Analysis of Foot-pressure Data to Classify Mobility Pattern

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***Abstract*—The pressure exerted by foot, while a person is standing still for a while or moving or doing any physical activity, is a rich source of information. The continuous signal obtained throughout the day, collected by pressure-sensors on shoe sole, could be analyzed to obtain simple to complex facts about the person's health conditions and habits. It could be used to measure body-weight and balance, while the person is standing. It could as well be used to find the total calorie burnt during movement activities throughout the day. Varied applications would need different number of sensors spread over inside or outside the shoe-sole. In this work, we restrict our investigation to simple applications like, measuring the body weight when the person is standing still, or the speed when the person is moving, or whether she/he is climbing up or down the stairs. Our aim is to use as few sensors as possible, and the algorithm simple and efficient. For measuring body-weight and movement speed, we could achieve nearly 100% accuracy. We could also classify between climbing up or down the stairs with 100% accuracy. All these could be accomplished by a single or a pair of sensors. It is also revealed that the optimum location of the sensor/s for the highest accuracy varies from person to person.**

***Index Terms*—Foot pressure data, Resistive sensor, Fast Fourier Transform, Artificial Neural Network.**

I. Introduction

With aging population growing in the rich world, health and wellness of the whole population in general and the aged people in particular, is one of the main social concern. Middle to old age people are adapting to a regimented lifestyle with exercise and healthy food. One of the safest and broadly advised exercise is walking and jogging. There are many instruments, with levels of sophistication, to measure calorie burnt during such activity, or over the day. Most of them are either cheap, crude and inaccurate, or costly and clumsy to wear. The motivation of this project is to embed this gadget with things we use in our daily life. A few thin sensors on shoe sole will collect the foot-pressure data, which will then be wireless communicated to smart phone for analysis. Smart phone will be used for user interface too.

One can imagine various applications using pressure data from shoe-sole. It is possible to predict the probability of fall and prevent such accidents. At present, personalized foot orthoses design is tedious, and is based on static data. Dynamic foot pressure data, collected during walking, could make the design better. Collection and analysis of real-time foot-pressure time-series data can be successfully used to help athletes to correct stance and improve performance. It is possible to calculate the calorie burnt over a period of time, while various activities like walking, jogging at various speeds etc. are combined.

The F-scan system [1], using very thin sensors placed inside footwear, could capture dynamic shoe insole pressure information. The Fscan system collects pressure data over the whole region of the foot. It can be used as a diagnostic tool by medical practitioner or by researchers. For most of the applications though, we hardly need so much information. The enormous volume of data is difficult to analyze real time using cheap processor and small memory, like the one available on smart phones. In addition, its prohibitive price restricts its possibility for wide-spread use. Our research target is to explore possible applications using single point pressure sensor/s. For different applications, the optimum locations for the sensors would be different, to gather relevant data. The motivation of this investigation is to know the minimum number of sensors needed for analyzing mobility speed, and locations of those sensors. We used several point pressure sensors to investigate which ones are important when the target application is to classify the mobility speed and whether the subject is using staircase or not. We tried different preprocessing and feature extraction techniques to minimize classification error. It was revealed that the optimum location to collect data is different for different subjects.

The rest of this paper is arranged as follows. Section II describes in brief the system and hardware used to collect data. Section III discusses about preparatory experiments done with different sensor locations, the features extracted for classification, including the classifiers used. Finally, in section IV, we summarize the present status of the work, and comparing the results with our previous work. We conclude the paper in Section V.

II. Experimental Setup and Hardware Description

We used low cost linear response resistive sensors manufactured by tekscan [2]. Multi-ELF system from tekscan is suitable to collect real-time dynamic pressure data from 6 point sensors simultaneously. The resistive sensors are connected to USB-handles. The sampling rate of the data collection could be as fast as 1024 Hz. The whole assembly is available off-the-shelf. A pressure sensor attached to a handle is shown in

Fig. 1. The handle is the hardware to facilitate interconnection between the pressure sensor to a USB port. We attached pressure sensors on the shoe insoles with adhesive tape, as shown in Fig. 2. Data was collected from different subjects while they were walking, jogging and climbing stairs.

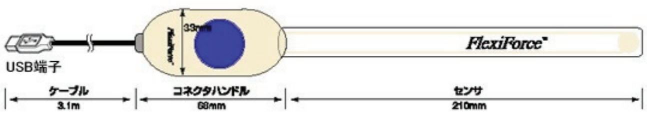

Fig. 1. FlexiForce Sensors and handle from TekScan

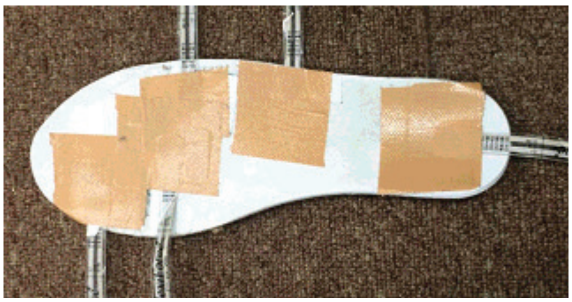

Fig. 2. Five sensors attached to shoe insole

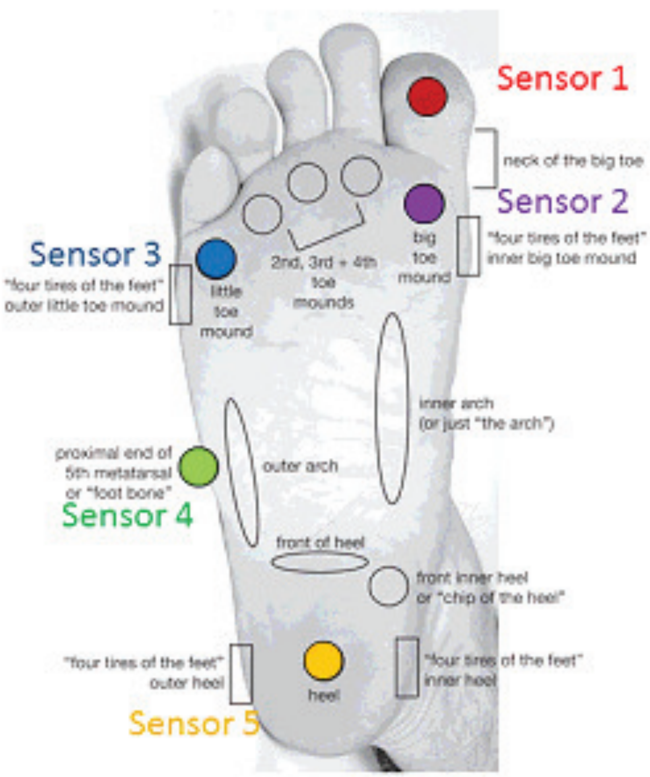

Fig. 3. Position of the five sensors

A. Sensor Locations

The motivation is to analyze the collected time-series pressure data to investigate how does it changes its characteristics from walking to jogging, or when someone uses staircase. These preliminary experiments were done with five sensors, the first one attached to the big-toe, the second one at the big-toe mound, sensor 3 is located at little-toe mound, the fourth sensor is at the outer arch and the fifth one is under the heel. The positions of the five sensors are shown in Fig. 3. Different handles collect data simultaneously, from five different sensors.

III. Feature Extraction and Classification

In this section, we will describe how the features are selected from the pressure data, and how they are classified. Though not shown here, the raw data collected from different sensors have different shapes, with a time correlation among them. In addition, the shape and correlation change with speed of movement. As expected, the period is reduced as the speed increases. To accurately extract the information from this multivariate time-series data, various preprocessing and feature extraction techniques are available. In our previous work [3], we separated the non-zero part of the pressure signal (one block from each step) and used wave-let transform on that. For example, if we collect data for 2 minutes, and the period is, say, 1 Second per step, we get 120 samples. As wave-let transform could capture the instantaneous frequency components, the extracted features could capture enough information about the shape of the pressure change over the time the foot is touching the ground. We did not include the interval between two steps, and thus step-period information was not used. Wave-let transform is computationally complex, and the number of features were large. Thus, classification was difficult. The results of the previous work [3] are briefly mentioned in section IV.

In this work, we will experiment with simple, efficient feature extraction algorithms. In addition, we increased the number of sensors, from 3 to 5, to investigate whether optimum sensor locations vary from person to person, by performing experiments and analyzing the results. The classifier used is multi-layer perceptron (MLP) trained using error back-propagation. Once trained, MLP can perform classification very efficiently. We discuss the feature extraction and classification algorithm in the next section.

1) Feature extraction: Fast Fourier Transform (FFT) is widely used and an efficient method to capture frequency components of a signal. By FFT, instantaneous dynamic behavior of the signal can not be captured though. We have in our mind to implement the whole system on a small mobile device like a smart phone. FFT is fast, and we did preliminary experiments to ensure that it could deliver satisfactory results for our purpose. FFT outputs frequency components and their corresponding amplitudes, present in the signal. We do not use any preprocessing technique, like selecting only the portion of the data when the pressure value is non-zero, as was done in our previous work [3]. Time-series pressure data was directly fed to the FFT. All frequency components of its spectrum were not used as features, as will be explained next.

Fig. 4 shows the result of FFT transform on the raw-pressure data. The signal collected during a period of 2 mins. is input to FFT. The upper graph is when the subject is walking at 5km/h, and the lower one is when the subject is running at 10km/h. From the FFT results, we clearly see that lower the speed is, lower are the FFT frequency-components with higher energy. Thus, the frequency components could be used to classify the speed.

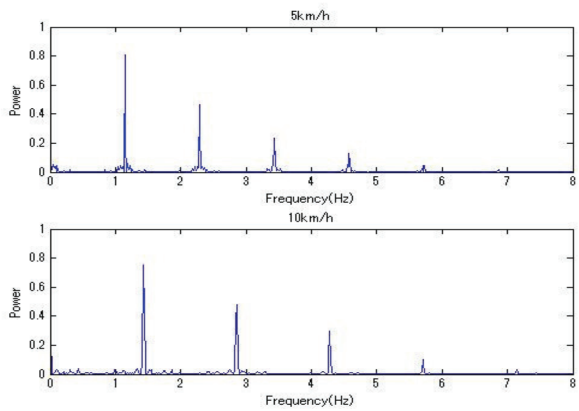

Fig. 4. FFT result - signal of 2 mins. duration is used

The output of FFT is a two-dimensional array of frequencies and their corresponding amplitudes. As we see in Fig. 4, there are a few prominent peaks, where the energy of the signal is concentrated. If we use the whole output from FFT, the feature vector will be too long, and modeling the classifier will be difficult. We identify the peaks and use that information, instead of the whole spectrum. That way, the number of features is much reduced.

As shown in Fig. 5, we see that two characteristics features could be important for speed classification, the peak amplitude values and the corresponding frequencies. We can visually observe that the first five peaks are prominent. If we limit our range to the first five locally strongest peaks, we get 10 features from every sensor. As we used five sensors, the dimension of the feature vector will be 50. We investigated whether all the five sensors are necessary or not. As we will see in Section IV, that it is not. We also tried to reduce the number of features further by using only the frequency values of the peaks. The result was worse. Results in Section IV are obtained when both frequency and amplitude were used as features.

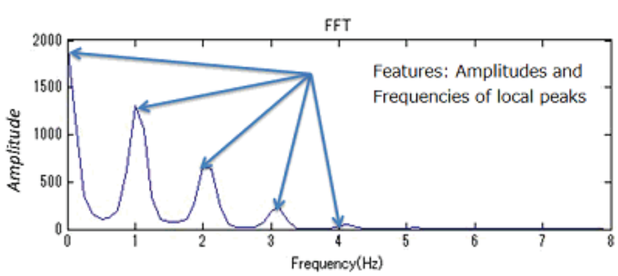

Fig. 5. Frequency Spectrum of the pressure signal

We look for a computationally simple algorithm to find the spectrum peaks and their corresponding frequencies. The method is explained in Fig. 6. There are major peaks (strongest in its neighborhood) appearing at regular intervals, as well as minor peaks in between. The aim is to pick-up the first five major peaks. A straight line is drawn, from the peak at frequency zero (DC value), to 6 Hz. or 7 Hz. (it does not matter). We calculate the difference between that of the straight line and the frequency spectrum values at all frequencies in the spectrum. Crests at major spectrum peaks will clearly emerge, as lowest difference points in their vicinity. From that, we find the spectrum peaks and their corresponding frequencies. We get 10 features from a single sensor data.

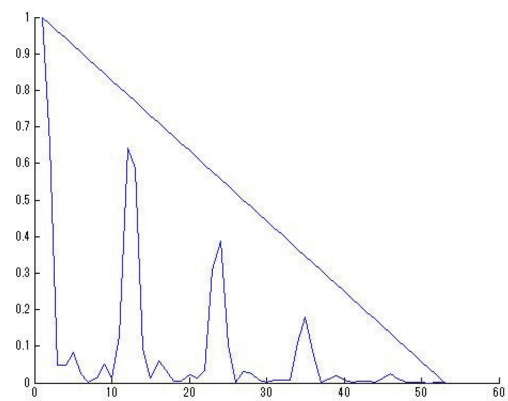

Fig. 6. Algorithm for Identification of peaks

A. Sample Data Generation

For every subject, with fixed speed of walking/jogging, we extracted a clean 2 mins. pressure data, from which we generate our samples to train the classifier. In the previous section, shown in Fig. 4, this whole 2 mins. pressure data was used for FFT. To train and test the classifier, we need many samples. We divide the whole data into small windows, run FFT on that window of interval, and slided the window slowly so that we get many samples. The detail is explained in the following.

The sampling rate at which pressure data was collected, was 64 Hz, i.e., 64 discrete samples were recorded every second. Data was collected from one foot, the right one. If the window interval is too small, say 2 seconds or less, it can not contain many important information like period of the steps etc. In addition, different window will contain different section of a whole period of change in the signal character. On the other hand, if the window interval is too long, the number of samples generated will be too small to train the classifier properly. It is therefore important to find the minimum window interval, which captures enough information about the pressure signal. We find it in an exhaustive way, slowly increasing the window length and checking the classification result. By classification result, we mean the percentage of time the trained classifier could correctly classify the speed of motion. As the window length increases, the accuracy of classification increases, but stabilizes at a certain window length. Increasing the time-duration of the window more than that do not improve the result any more.

Table I shows the experimental results, as the window length is increased. The sampling rate is 64 Hz. Therefore, window length of 128 samples means, it is 2 seconds in duration. Similarly, 256 samples means the window length is 4 seconds. We can see that at 512 samples length, i.e., when the window length is 8 seconds, we get the best classification result. Beyond that, the accuracy is decreased. One possible reason is that the number of samples is low for proper training. In this experiment, we have used nine-tenth of the data for training and the rest for testing. This is done for once only. Cross-validation would give more reliable result. Yet, the results conclusively indicates that the window length of 512 is optimum. Here, we would also like to mention that, as we used CooleyTukey algorithm [4] for FFT, we need a window size in power-of-two. The results of classification accuracy, with different window sizes, are shown in Table. I. With 120 seconds of the whole data, window size 8 seconds, and sliding at a rate of 2 seconds, we get 57 samples from each collected data.

TABLE I
RESULT

	Subject A		Subject B		Subject C	
	Ave	Std	Ave	Std	Ave	Std
128samples	52.2	0.2	51.1	0.2	72.2	0.1
256samples	70.0	0.2	74.4	0.2	71.1	0.2
512samples	82.2	0.1	83.3	0.1	82.2	0.2
1024samples	78.9	0.2	75.6	0.2	77.8	0.1

B. Classifier

We used multilayer perceptron classifier [6], to classify whether the subject is walking or jogging or using a staircase. For every subject, we used separate classifier, which is trained by the data collected from that subject. The structure of a MLP is as shown in Fig. 8. We need a set of samples with known classes, which are used for training the connection weights between nodes of different layers. After the data is collected and normalized, part of the data is used to train the network. The rest, not used during training, are so called test data. As our model is fixed (with fixed number of hidden layer nodes), we do not need validation data. The generalization performance of the classifier is tested by recording correct classification using the test samples. We performed 10-fold cross-validation. Out of 57 samples, 5 or 6 samples are set aside for testing and the rest is used from training. The experiment is repeated 10 times, by changing the set of test samples. All the results in section IV are the average of ten runs of 10-fold cross validation.

As shown in Fig. 7, the classification is done in two steps, separate walking from using stairs in the first step, shown as ”*Walk or stair*” in the flow-chart. In case, it is identified as walk (or run), the speed is determined, in box ”*Walking Velocity*”. In case of using staircase, it is determined whether the subject is climbing up or down the stairs, in the box ”*Up or down the stairs*”.

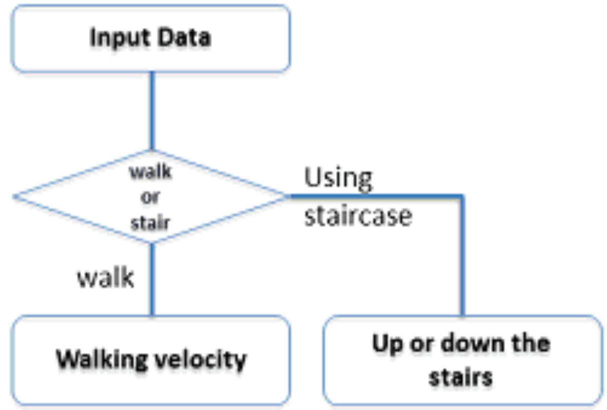

Fig. 7. The Flow-chart of the algorithm

The detail of the classifier, ”*Walking velocity*” is shown in Fig. 8. The classifier is an artificial neural network, trained by error back-propagation [6]. As the number of features are 50, we have 50 input nodes plus one for bias. The feature values extracted from the data are fed at input nodes. The number of hidden units used were 10. As we classify 6 different speeds, we have six outputs. For every set of data, training and testing is done 10 times, as 10-fold cross-validation, and the average is presented as the final classification rate.

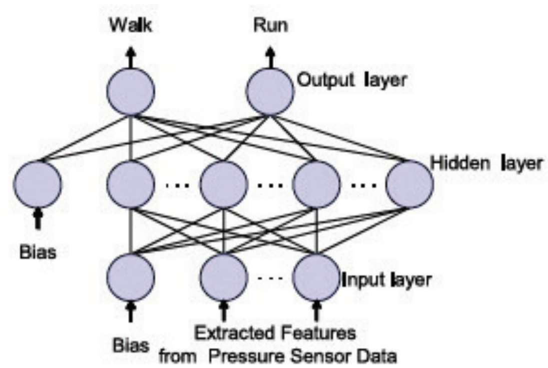

Fig. 8. The structure of the Neural network used for classification

IV. EXPERIMENTS AND RESULTS

A. PREVIOUS WORK

In our previous work, we used wavelet transform on segments of the signal, for the time when the foot is in contact with the ground. For a single session of data collection, while jogging at a specific speed, we get many data, as every step generate one data. Stable signal, from three sensors, collected for a period of about 2 mins., were used. The sampling rate was 64 Hz.. The number of steps varies with the speed, and ranges between 0.75 steps/second while walking to about 1.4 steps/second while jogging. The exact number changes from person to person. On the other hand, while walking the foot touches the ground for a longer period of time. For a session of walking with a specific speed, we get about $0.75 \times 120 = 90$ steps of data, while jogging for the same period we get about $1.4 \times 120 = 168$ number of foot steps of data. We extract feature vector from every step, for the duration while the foot is touching the ground. That part can be easily extracted from the whole data signal. For walking, this duration is about 1 Sec., while for running it is much less. We use wavelet transform with 7 frequency bands, 0-1 Hz, 1-2 Hz, ..., 6-7 Hz. To decide the suitable bandwidth, we FFT the whole signal, and found that most of the energy lies within 7 Hz. The result of wavelet transform will give the signal strength at different frequency bands at time instants. Data were taken at speed intervals of 2 Km/h. MLP trained by Error-Back-Propagation was used for classification. We used 10-cross validation. Classification accuracy of nearly 80% or more, for the test samples were achieved. The results, as shown in Table. II, were good and stable, though complex and computationally heavy.

TABLE II
RESULTS WITH FEATURES EXTRACTION USING WAVELET TRANSFORM

	Subject A	Subject B	Subject C
Average	81.33	79.17	85.5
Std	0.102	0.105	0.105

B. Present work and results

1) Experimental details: The motivation of this work is to classify whether a person is moving or using a staircase. Further, to determine the speed of movement when the person is walking or jogging, and climbing up or down the stairs, when using staircase. For movement, we use speeds from 5 Km/hr. to 10 Km/hr., with increments of 1 Km/hr. Five subjects, all male, age between 20 to 24 years, participated in the experiment. They were asked to run on a trade-mill machine, whose speed can be controlled accurately. Data for every step, i.e., 5 Km/hr, 6 Km/hr. and so on, are taken. For every speed, data is collected for 3 to 4 mins., from which data of 2 mins. duration is truncated and used. Similarly, all the five subjects were told to use staircase of 84 steps (in 6 blocks) and the data was collected.

In a separate experiment, 10 subjects, who are different from the 5 subjects above, are told to stand still, and the data is collected from the sensor attached to the heel. They are plotted and connected by cubic spline. Using that chart, the weight of the 5 subjects were calculated. The result closely tallied with actual body weights.

2) Result: In Table. III, the classification result for every cross-validation test, for subject B, is shown in detail. As we can see, when the actual walking speed is 5 KM/hr., it was incorrectly classified as 6 Km/hr. only once. Similarly, for 6 Km/hr. only once it is mistaken as 7 Km/hr. But, while we calculate the percentage of correct classification, a mistake is always counted as 1, irrespective of the fact that the absolute error in classification is small. Of course, we can calculate in terms of absolute error, as in the following equation.

$$Error = \frac{\Sigma |\frac{Correct\ data - Output\ data}{Correct\ data}|}{Number\ of\ data} \tag{1}$$

TABLE III
SPEED CLASSIFICATION RESULTS FOR SUBJECT-B (KM/H)

Correct value	5	6	7	8	9	10
Obtained Value	5	6	7	8	9	10
	5	6	6	8	7	10
	5	6	6	8	7	9
	6	6	7	8	9	10
	5	6	7	8	9	10
	5	6	7	8	9	10
	5	6	7	9	9	10
	5	6	7	8	9	10
	5	7	7	8	9	10
	5	6	7	8	9	10
Std. deviation	0.3	0.3	0.4	0.3	0.0	0.3

In Table. IV, we show classification results when data from a single sensor is used for classification of walking or running speed. The two best classification results, for a particular subject, are written in bold letters. For example, for subject A, sensors 1 and 2 delivered the best results. On the other hand, for subject B, they are sensors 1 and 4. We can easily notice that the best two sensors are different for different subject. In the last row, we combine the features obtained from the best two sensors (makes the feature vector of length 20), and perform training and classification. Those results are depicted in the last row. Of course, this does not ensure the best from all possible two-sensors combination. To avoid the combinatorial searching complexity, we took this easy method. Even then, we could get classification result of nearly 90%.

TABLE IV
RESULT OF SPEED MEASUREMENT - BEST SENSOR LOCATIONS FOR DIFFERENT SUBJECTS

Subject →	A	B	C	D	E
Sensor1	**73.8**	**81.3**	77.0	62.2	70.0
Sensor2	**74.5**	78.7	**81.0**	70.2	69.3
Sensor3	72.3	65.0	67.8	64.2	**80.3**
Sensor4	72.3	**84.3**	80.7	**72.5**	**79.8**
Sensor5	55.8	78.7	**92.7**	**78.2**	71.2
Combine 2 best sensors	**85.7**	**91.5**	**95.0**	**94.0**	**92.2**

Table. V shows the result of classification, whether the subject is climbing up or down the stairs. Results while a single sensor is used is shown in the first five rows. Please note that the bold figures, in this table, are not the best classification results. We marked bold the same sensors, which were selected in Table. IV. The reason is that we restrict the number of sensors to be two. Speed classification is given priority, because it is more difficult. In Table. V, even though the two best performing sensors are not selected, the classification result is still 100% or nearly so.

TABLE V
RESULT OF CLASSIFICATION OF CLIMBING UP OR DOWN THE STAIRS

Subject $\rightarrow$	A	B	C	D	E
Sensor1	**92.5**	**94.5**	96.5	86.5	97.0
Sensor2	**88.0**	89.0	**97.0**	99.5	88.0
Sensor3	97.5	98.5	95.5	100	**86.5**
Sensor4	96.5	**99.0**	86.5	**100**	**97.0**
Sensor5	98.0	96.5	**95.0**	**100**	97.5
Combine 2 best sensors	**100**	**100**	**100**	**100**	**97.0**

V. CONCLUSION AND FUTURE WORK

The important results we could achieve are:

1) It is possible to accurately classify the speed of walking or jogging.
2) Only two pressure sensors are sufficient to achieve a classification accuracy of 90% or more.
3) The location of the sensor, to gather the best data for speed classification, are different for different subjects.
4) Misclassifications are tolerable, as they lie within ± 1 Km/Hr of the correct value.
5) We could classify whether the subject is climbing up or down a staircase, with 100% accuracy.

From the above results, it is possible to design a shoe, that would give the calorie burnt over a period, combining different activities classified correctly during that period. To implement such a shoe, the technology is already available. It is easy to install a rechargeable cell (Ni-Cd or Nickel Metal Hydride) in the shoe-heel. The pressure sensor would then be able to communicate with the user's smart phone using blue-tooth. The burnt energy in a day could be calculated on the smart phone, and stored for further use.

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