being able to properly distinguish between a gait event and weight shifting or events such as tapping of the feet [9]. Inclinometers used on their own also suffer from a similar problem [5]. Pressure mats are impractical for non-medical use since they are sensors built into the external environment. Gyroscope based systems require more than one sensor within different positions of the leg to correct for drift caused by changes in the direction of motion [4]. Hence they are not the best option in terms of wearability. GPS based systems are very accurate up to 3m but do not work indoors and frequently lose the signal outdoors which hinders their usefulness [10]. Accelerometers are possibly the most popular choice, mostly in commercially existing systems due to their simplicity, affordability and ability to provide data in unrestricted environment. Accelerometer based step counters are generally accurate in ideal walking conditions and as long as the device is placed in optimal position but their accuracy can get significantly affected when used by the elderly or when, for example, the user is driving a car [11]. The system proposed here is based on the use of force sensing resistors (FSR). FSRs are a form of foot switch, but instead of only switching on or off on activation, their resistance is inversely proportional to the force applied. Hence the gait related information contained in this force can also be used to improve stride detection. FSRs also provide a good choice for wearable systems since due to their small size they can be placed in the insole of a shoe whilst still being unnoticeable to the subject. An additional advantage of having the sensors integrated into the shoes is that this does not require any variation in the user's daily routine activities. This can be of significant benefit if used to monitor levels of activity in the elderly.

E. Rodriguez-Villegas is with the Department of Electrical and Electronic Engineering, Imperial College London (e-mail: e.rodriguez@imperial.ac.uk).

II. THE SYSTEM

Work by [12] suggested that the minimum number of FSR required to detect strides is two. Keeping components to a minimum is important since cost is one of the constraints of the design. However, the combination of sensors plus signal processing must ultimately be able to accurately differentiate between stride based activities (walking, walking fast, running) and other types of motion activities (tapping of the toes, tapping of the heel, jumping..).

In the process of walking, a gait cycle is defined as the time from initial ground contact of one foot to subsequent ground contact of the same foot [12]. Due to subject specific variations in terms of for example weight, height and age, the ground contact is used to define the beginning of a cycle as this is a common feature found in all gaits. The gait cycle is subdivided into stance and swing phases. The period when the foot is on the ground is classified as the stance phase and begins with the ground contact. The swing phase begins when the foot is lifted from the ground and ends when it returns to it. A normal gait will have a symmetrical profile between left and right legs whilst an abnormal gait will have an asymmetrical profile. A complete gait cycle from the initial contact of the heel with the ground (heel strike) to another of the same foot is defined as a stride. A step, on the other hand, is classified with a heel strike of one foot followed by another heel strike of the opposite foot.

Previous work carried out with air pressure sensors [13] characterized the force distribution across the foot for the different gait events. It was shown that the greatest amount of force is applied to the heel and toe areas but not at the same time. Heel strike causes force to be concentrated around the ball of the heel. The largest force is during the loading response in the heel, since almost the entirety of body mass is being carried by it, with some force also being applied to the fifth metatarsal. Based on this information, in our system, the two FSRs sensors were placed as shown in Figure 1. Since the majority of the force is applied at the heel and toe during the stance phase, these are obvious location choices. By placing the sensor underneath the subject's first/second metatarsal forces could be measured across an area as large as possible. This particular placement of the sensor also helped to detect movement of the toe due to it being close to the hallux. The outputs of the sensors were connected to inverting amplifiers whose outputs were digitized and processed by an MSP430 low power microcontroller chip, interfacing with a microSD card. Note that in an alternative version of the system the microSD card could be substituted by a low power transmitter. In this implementation the former was chosen for the sake of simplifying the proof of concept design, since the latter put a bigger emphasis on algorithm performance than on system optimization.

Figure 1: Placement of the two force sensing resistors (FSR) in the insole of the shoe

III. ALGORITHM DESIGN

Despite there being a variety of gait detection algorithms, reliability and accuracy are commonly questioned [14]. The best result of algorithms processing signals solely obtained from FSR sensors has been reported in [8], which claims 94.5% sensitivity. This algorithm was based on individually adapted threshold detection. Despite of the overall result, it was clear from that work that threshold detection can pose a problem in situations where the FSR signal does not reach its threshold value in loading response, due to for example step-by-step variability in landing position of the foot.

The rationale of the algorithm proposed in this paper is described in the simplified flowchart in Figure 2. The algorithm is based on identifying the changing variance of both toe and heel signals, and by multiplying them together obtain an output which increases with large changes in both of them. Using a statistical function instead of just differentiation allows comparison of the signal with the points around it. Hence if over a period of time the toe or heel output voltages do not change very much and are of similar value, the moving variance will be low and close to zero. If, however, over the same period of time either of the output voltages drops sharply due to the subject entering a particular phase of the gait cycle, the moving variance will be high since each consecutive point is deviating further away from the initial value within the window.

In the final algorithm in order to account for inter-subject variations the combined moving variance is scaled by a coefficient which linearly decreases with the weight of the subject. Also, in order to eliminate small peaks due to small insignificant movements of heel and toe a constant threshold is introduced so that anything below it is considered as noise. In the same way to eliminate large peaks that can appear during jumping another constant threshold is introduced so that anything above it is considered as artefact. A stride is thus detected if there is a peak with a trough on either side, and each peak and trough is within the threshold limits specified.

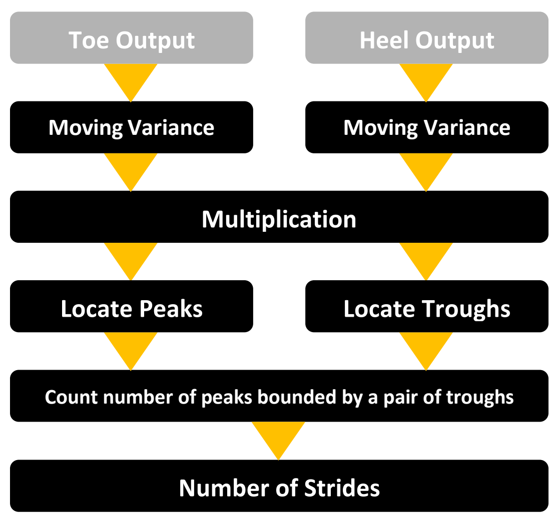

Figure 2: Simplified flowchart of the proposed algorithm

In order to illustrate how the algorithm works, Figure 3 shows the moving variance during a walking test (after filtering and scaling for better visualization). It can be seen how both heel and toe outputs follow very similar moving variance profiles. Both moving variance traces are initialized at zero since the subject is standing and there is no change in applied force. A small increase in output voltage of both toe and heel due to a reduction in force prior to the first stride correlates to a minimal increase in moving variance. When the first stride occurs, an increase in heel force during the initial contact and loading response causes the gradient of the heel output to become negative. The heel moving variance changes in response to this and increases in an opposite manner to the output voltage. Since in these gait events the toe does not exert any force and remains fairly constant, its moving variance remains at zero. As the heel output voltage approaches a minimum, the gradient becomes less steep, and the moving variance reaches a maximum, now having a negative gradient. The minimum of the heel output also causes a local minimum of the heel moving variance because the heel output has less of a deviation from its surrounding values. When the heel output has a positive gradient as the force applied starts to reduce, the moving variance pattern re-occurs in the opposite direction. The toe moving variance follows the exact same pattern as the heel. Mid stance can be detected when the toes moving variance increases from zero. By the time no heel force is applied and terminal stance is entered, the moving variance has returned to zero having created a double peak outline. Pre-swing occurs when the gradient of the toe moving variance is negative and swing can be seen when both moving variance traces are approximately zero. By multiplying the toe and heel moving variances, the period when both are exhibiting a large change, namely, during mid stance, can be used to characterise a stride. Note that the delay in the variance plot in Fig. 3 is due to a filtering effect.

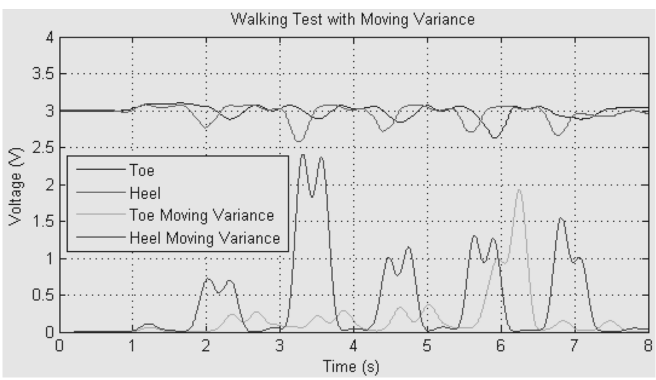

Figure 3: Walking test from subject 3 showing toe and heel moving variances

IV. RESULTS

In order to test the algorithm performance a experimental protocol was designed that aimed to both, reflect normal day-to-day walking activities, as well as potential non-walking artefacts. This protocol consisted of 8 different tests which are briefly described as follows:

Normal walk: The subject would start from a standstill and walk at a normal pace (~4kmph) for 4 strides; and on a final stride, keep the foot on the floor to return to a standstill.

Fast walk: The subject would start from a standstill and walk briskly (~6.5kmph) for 4 strides; and on the final stride, keep the foot on the floor to return to a standstill.

Run: The subject would start from a standstill and run equivalent to a fast jog (~9.5kmph) for 4 strides and on the final stride, keep the foot on the floor to return to a standstill.

Toe tap with heel in air: The subject would start with their toes on the ground and heel in the air and tap their toes on the ground, keeping their heel in the air, at a steady rate 10 times. The left foot should remain stationary.

Toe tap on floor: The subject would start with their foot on the ground and tap their toes on the ground, whilst not moving their heel, at a steady rate 10 times. The left foot should remain stationary.

Heel tap with toe in air: The subject would start with their heel on the ground and toes in the air and tap their heel on the ground, keeping their toes in the air, at a steady rate 10 times. The left foot should remain stationary.

Heel tap on floor: The subject would start with their foot on the ground and tap their heel on the ground, whilst not moving their toes, at a steady rate 10 times. The left foot should remain stationary.

Jump: The subject would start with their feet on the ground and jump 10 times at a steady rate, returning to a standstill on the final jump.

Five volunteers with weights $(62.5 \pm 7.5)\text{kg}$ were recruited each one of whom repeated each test five times. In order to simplify the experimental procedure, the same insole was used for each subject but the position of the sensors was adjusted appropriately to the subject's heel and first/second metatarsal positions in accordance to the difference in feet size. The insole was then inserted on top of the subjects' own insoles in their right foot. This added an extra 5mm between foot and the ground but did not affect the ground contact force nor cause any irregularity in gait. The performance of the algorithm was quantified using the following metrics:

- Accuracy = (TP+TN)/(TP+TN+FP+FN)
- Sensitivity =TP/(TP+FN)
- Specificity = TN/(TN+FP)

where a true positive (TP) is a stride correctly identified as a stride; a false positive (FP) is a non-stride incorrectly identified as a stride; a true negative (TN) is a non-stride correctly identified as a non-stride; and a false negative (FN) is a stride incorrectly identified as a non-stride.

The performance is illustrated in Figure 4 to Figure 6. Fig. 4 represents the algorithm sensitivity for all walking activities; whereas Fig.5 and Fig.6 show the specificity and accuracy across all the different tests respectively. It can be seen how the algorithm proves to have very high accuracies of over 90% for the walking activities and 94% overall.

Breaking down these results further, walking and fast walking tests have higher accuracies- 94% and 93% respectively- but running reduces the average by having an overall accuracy of 81%. Accuracy of non-walking activities is very high at 98%. The problem with running is that the gait cycle becomes shorter as the foot is in contact with the ground for a shorter time. This also has the effect of creating sharper toe ground contact forces in terminal stance and pre-swing creating a moving variance, which also rises, and falls very sharply. With a shorter gait cycle, the start of the next cycle approaches much quicker, preventing the moving variance from decreasing enough to register a trough and thus a stride. In an optimized version of the algorithm it might be possible to correct for this by dynamically adapting the thresholds as a function of the calculated walking speed. It should also be noted that the overall results get significantly skewed by the bad performance of the heel tapping test in subject 5 (82% accuracy as opposed to over 98% for all other subjects). The reason for this, observed in the individual waveforms, was that the subject was moving his toes whilst tapping with the heel on the floor. The application of significant instantaneous force by both heel and toes at the same time resulted in sharp increases in moving variance and consequently false positives. If this motion is fast and repetitive then a trough will not be detected and thus neither a stride. On a one-off basis, however, the algorithm may struggle to detect a simultaneously anomalous heel and toe force as a true negative. Despite this result, it is worth pointing though that this is hardly ever a normally occurring situation.

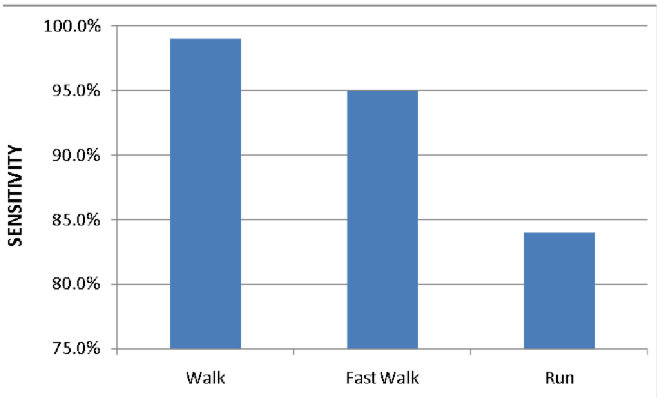

Figure 4: Algorithm sensitivity for walking activities

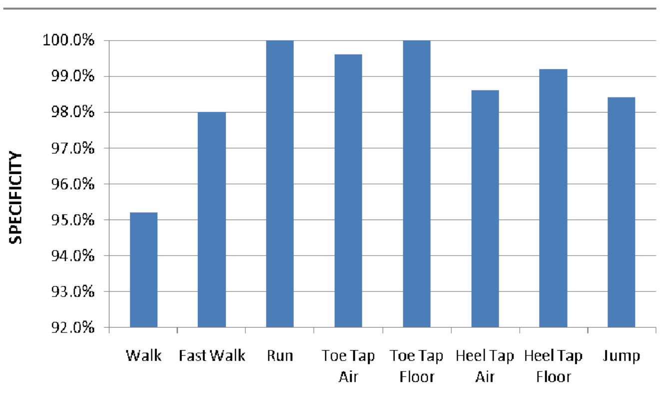

Figure 5: Algorithm specificity for the different tests

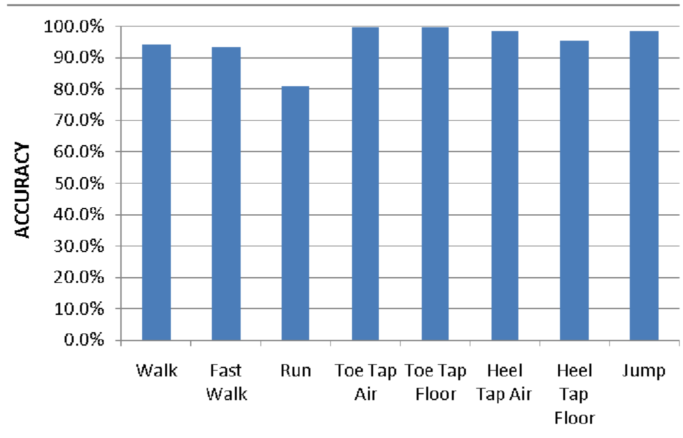

Figure 6: Algorithm accuracy for the different tests

V. CONCLUSIONS

The algorithm used in the shoe-based activity monitoring system presented in this paper has proven to be effective in accurately determining the number of strides taken by a subject, with 275 out of 300 strides being correctly detected. Additionally the algorithm has also proven to perform well against detection of false positives in non-walking activities with an overall specificity of 98%. This proves the hypothesis that an accurate measure of the number of strides taken can be carried out with just two force sensing resistors. This method is however not able to classify different gait events or determine the start and end of a gait cycle.

REFERENCES

[1] Tudor-Locke C, Bassett DR Jr. "How many steps/day are enough? Preliminary pedometer indices for public health," *Sports Med.*, 2004.

[2] Pappas IPI et al. "Surface-Stimulation Technology for Grasping and Walking Neuroprostheses," *IEEE Eng. Med. and Biol.* , Jan 2001.

[3] DeLisa JA. "Gait Analysis in the Science of Rehabilitation," *Dep. of Veterans Affairs, Veterans Health Administration*; 1998.

[4] Tong K, Granat MH. "A practical gait analysis system using gyroscopes," *Medical Engineering & Physics*, 87-94, March 1999.

[5] Dai R et al. "Application of tilt sensors in functional electrical stimulation," *IEEE Trans. on Rehabilitation Eng.*, 63-72, June 1996.

[6] Terrier P, Schutz Y. " Variability of gait patterns during unconstrained walking assessed by satellite positioning (GPS)," *European Journal of Applied Physiology*, 554-561,2003.

[7] Williamson R, Andrews BJ. "Gait Event Detection for FES Using Accelerometers and Supervised Machine Learning." *IEEE Transactions on Rehabilitation Engineering*, 312-319, Sep. 2000.

[8] Smith et al. "Evaluation of Force-Sensing Resistors for Gait Event Detection to Trigger Electrical Stimulation to Improve Walking in the Child with Cerebral Palsy," *IEEE Trans. on Neural Syst*, Mar2002.

[9] Pappas IPI et al. " A Reliable Gait Phase Detection System, " *IEEE Trans. Neural Systems and Rehabilitation Eng.*, 113-124, June 2001

[10] Piras, M.; Cina, A., "Indoor positioning using low cost GPS receivers: Tests and statistical analyses," *IPIN*, 15-17 Sept. 2010.

[11] C G Ryan et al. "The validity and reliability of a novel activity monitor as a measure of walking" *Brit. Jour. Sports Medic.*,2006

[12] Skelly MM, Chizeck HJ. "Real-Time Gait Event Detection for Paraplegic FES Walking," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 59-68, March 2001.

[13] Kong K, Tomizuka M. "A Gait Monitoring System Based on Air Pressure Sensors Embedded in a Shoe," *IEEE Transactions of Mechatronics*, 358-369, June 2009.

[14] Senanayake CM, Senanayake A. "Evaluation of Gait Parameters for Gait Phase Detection during Walking," *IEEE MFI*, 127-133, 2010.