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COMPENSATION OF SMARTPHONE WALKING PATTERN RECOGNITION BASED ON PRINCIPAL COMPONENT ANALYSIS

Namkeun Kim[1] and Jaehyun Park[2,*]

[1]Department of Mechanical Engineering
[2]Department of Industrial and Management Engineering
Incheon National University
119 Academy-ro, Yeonsu-gu, Incheon 406-772, Korea
nkim@inu.ac.kr; *Corresponding author: jaehpark@inu.ac.kr

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Abstract. *This study suggests a method for walking pattern recognition using the support vector machine (SVM) in a real-world situation, and aims to improve the algorithm based on the principal component analysis (PCA). For the experimental device, a smartphone was used to assess signals from the accelerometer, gyroscope, and magnetometer sensors. The participants were required to walk repeatedly on a treadmill at 3 km/h and 5 km/h for 3 min each. The results indicate that the PCA-SVM algorithm turned out to be more reliable than the non-PCA algorithm. In addition, the methodology used in this study, showed a robust performance, regardless of the sampling rates of the experimental device, which were from 10 to 50 Hz. The results of this study are expected to help researchers investigate physical movement patterns.*
Keywords: Walking pattern recognition, Support vector machine (SVM), Principal component analysis (PCA), Smartphone pedometer

1. **Introduction.** Studies on measuring physical movement have been widely conducted. Among such studies, walking pattern recognition has been regarded as the basic research for dynamic movements including running, stepping up and down, and falling [1-3]. Strides, the number of steps, and the calories burned are all important parameters for predictions or measurements in studies on walking pattern recognition [4,5]. Some studies have compared the walking patterns of ordinary persons with those of disabled persons [6].

Meanwhile, as technologies advance at a fast rate, recently released smartphones can provide sophisticated physiological information. Mobile devices have recently adopted inertial measurement units (IMUs) consisting of an accelerometer, gyroscope, and magnetometer. While such sensors have been used for studies on walking pattern recognition [7-10], more recent studies have tended to use a smartphone as an experimental device loading IMU [2].

This study aims to improve the algorithms used in walking pattern recognition based on the application of a support vector machine (SVM). Procedures and tasks are described in the methods session. In detail, the principal component analysis (PCA) was intended to refine the sensor signals from the accelerometer, gyroscope, and magnetometer. Although several studies have applied the PCA in combination with the SVM [4], few studies using IMU sensors have utilized the PCA for compensating the tilting of the devices. Note that this study postulates a real-world situation such as a smartphone tilting in the user's pocket. This point is explained in the discussion and conclusion session.

2. **Methods.** A total of five participants took part in the experiment, with an average age of 26.0 (±4.2). None of the participants noted any problems or diseases related to

walking or their overall health. Because this was a preliminary study, no detailed physical information was gathered and the sample size was kept relatively small.

A Samsung Galaxy S4 was used as the experimental device, which has nine-axis inertial motion sensors embedded, including a three-axis accelerometer, three-axis gyroscope, and three-axis magnetometer. The accelerometer, gyroscope, and magnetometer have sufficient capability to operate a pedometer (Table 1). The application programming interface (API) of the Google Android sensors was used to assess the signals from the smartphone. Note that the z-axis value of the accelerometer was used to adjust the acceleration of gravity (9.8 m/s^2).

TABLE 1. Sensor specifications of the apparatus

Sensor type	Range	Resolution
Accelerometer	±2 g	±0.01 m/s^2
Gyroscope	±500°/s	±0.057°/s
Magnetometer	±1200 μT	±0.15 μT (x/y axis), ±0.25 μT (z axis)

Each participant was required to walk at 3 km/h and 5 km/h for 3 min. A traditional treadmill machine was used for analyzing the walking patterns. During the experiment, an assistant checked the number of steps required to compensate the result from the Android pedometer API. The participants repeatedly conducted the walking experiments using sampling rates of 10, 20, 30, 40, and 50 Hz. Note that most walking pattern studies have been conducted using a sampling rate of over 50 Hz [2].

The first step of the pre-processing was to create a dataset from the sensor signals. The raw data were obtained at each time stamp, which varies over the sampling rates. As noted above, sensor signals were adjusted using the Android sensor API. Noticeable noises seemed to be cancelled out by Android's own algorithm. The dataset gathered using the experimental device was as follows.

$$Data = \left\{A_i^{SR}, A_j^{SR}, A_k^{SR}, G_i^{SR}, G_j^{SR}, G_k^{SR}, M_i^{SR}, M_j^{SR}, M_k^{SR}\right\} \tag{1}$$

where SR denotes the sensor sampling rate; A, G, and M indicate the accelerometer, gyroscope, and magnetometer, respectively; and i, j, and k are the three axes. For instance, a moving average of $\cos\alpha$, derived using the three-axis accelerometer vectors, varies over time, as shown in Figure 1.

Second, the dataset was appropriately refined to apply the SVM analysis [11]. The dataset obtained was randomly divided into two sets, where 70% of the data were used

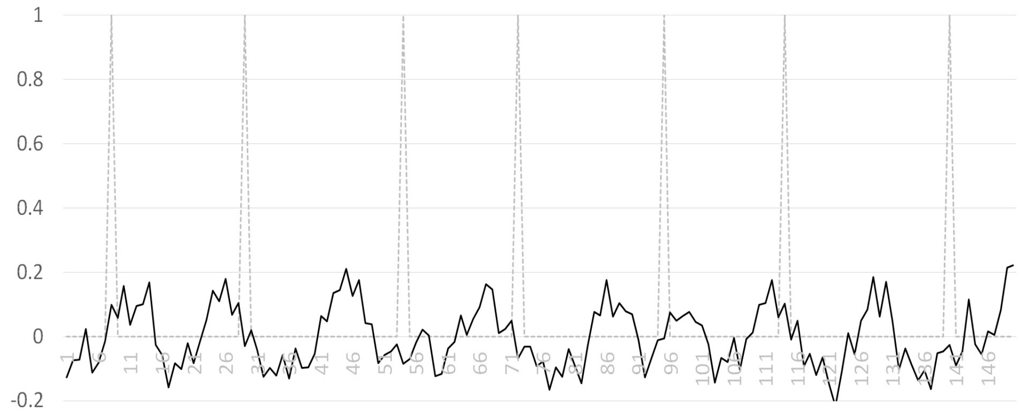

FIGURE 1. Moving average of $\cos\alpha$ at 50 Hz (Dotted line indicates the actual steps)

for the training partition, and 30% were used for the test partition. Sensor signals were sampled using sliding windows with a fixed time, which was expected to take half a step, with a 50% overlap. A total of 18 features were forced to analyze the SVM, which consisted of the mean and standard deviation of the sensor signals. Note that the PCA was applied to the accelerometer, gyroscope, and magnetometer prior to a calculation of the mean and standard deviation.

We trained a dataset consisting of samples ($\{(x_i, y_i), i = 1, 2, \ldots, N\}$), where y_i is the given label for each sample x_i, and $y_i = \pm 1$. Note that a positive y_i indicates the impact of the foot striking the ground. A standard binary SVM could then be learned through a linear classification function, as follows.

$$f(x) = w^T x + b \tag{2}$$

where w and b can be defined according to

$$\min J(w, \xi) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N} \xi_i \tag{3}$$

where C indicates an additional constraint on the Lagrange multipliers, and ξ_i is a non-negative slack variable, which means the degree of misclassification of data x_i. In this study, we applied a kernel function to map vector x to a higher-dimensional space through a nonlinear mapping, $\Phi(x)$, using the kernel concept, $K(x_i, x_j) = \Phi^T(x_i)\Phi(x_j)$.

3. **Results.** After applying the SVM, the average degree of accuracy related to the impact of the foot striking the ground was about 0.72 (Figure 2). The results with the SVM after applying the PCA turned out to be more reliable than those with a non-PCA dataset, at 0.72 versus 0.71, respectively. As the sampling rate increased, the effect of the application of the PCA also seemed to increase. In addition, the sampling rates did not seem to have an influence on the accuracy. Note that a preliminary study showed that the accuracy of the threshold-based smartphone pedometer seems to be related to the sampling rates.

In terms of the receiver operating characteristic (ROC) curve, the area under the curve (AUC) turned out to be high and reliable. Unlike the accuracy, for some datasets, the AUC with the PCA-SVM algorithm did not show a better performance than the AUC without the PCA (Figure 3). Because the number of steps was not controlled during the experiment or pre-processing sessions, the AUC tended to perform inconsistently. Future work will need to consider controlling this effect.

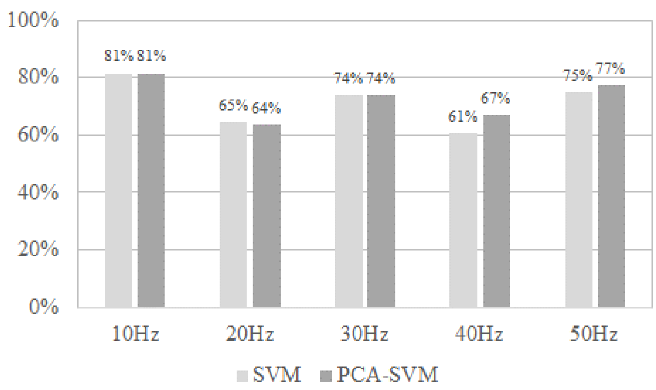

Figure 2. Comparison of accuracy of algorithms

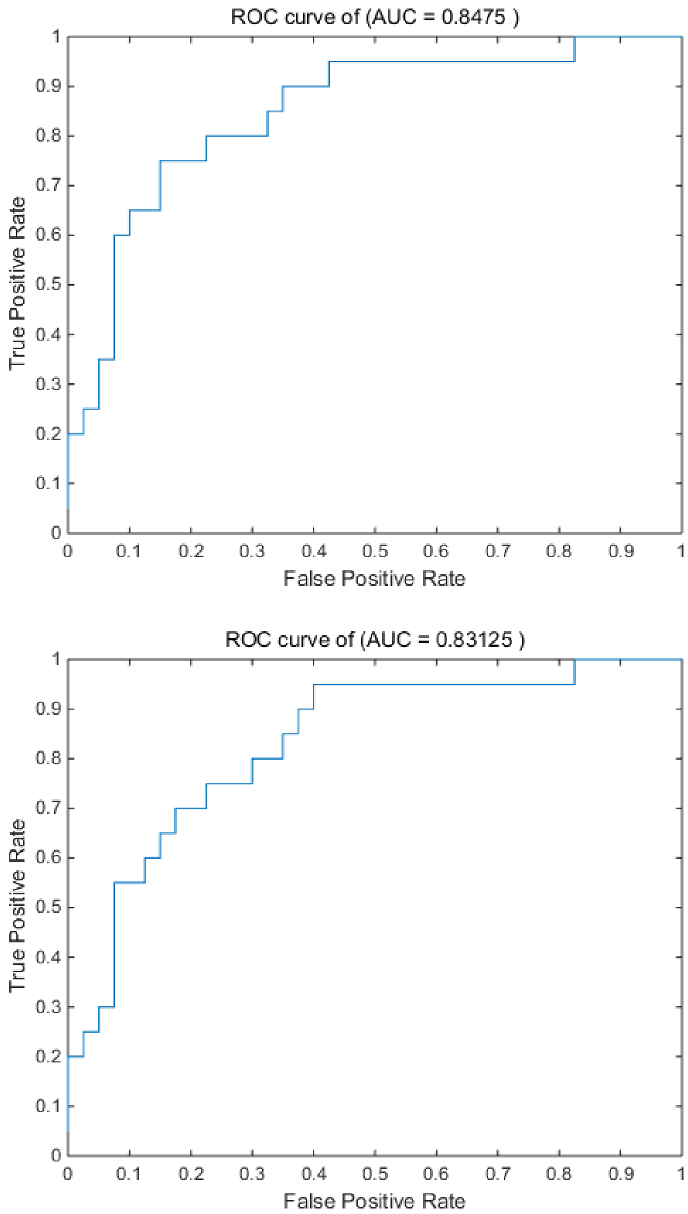

FIGURE 3. ROC curve of SVM (up) and PCA-SVM (down) at 30 Hz

4. **Discussion.** Research on walking patterns has been carried out for many years. This study assessed sensor signals for a real-world type of situation. There were several considerations regarding the physical behavior analysis using a smartphone. First, as a signal assessment device, a smartphone can be tilted to one side or the other. Hence, the PCA has to be applied to compensate the random inclinations occurring in the user's pocket. The results when using a PCA seem to be more reliable, and indicate that the inclinations of the device may be adjusted.

Second, the sampling rate might not be controllable in a real-world situation. As a consumer electronic product, a smartphone is a general purpose device. We can use such a device for various functions, including as a music player, navigational instrument, scheduler, note pad, or for searching the Internet. However, with many applications running in the background, some primary applications may have an unexpected lag, which may lead to difficulties when conducting a motion signal analysis. Note that a normal smartphone has a limited memory capacity.

Therefore, the methodology for walking pattern recognition used in this study turned out to be reliable, regardless of the application of the PCA. However, when using a low sampling rate (e.g., less than 20 Hz), an increase in accuracy is important. For future work, diverse algorithms along with the PCA are needed to refine and improve the methodology used.

5. **Conclusions.** This study aimed to increase the performance of the algorithm used to predict the impact of a foot striking the ground. Unlike traditional studies on walking pattern recognition, the experimental device was not tightly fixed to the body of the subject, and was instead placed in the subject's pocket. For this reason, the PCA was applied to the sensor signals of the accelerometer, gyroscope, and magnetometer of the smartphone device used.

The results indicate that datasets using a PCA-SVM are more reliable than non-PCA datasets. Although for some datasets, the use of a PCA has shown little effect; for other datasets, noticeable performances have been achieved using the PCA. Future work will be conducted to confirm the relationship between the sensing capability and the effect of a PCA. The results of this study are expected to help researchers investigate walking patterns in real-world situations.

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REFERENCES

[1] R. Cuberek, W. E. Ansari, K. Frömel, K. Skalik and E. Sigmund, A comparison of two motion sensors for the assessment of free-living physical activity of adolescents, *International Journal of Environmental Research and Public Health*, vol.7, no.4, pp.1558-1576, 2010.

[2] M. B. Del Rosario and S. J. Redmond, Tracking the evolution of smartphone sensing for monitoring human movement, *Sensors*, vol.15, no.8, pp.18901-18933, 2015.

[3] G. C. Le Masurier and C. Tudor-Locke, Comparison of pedometer and accelerometer accuracy under controlled conditions, *Medicine and Science in Sports and Exercise*, vol.35, no.5, pp.867-871, 2013.

[4] Z. Peng, C. Cao, Q. Liu and W. Pan, Human walking pattern recognition based on KPCA and SVM with ground reflex pressure signal, *Mathematical Problems in Engineering*, 2013.

[5] N. Zhao, Full-featured pedometer design realized with 3-axis digital accelerometer, *Analog Dialogue*, vol.44, pp.1-5, 2010.

[6] M. Marschollek, M. Goevercin, K. H. Wolf, B. Song, M. Gietzelt, R. Haux and E. Steinhagen-Thiessen, A performance comparison of accelerometry-based step detection algorithms on a large, nonlaboratory sample of healthy and mobility-impaired persons, *The 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2008.

[7] D. Anguita, A. Ghio, L. Oneto, X. Parra and J. L. Reyes-Ortiz, Human activity recognition on smartphones using a multiclass hardware-friendly support vector machine, *Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics*, pp.216-223, 2012.

[8] T. O. Oshin and S. Poslad, ERSP: An energy-efficient real-time smartphone pedometer, *IEEE International Conference on Systems, Man, and Cybernetics*, pp.2067-2072, 2013.

[9] M. Tomlein, P. Bielik, P. Krátky, S. Mitrík, M. Barla and M. Bieliková, Advanced pedometer for smartphone-based activity tracking, *Proc. of the International Conference on Health Informatics*, 2012.

[10] W. Wu, S. Dasgupta, E. E. Ramirez, C. Peterson and G. J. Norman, Classification accuracies of physical activities using smartphone motion sensors, *Journal of Medical Internet Research*, vol.14, no.5, 2012.

[11] V. N. Vapnik, *The Nature of Statistical Learning Theory*, Springer-Verlag, 1995.