SAS 2007 – IEEE Sensors Applications Symposium
San Diego, California USA, 6-8 February 2007

Adaptive Step Length Estimation Algorithm Using Low-Cost MEMS Inertial Sensors

S. H. Shin, *Student Member, IEEE* and C. G. Park, *Member, IEEE*
J. W. Kim, H. S. Hong and J. M. Lee

***Abstract*— In this paper we introduce a MEMS based pedestrian navigation system (PNS) which consists of the low cost MEMS inertial sensor. An adaptive step length estimation algorithm using the awareness of the walk or run status is presented. Future u-Health monitoring systems will be essential equipment for mobile users under the ubiquitous computing environment. It is well known that the energy expenditure in human walk or run changes with the speed of movement. Also the accurate walking distance is an important factor in calculating energy expenditure in human daily life. In order to compute the walking distance precisely, the number of occurred steps has to be counted exactly and the step length should be exactly estimated as well. However the step length varies considerably with the movement's speed and status. Therefore, we recognize the movement status such as walk or run of a pedestrian using the small-sized MEMS inertial sensors. Based on the result, a step length is estimated adaptively. The developed method can be applied to PNS and health monitoring mobile system.**

***Index Terms*— Adaptive algorithm, Step detection, Step length estimation, Pedestrian, PNS**

I. Introduction

Future u-Health monitoring systems will consist of low-power on-body wireless sensors attached to mobile users that interact with an ubiquitous computing environment. It is well known that the cost of energy expenditure in human walking changes with the speed of movement. Also the accurate walking distance is an important factor of the calculating energy expenditure in human daily life. Recently pedestrian navigation system (PNS) has been researched actively. PNS is one of many applications based on the MEMS accelerometer and gyro. Also PNS is very useful in providing the human's walking distance regardless of indoor or outdoor.

The portable navigation system has been developing based on the E911 (Enhanced 911) implementation requirements that were reported by the Federal Communication Commission (FCC) in 1996. This set out explicitly defined requirements that position information for emergency calls made from mobile phones must be transferred to the 911 public safety answering point (PSAP) with an accuracy of 67% CEP 50 m and 95% CEP 150 m. The portable navigation system has been implemented using GPS, CDMAs pilot signals, AGPS/TDOA, etc. However, these techniques have several limits such as restrictions on the use of GPS signals, many error sources in the CDMA signals, etc.

Another research area for the navigation system is MEMS based pedestrian navigation system. In recent years, MEMS technology has allowed production of inexpensive lightweight and small-size inertial sensors with low power consumption. These are all desirable properties for components of a portable navigation system. The quality of the MEMS inertial sensors is, however, conspicuously low. So, a new algorithm is required to enhance the performance of the portable navigation system implemented using the MEMS inertial sensors. The technical limit and necessity led the development of algorithms for PNS. Provided that a pedestrian moves only by walking behavior, PNS is based on the step information, which can be obtained using inertial sensors. The main idea is to find accurately the walking distance from the number of steps and the estimated step length. PNS can be utilized anywhere, anytime and any circumstances because it is autonomous and not susceptible to external jamming.

One of the key difficulties in PNS is to estimate the step length according to the status of walk or run. Various systems and algorithms for PNS have been introduced. Most of the proposed methods utilize inertial sensors and step detection algorithms. *Jirwimut* modeled the step length error as a first-order Gauss-Markov process, and the step length is estimated using a Kalman filter and GPS [1]. The step length is modeled as a linear combination of a constant and step frequency [2], as that of a constant, step frequency and variation of the accelerometer [3,4], or as that of a step frequency, variance of the measured acceleration magnitude and the vertical velocity [5]. *Fyfe*, *Sagawa* and *Cho* calculated the step length by integrating the accelerometer and compensating for the bias using the information that the velocity of the foot is zero when the walking phase is a stance phase [6,7]. *Gabaglio* modeled walking speed as a linear combination of a constant and a function of acceleration

S. H. Shin is with the Navigation Electronic System Laboratory, School of Mechanical and Aerospace Engineering, Seoul National University, SEOUL, 151744, KOREA (e-mail: mad2407@snu.ac.kr)

C. G. Park is with the School of Mechanical and Aerospace Engineering , Seoul National University, SEOUL, 151744, KOREA (corresponding author to provide phone: 82-2-880-1675; fax: 82-2-888-7958; e-mail: chanpark@snu.ac.kr; homepage: http://nesl.snu.ac.kr)

J .W. Kim, H. S. Hong and J. M. Lee is with Advanced Technology Lab, Telecommunication R&D Center, Telecommunication Network, the Samsung Electronics Corporation Ltd., SUWON, 443742, KOREA (e-mail: jinwon_kim@samsung.com, hyunsu.hong@samsung.com and jm00.lee@samsung.com)

variability [8]. *Aminian* proposed a neural network to estimate the inclination and the walking speed [9].

The research about the awareness of the user's context has been performed. Attempts have been made at recognizing user's activity from accelerometer data [10,11]. Bao & Intile have used 5 biaxial accelerometers on different parts of the body as they performed a variety of activities like walking, sitting, running, etc[12]. Lukowicz & Ward have developed the recognizing workshop activity using body worn microphones and accelerometers[13].

In this paper we propose an adaptive step length estimation algorithm for PNS with a movement status (walk or run) awareness algorithm of pedestrians. Section II describes the PNS hardware module. In section III, the step detection and step length estimation algorithm we used are introduced. Section IV presents how to recognize the movement status of walk or run. Finally, the conclusions are drawn in Section V.

II. SYSTEM DESCRIPTION

So far, several types of PNS are proposed on the papers and patents [3,4,5,6,7]. The system can be attached on the waist, the thorax, the shoe, etc. The proposed system consists of an IMU (Microinfinity, MI-A3330LS-U) and a bluetooth module (Comfile Technology AIRCODE300).

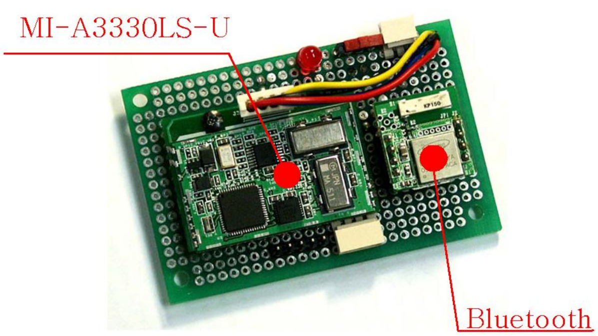


Figure 1. The sensor module for PNS.

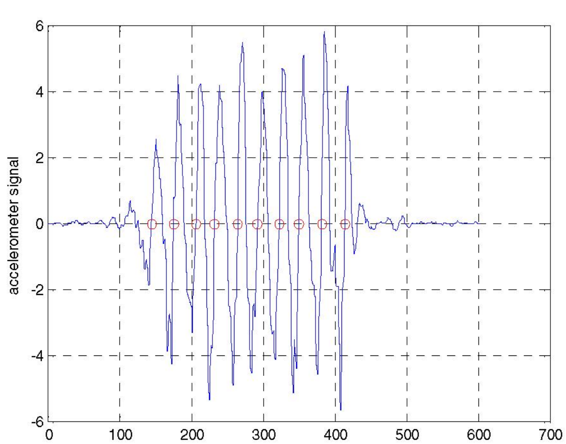


Figure 2. Step detection.

The components of the system are small-sized and low-cost. The used IMU consists of accelerometer and gyro. In order to recognize the movement status, a biaxial accelerometer is only used but gyros are often used to develop some other adaptive estimation algorithms like the adaptive estimation algorithm of the sensor equipped location.

III. PEDESTRIAN NAVIGATION ALGORITHM

A. Step Detection Algorithm

Recently, step detection methods using accelerometers have been presented in PNS investigation. There are three types of methods: peak detection, zero crossing detection and flat zone detection using acceleration differential. The peak detection method is not appropriate to detect steps because the peak of the accelerometer output is greatly affected by the user's walking velocity. The flat zone of the signal is not detected when the accelerometer is attached to the user's waist. Therefore, the user's step is detected using a zero crossing method which is resilient to the user's walking velocity.

The accelerometer sensors attached to the body are influenced not only by the acceleration of the body but also noise and other factors such as the bias of the accelerometer, gravity, etc. In order to remove the noise from the output of the accelerometer, the signal is summed over the sliding window established previously. The signal is differentiated to eliminate various error sources. The zero crossing point of the output of the accelerometer is detected using this signal. Figure 2 shows the result of step detection algorithm.

B. Step Length Estimation Algorithm

According to the result of our investigation, the step length is influenced in linear pattern by walking frequency and a variance of the accelerometer signals during one step. Figure 3 shows the relations between step length and walking characteristics such as walking frequency and acceleration variance. Therefore we can determine the step length using a linear combination of walking frequency and variance of the accelerometer as follows:

$$\text{Step Length} = \alpha \cdot f + \beta \cdot v + \gamma \tag{1}$$

where α, β, γ are the parameters pre-learned during a pre-calibration stage. Then, walking distance is obtained by

$$\text{Walking Distance} = \sum_{i=1}^{n} (\alpha \cdot f_i + \beta \cdot v_i + \gamma) \tag{2}$$

where n denotes the number of occurred step.

The inputs for the linear combination are walking frequency and the variance of the accelerometer signals and they are obtained from

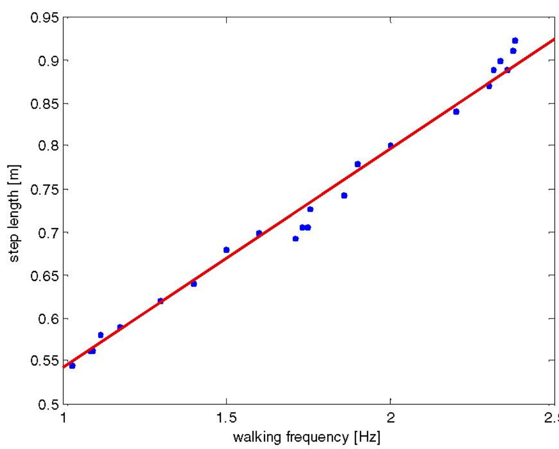
$$f_k = 1/\left(t_k - t_{k-1}\right) \tag{3}$$

$$v_k = \sum_{t=t_{k-1}}^{t_k} \frac{\left(a_t - \bar{a}_k\right)^2}{N} \tag{4}$$

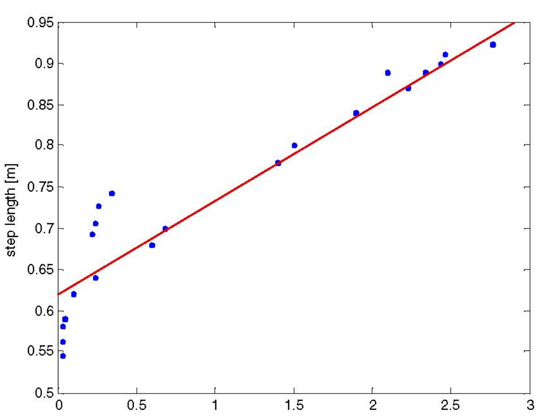
where t_i denotes detection time of the i[th] step; a_t, $\bar{a}_k$ and N stands for the accelerometer signal at time t, the average of the accelerometer signals during one step and the number of sensor outputs during one step, respectively.

IV. ADAPTIVE STEP LENGTH ESTIMATION

From Figure 3, it is shown that linear fits to the step length and walking frequency or the acceleration variance for slow, normal, and fast walks provide a great performance. Do you think that the linear model can directly apply to the case of run? We can find out the answer from Figure 4 which shows the pre-learning data of the five cases – three-type walks and two-type runs with different speed. If the linear model is fitted with the five data sets, the performance of step length estimation will never be enough. In this case, the accuracy of step length estimation is about 80% at worst. This result indicates that the step length cannot be accurately estimated with one linear regression model for both walk and run. Therefore we find two linear fits using learning data for run and walk respectively. And then each linear fit must be adaptively applied to walk frequency and acceleration variance data obtained from sensors according to the movement status such as run or walk.



(a) Walking Frequency versus step length



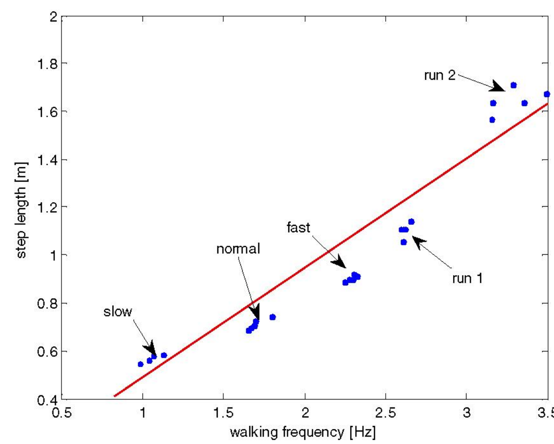
(b) Acceleration Variance versus step length

Figure 3. Walk data for learning

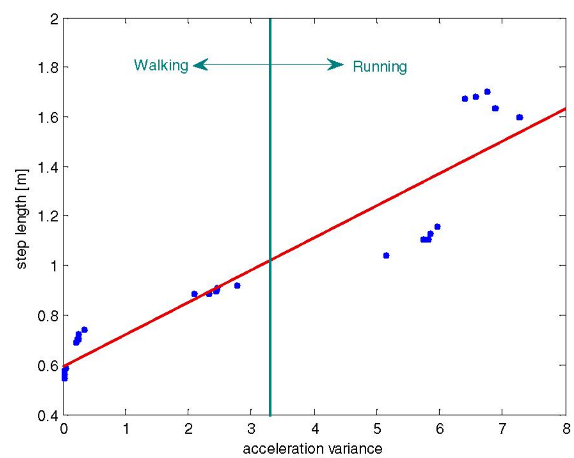
When we extract the walk frequency and acceleration variance information from the accelerometer, how can we decide the movement status? The definition of the walk is to take steps with the feet at a slower pace than run. Thus we think that the status can be classified by the walk frequency in general. However we can see from Fig. 4(a) that it is not easy to separate the walking status from the running status by the walk frequency because a very small difference between the fast walk and the slow running data may occur. This means the pedestrian can walk or run with the same velocity.

On the other hand, the difference in acceleration variance is very large as seen in Fig. 4 (b). This is why the impact between foot and the ground is large even though the pedestrian is running slowly. Therefore the linear fit should be chosen according to the movement status determined by the acceleration variance.

Figure 5 shows the flow of the adaptive step length estimation algorithm designed with the awareness algorithm of the movement status in this paper. First, the step is detected using the output of accelerometers. Second, the movement status is determined. Finally, the step length and the total walking distance are estimated.



(a) Walking frequency versus step length



(b) Acceleration variance versus step length

Figure 4. Walk and run data for learning

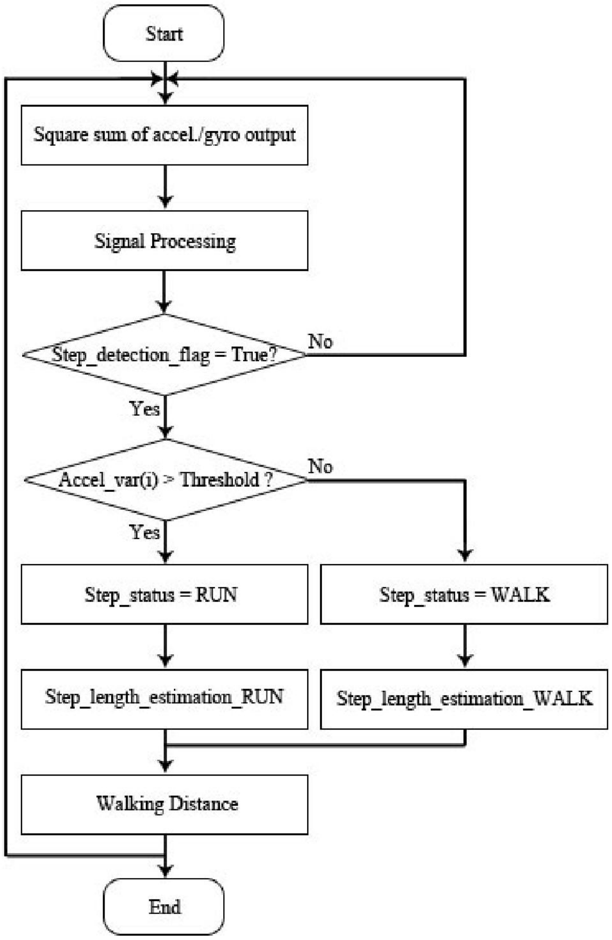


Figure 5. The adaptive step length estimation algorithm

V. EXPERIMENTAL RESULT

Walking tests were conducted at the Seoul National University, Korea, in order to show the performance of the proposed algorithm. Leaning is first done to estimate some parameters for the step length estimation through walking and running on the appropriate trajectory. And then walking tests were performed on the assumption that pedestrians normally walk and run. Highly non-uniform motions such as pedestrians commute, which might be found during daily life, were not considered because these do not always satisfy walking characteristics in Figures 3 and 4. Also we did not consider that pedestrians walk on stairs or steep roads since these cases require somewhat different algorithm or parameters from ours.

Figure 6 shows the sensor data acquisition program. The sensor data was logged in the memory of the navigation computer board. The accelerometer data was logged at 100Hz. The sensor data could be seen in the monitor program loaded on the notebook PC. Step detection based on the accelerometer data was performed. The adaptive step length was estimated at the point of the step detected. The accuracy of step detection algorithm is about 98% at the worst case.

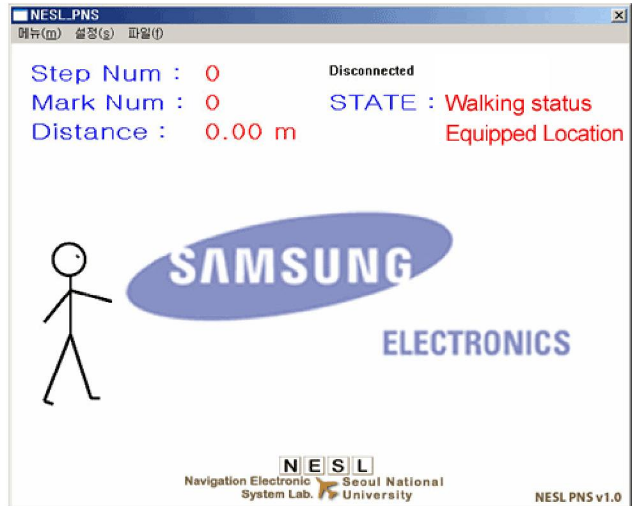


Figure 6. Sensor data acquisition program

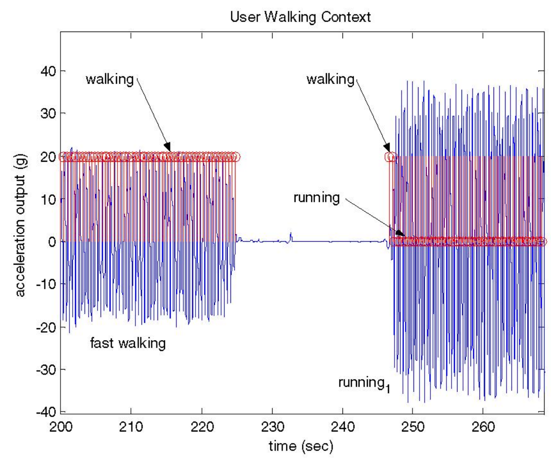


Figure 7. The result of movement status

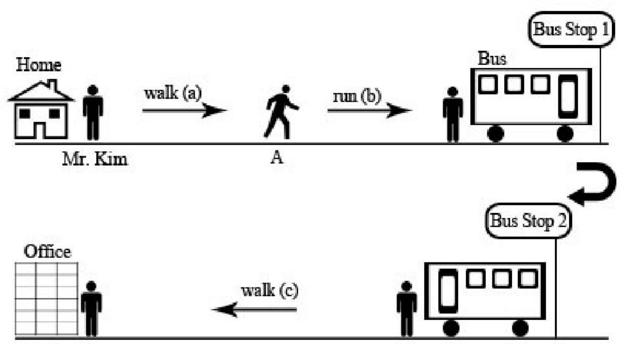


Figure 8. Mr. Kim's office-going

Table 1. Result of step length estimation (walk)

Velocity / Accuracy	slow	normal	fast
Accuracy (%) At the worst case	95	96	96

Table 2. Result of step length estimation (run)

Velocity / Accuracy	run 1	run 2
Accuracy (%) At the worst case	96	96

Figure 7 shows the result of the movement status awareness algorithm. For the purpose of distinction, the walking status is represented by a circle at (S_t,20) and the running status is marked by a circle at (S_t,0). S_t stands for the step detection time. However, there are some false results at the first 2 or 3 steps and at the last 2 or 3 steps by the reason that there are an accelerated time and decelerated time. The accuracy of the adaptive step length estimation is about 95% at the worst case. Tables 1 and 2 show the experimental results of the presented adaptive step length estimation algorithm. These results presented in this paper are computed in real-time. The performance of the developed adaptive step length estimation algorithm for pedestrian navigation system is good on the whole.

The MEMS based pedestrian navigation system we developed can be applied to daily pedestrian life. Using the system, for instance, Mr. Kim's energy expenditure can be estimated for his office-going time as shown in Figure 8. It is supposed that he goes to work by bus every morning. He walks to the bus stop from home. Just then the bus is about to leave the bus stop. So, Mr. Kim starts to run at point A not to miss the bus and he can take the bus just in time. Some times later, he takes off the bus and goes to his office. In this situation, our system can calculate Mr. Kim's energy expenditure by estimation of his total walking distance $(a + b + c)m$ and the movement status for the office-going hour. We do not need to handle induced motion from the bus because Mr. Kim does not spend his energy for taking the bus.

VI. CONCOUSION

This paper has presented an adaptive step length estimation algorithm for PNS using the awareness of the walking status of pedestrians. The pedestrian navigation system (PNS) utilizing the proposed algorithm is more effective to calculate the energy expenditure of pedestrians. The sensors used in this research are MEMS-type accelerometers and gyros. The step length is estimated by a simple linear combination of the walking frequency and the acceleration variance. In order to enhance the performance of the step length estimation algorithm, we proposed the adaptive algorithm using the different linear fits by recognizing the movement status such as walk or run. Many walk and/or run tests were performed in order to confirm the algorithms. Results show that PNS with the proposed adaptive step length estimation algorithm can be effectively applied to the u-Health monitoring systems.

In the future, we have to consider the various walking cases such as on stairs and steep roads to complete adaptive step length estimation algorithms.

ACKNOWLEDGMENT

We acknowledge that this work has been supported by Samsung Electronics Co. Ltd. and Samsung Advanced Institute of Technology, Korea.

REFERENCES

[1] R. Jirawimut, P. Ptasinski, V. Garaj, F. Cecelja, W. Balachandran, "A Method for Dead Reckoning Parameter Correction in Pedestrian Navigation System," Proceedings of the 18th IEEE Instrumentation and Measurement Technology Conference, 2001.
[2] R. W. Levi, T. Judd, "Dead Reckoning Navigational System using Accelerometer to Measure Foot Impacts," United States Patent No. 5,583,776, 1996.
[3] Quentin Ladetto, "On foot navigation : continuous step calibration using both complementary recursive prediction and adaptive Kalman filtering," Proceedings of ION GPS 2000, pp.1735~1740.
[4] S. H. Shin, C. G. Park, H. S. Hong, J. M. Lee, "MEMS-based Personal Navigator Equipped on the User's Body." Proceedings of ION GNSS 2005.
[5] J. Kappi, J. Syrjarinne, J. Saarinen, "MEMS-IMU Based Pedestrian Navigator for Handheld Devices," Proceedings of ION GPS 2001, pp.1369~1373.
[6] K. Sagawa, M. Susumago, H. Inooka, "Unresticted Measurement Method of Three-dimensional Walking Distance Utilizing Body Acceleration and Terrestrial Magnetism," Proceedings of the International Conference on Control, Automation and Systems, 2001, pp.707~710.
[7] S. Y. Cho, C. G. Park, G. I. Jee, "Measurement System of Walking Distance using Low-Cost Accelerometers," Proceedings of the 4th ASCC, 2002.
[8] Vincent Gabaglio, "Centralised Kalman Filter for Augmented GPS Pedestrian Navigation," Proceedings of ION GPS 2001, pp.312~318.
[9] K. Aminian, Ph. Robert, E. Jequier, Y. Schutz, "Level, Downhill and Uphill Walking Identification using Neural Networks," Electronics Letters 19th August, 1993, Vol.29, No.17.
[10] Lee, S., and K. Mase, "Activity and Location Recognition using Wearable Sensors." IEEE Pervasive Computing 24-32, 2002
[11] Ravi, N. ; Dandekar, N. ; Mysore, P. ; Littman, M. L. "Activity Recognition from Accelerometer Data." Proceedings of the National Conference on Artificial Intelligence, v.20 no.3, 2005, pp.1541-1546
[12] Bao, L., Intille, S.S. "Activity recognition from user annotated acceleration data." Proceedings of the 2nd International Conference on Pervasive computing, 1-17
[13] Lukowicz, P. ; Ward, J. A. ; Junker, H. ; Stager, M. ; Troster, G. ; Atrash, A. ; Starner, T. "Recognizing Workshop Activity Using Body Worn Microphones and Accelerometers." Lecture notes in computer science, v.3001, 2004, pp.18-32