# Real-Time Locomotion Mode Recognition Employing Correlation Feature Analysis Using EMG Pattern

Deok-Hwan Kim, Chi-Young Cho, and Jaehwan Ryu

**This paper presents a new locomotion mode recognition method based on a transformed correlation feature analysis using an electromyography (EMG) pattern. Each movement is recognized using six weighted subcorrelation filters, which are applied to the correlation feature analysis through the use of six time-domain features. The proposed method has a high recognition rate because it reflects the importance of the different features according to the movements and thereby enables one to recognize real-time EMG patterns, owing to the rapid execution of the correlation feature analysis. The experiment results show that the discriminating power of the proposed method is 85.89% (± 2.5) when walking on a level surface, 96.47% (± 0.9) when going up stairs, and 96.37% (± 1.3) when going down stairs for given normal movement data. This makes its accuracy and stability better than that found for the principal component analysis and linear discriminant analysis methods.**

**Keywords: EMG, locomotion mode, pattern recognition, correlation feature analysis.**

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Deok-Hwan Kim (phone: + 82 32 860 7424, deokhwan@inha.ac.kr) and Jaehwan Ryu (yjh1210@iesl.inha.ac.kr) are with the Department of Electronic Engineering, Inha University, Incheon, Rep. of Korea.

Chi-Young Cho (cycho@bufs.ac.kr) is with the Department of Japanese Business, Busan University of Foreign Studies, Busan, Rep. of Korea.

## I. Introduction

This paper discusses a biosignal recognition system that analyzes signal patterns from surface electromyography (EMG) sensors attached onto the lower limbs of prosthetic leg systems. The EMG signals from the moving muscles are expressed as waves subject to time. These waves can be used to determine such time-domain (TD) features as the average rectified value and the root mean square and such frequency-domain features as median frequency and mean frequency. These features are used for such classifiers as principal component analysis (PCA), linear discriminant analysis (LDA), and artificial neural networks, including self-organizing feature maps (SOFMs) [1], [2]. It should be noted that to employ the real-time recognition process of the EMG signals, the total amount of time available for signal acquisition and pattern recognition cannot exceed 300 ms [3]. Therefore, much attention must be paid to determining the elements needed for high-speed execution, such as an EMG signal windowing strategy and classifier selection [4].

In this paper, we present a real-time locomotion mode recognition method using an EMG pattern. The EMG signals are transformed into six TD features: mean absolute value (*MAV*), zero crossings (*ZC*), slope sign changes (*SSC*), waveform length (*WL*), Willison amplitude (*WAmp*), and variance (*VAR*) [5]. A correlation feature analysis is applied to these six TD features. The pattern classification is performed by applying weights according to each movement to the six subcorrelation filters.

The proposed method enhances the entire recognition rate process since it gives appropriate weights to the subcorrelation filters generated from the TD features to enable the recognition of each movement and classify these movements in real time due to the rapid execution of the correlation feature analysis.

## II. Related Works

It is difficult to perform efficient EMG pattern recognition because EMG signals have their own noise and variation. Therefore, original EMG signals need to be characterized as other types of signals and then the EMG pattern recognition performed with various classifiers, such as PCA, LDA, and SOFM [1], [2], [6]-[8].

The PCA and LDA methods measure similarities according to the degree of dispersion of the EMG signals. PCA is a suitable method for dimension reduction but does not have high performance regarding classification. LDA performs the classification better than PCA, but it is poor for other data representation, except for that data used in the classifier creation. To resolve these problems, we propose a correlation feature analysis method that can create a recognition filter with less sample data for EMG signal classification and even renew the recognition filter. However, in this study, we do not cover the filter modification of correlation analysis but just focus on the application and performance verification of correlation analysis for the EMG pattern recognition.

The correlation analysis is a statistical method that transforms the recognized target signals and base signals used for detection into frequencies before analyzing them. Correlation analysis has been used in the visual object tracking areas of image processing. For video object tracking, the Minimum Output Sum of Squared Error (MOSSE) method [4] and the Average of Synthetic Exact Filters method [9] are representative approaches using correlation analysis. MOSSE is an algorithm for producing adaptive correlation filters from fewer training samples [4].

The principle of correlation analysis, which is the background of MOSSE, starts from (1). Correlation is the convolution in the frequency domain, which produces the result ($G$) with a certain signal $F$ and element-wise multiplication of filter $H^*$ for that signal [4].

$$G = F \odot H^*. \tag{1}$$

The MOSSE filter $H^*$ is expressed by

$$H^* = \frac{\sum_i^N G_i \odot F_i^*}{\sum_i^N F_i \odot F_i^*}, \tag{2}$$

where $N$ is the number of training samples, $F_i$ is the transformation of the input signal $f_i$ into the frequency domain, and $F_i^*$ is a conjugate complex number of $F_i$. $F_i \odot F_i^*$ is the multiplication of these two complex numbers; usually, we refer to this operator as the correlation in the frequency domain. $G_i$ is the mapping function of TD input signal $g_i$, annotated for certain movements in the frequency domain.

The identification of a certain input signal, $f$, starts with computing $G$ by element-wise multiplication of $F$ and $H^*$. After this identification, the peak-to-sidelobe ratio (PSR) is applied to $g$, which is the inverse fast Fourier transform (FFT) of $G$. Variable $PSR$ represents a simple measurement of peak strength, and the bigger its value is, the closer input signal $f$ gets to annotation $g$ of a specific signal. MOSSE outperforms other methods in terms of execution speed. Therefore, it can be applied to real-time EMG pattern recognition. However, we need to add several processes for EMG pattern recognition since MOSSE was originally presented for object tracking.

The important factor is the feature selection for class discrimination in the pattern recognition system. Feature selection has an influence on recognition performance. Recognition systems based on EMG signals are used with TD features because these features have high computational efficiency. Previous studies have evaluated the ability of various TD features [5]. We use the following TD features.

$MAV$ represents the mean absolute value of signal $x$ in an analysis window with $N$ samples.

$$MAV = \frac{1}{N}\sum_{k=1}^{N} |x_k|. \tag{3}$$

$ZC$ is the number of zero crossings in an analysis window with $N$ samples. Threshold $\varepsilon$ is included to avoid signal crossing counts due to low-level noise.

$$\begin{aligned}&\{(x_k > 0 \text{ and } x_{k+1} < 0) \text{ or } (x_k < 0 \text{ and } x_{k+1} > 0)\}\\ &\text{and } |x_k - x_{k+1}| \geqq \varepsilon.\end{aligned} \tag{4}$$

$SSC$ is the number of slope sign changes within an analysis window. Threshold $\varepsilon$ is included to reduce the influence of noise.

$$\begin{aligned}&\{(x_k > x_{k-1} \text{ and } x_k > x_{k+1}) \text{ or } (x_k < x_{k-1} \text{ and } x_k < x_{k+1})\}\\ &\text{and } \{(|x_k - x_{k+1}| \geqq \varepsilon) \text{ or } (|x_k - x_{k-1}| \geqq \varepsilon)\}.\end{aligned} \tag{5}$$

$WL$ is the total length of the EMG waveform within an analysis window of $N$ samples.

$$WL = \sum_{k=1}^{N} |\Delta x_k|; \text{ where } \Delta x_k = x_k - x_{k-1}. \tag{6}$$

$WAmp$ represents the number of times that the EMG signal amplitude exceeds a given threshold within an analysis window of $N$ samples.

$$WAmp = \sum_{k=1}^{N} f(|x_k - x_{k+1}|) \text{ where } f(x) = \begin{cases} 1, & x > \varepsilon, \\ 0, & \text{otherwise.} \end{cases} \tag{7}$$

*VAR* represents the power of the EMG signal within an analysis window of *N* samples.

$$VAR = \frac{1}{N-1} \sum_{k=1}^{N} x_k^2. \tag{8}$$

## III. Proposed Method

Leg EMG patterns change over time within the same locomotion mode. Fortunately, the muscle activation patterns for the same locomotion mode are similar at the same gait phase. Therefore, we use the classification system illustrated in Fig. 1. Similar systems have been used in prior studies [10]-[12].

We construct an EMG pattern recognition filter by using their correlation. Since EMG signals pose a great deal of noise and change, to successfully apply the correlation analysis to the EMG pattern recognition, we use the six TD features found in Table 1. The recognition filter creation consists of two steps. The first step is shown in Fig. 2 and the second step is shown in Fig. 3.

In the first step of the process, the EMG signals are extracted and then characterized into six subfeatures. $F_1$ through $F_6$ represent the six subfilters from the TD. Wave 1 through Wave 6 represent the TD feature waves to which FFTs are applied. The window size for each channel is 256 ms when obtaining the EMG signals. To create the first recognition filter, a training signal is obtained on the basis of the one sole pressure sensor. The foot pressure sensor is used supplementarily to separate the gait phases more exactly. By sequentially combining the channels, the training signals are rearranged into 1,024 ms of data. From this, six TD feature waves (1 to 6) are created by applying a 100-ms sliding window to these reconstructed signals. The window slides at 1-ms intervals in the reconstructed signals; with each slide, six values of the TD feature waves are obtained. Finally, they are transformed into 924 vectors of the feature waves. 50 ms of dummy data is appended to the head and tail of the reconstructed feature waves, respectively. The 50 ms of dummy data is filled with the minimal values among the result values of the 924 vectors of the feature waves. After this, we run FFTs for each of them. Finally, the six subfeatures are created.

In the second step of the recognition filter creation, six subcorrelation feature filters are created. Correlation analysis is applied to the six subfeatures, enabling the six subcorrelation filters to be created. Figure 3 shows this process; each

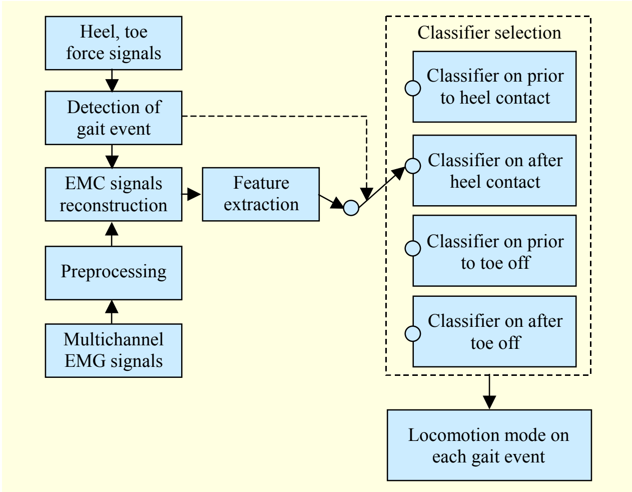


Fig. 1. Locomotion mode classification system structure.

Table 1. Accuracy of WPs (*N*=15, *T*=100, and * denotes WP in case that $p<0.05$ in one-way ANOVA).

| WP | *MAV* | *WL* | *VAR* | *ZC* | *SSC* | *WAmp* | *Walk* (%) | *Up* (%) | *Down* (%) |
|---|---|---|---|---|---|---|---|---|---|
| A | 1 | 0 | 0 | 0 | 0 | 0 | 84.68 | 73.14 | 75.91 |
| B | 0 | 1 | 0 | 0 | 0 | 0 | 94.14 | 93.59 | 90.70 |
| C | 0 | 0 | 1 | 0 | 0 | 0 | 70.62 | 98.31 | 64.00 |
| D | 0 | 0 | 0 | 1 | 0 | 0 | 55.54 | 52.92 | 53.22 |
| E | 0 | 0 | 0 | 0 | 1 | 0 | 63.16 | 54.89 | 63.61 |
| F | 0 | 0 | 0 | 0 | 0 | 1 | 78.38 | 70.02 | 75.73 |
| G | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 | 91.66 | 90.32 | 91.90 |
| *H | 0.3 | 0.5 | 0 | 0 | 0 | 0.2 | 94.14 | 93.52 | 90.97 |
| *I | 0.25 | 0.6 | 0 | 0 | 0 | 0.15 | 93.95 | 93.48 | 92.87 |
| *J | 0.2 | 0.7 | 0 | 0 | 0 | 0.1 | 93.83 | 93.56 | 93.35 |
| *K | 0.1 | 0.8 | 0 | 0 | 0 | 0.1 | 93.73 | 93.50 | 93.89 |
| *L | 0.05 | 0.9 | 0 | 0 | 0 | 0.05 | 94.08 | 93.37 | 92.75 |

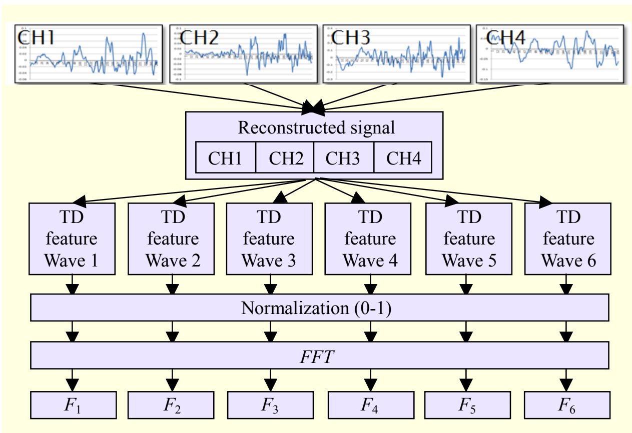


Fig. 2. EMG signal feature extraction from specific area.

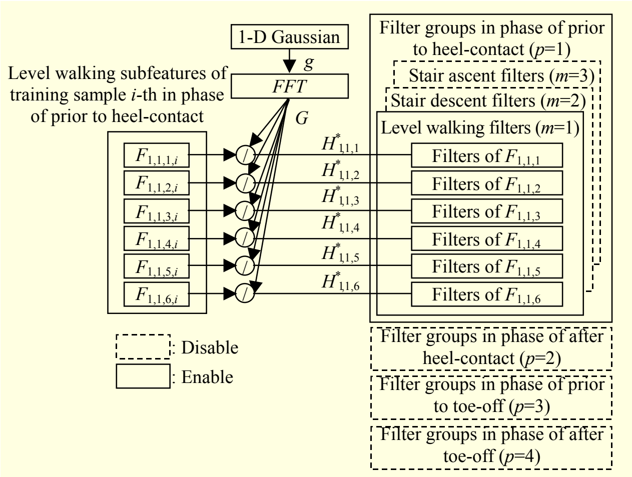


Fig. 3. Filter creation process of specific movement.

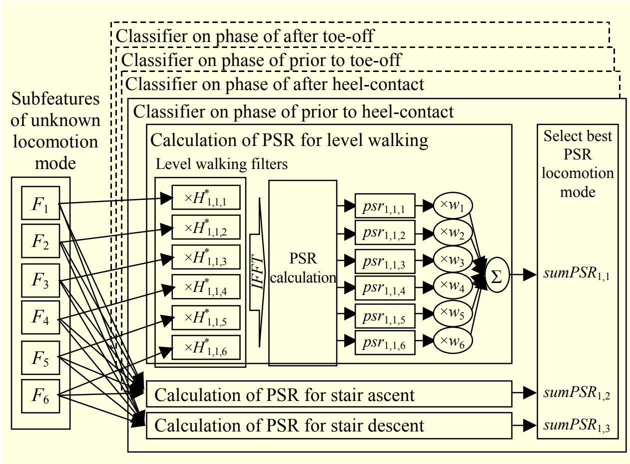


Fig. 4. Locomotion mode recognition process.

subcorrelation filter is created using (9). $H_1$ through $H_6$ represent the final subcorrelation filters.

$$H^*_{p,m,ft} = \frac{\sum_i^N G \odot F^*_{p,m,ft,i}}{\sum_i^N F_{p,m,ft,i} \odot F^*_{p,m,ft,i}}, \tag{9}$$

where $p$ represents each gait phase, $m$ represents each locomotion mode, $ft$ means subfeature, and $N$ is the number of training samples of EMG signal. The recognition filter $H^*_{p,m,ft}$ for each gait phase for each locomotion mode is calculated by (9).

The recognition process begins with the reconstruction of the subfeatures, as shown in Fig. 2. Figure 4 shows the full recognition process. $F_1$ through $F_6$ in Fig. 4 are the reconstructed subfeatures from the EMG signals. The recognition convolutes these subfeatures with the $H_1$ through $H_6$ subcorrelation filters in a 1:1 correspondence.

$$G'_{p,m,ft} = F_{ft} \odot H^*_{p,m,ft}. \tag{10}$$

In (10), the correlation is a simple multiplication of the FFT of the input signal and recognition filter for a certain gait phase and certain locomotion mode. $H^*_{p,m,ft}$ is the recognition filter to minimize the difference between the convolution result of training subfeatures and FFT($G$) of 1-D Gaussian $g$. If input subfeature $F_{ft}$ of an unknown locomotion mode is similar to a certain group of training subfeatures, $G'$ will have a similar pattern to that of $G$.

$$g'_{p,m,ft} = IFFT(G'_{p,m,ft}). \tag{11}$$

$g'_{p,m,ft}$ is the inverse FFT of $G'_{p,m,ft}$ and experiences a strong effect when the frequency coefficients of $G'$ change.

$$psr_{p,m,ft} = PSR(g'_{p,m,ft}). \tag{12}$$

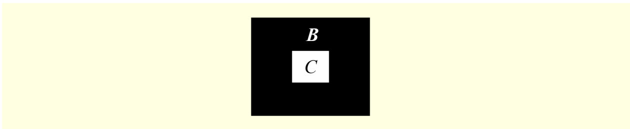


Fig. 5. $g'$ region for PSR.

The PSR value is obtained from $g'$ using (12), and then we can identify the distortion of the Gaussian shape and measure its peak strength.

Such a recognition pattern can be performed at a high speed. Therefore, this process can be used in real time. The result of applying the classification filter to specific EMG signals is judged by the PSR, which is a measurement that represents the signal intensity of a certain area. Equation 13 is used to calculate $PSR$.

$$PSR = \frac{g_{\max} - \mu}{\sigma}, \tag{13}$$

where $g_{\max}$ is the highest intensity of central area $C$ and $\mu$ and $\sigma$ are the mean and standard deviation, repectively, of the signal intensity in sidelobe area $B$. Figure 5 shows the region of $g'$ to which (13) should be applied. The sidelobe is the outer portion of the central area including $g_{\max}$. The higher the signal intensity is, the higher the concentrating rate and the lower the noise become. The PSR indicates how much of the signal intensity in the central area is high.

$$sumPSR_{p,m} = \sum_{ft}^{N} (w_{ft} \bullet psr_{p,m,ft}). \tag{14}$$

When a standard PSR value is produced after applying the six subfeatures to each of the subcorrelation filters, the result from each subcorrelation filter receives a weight. These weights are predefined values according to the importance of the TD features based on movements. These weights are


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shown in Table 1. Different weight parameters are associated with the recognition of different gaits of different movements. As shown in (14), the total sum of the product of PSR value of each subfeature and weight of each subcorrelation filter produces the recognition result as *PSR*.

The PSR value can be small or large according to the similarity of the frequency components regarding the input EMG signals prepared in advance for the recognition. The greater the similarity is, the higher the PSR value is. The PSR value is subject to the size of the window used to detect the signal intensity.

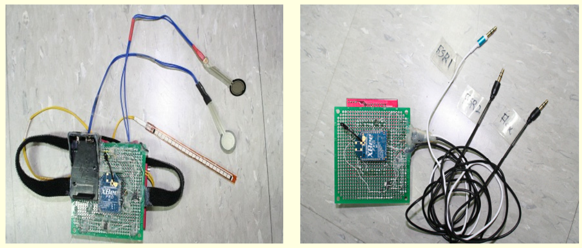
## IV. Experiment Results

Four able-bodied subjects participate in the experiment. Surface EMG signals are collected from eight electrodes attached to the m. tensor fasciae, m. adductor longus, m. vastus medialis, and semitendinosus muscles of a human thigh. Biopac MP150CW and BN-EMG2s are used to measure the EMG signals, which are preprocessed by a 60-Hz band stop filter and a 10-Hz to 500-Hz band pass filter. Three movement modes with four gait phases are investigated: level walking, ascending stairs, and descending stairs. These three locomotion modes are frequently used for the purpose of rehabilitation.

In the case of level walking, subjects are instructed to walk 15 m down a straight hallway at a comfortable speed. For the tasks of ascending stairs and descending stairs, a ten-stair staircase is used and the staircase is 16.5 cm high, 140 cm wide, and 27 cm deep. Level walking movement is repeated six times, and at least ten complete stride cycles of each trial are recorded. Ascending stairs and descending stairs movements are repeated eight times, respectively.

The four gait phases are aligned with time windows: prior to toe-off, after toe-off, prior to heel-contact, and after heel-contact. To create a recognition filter, we analyze EMG training signals of each interval by using physical data when physical data and EMG signals are synchronized. The physical data is measured from the toe and heal of the foot and synchronized with the EMG signals. We use UST-SNR-FSR no. 402 force sensors from the US Technology Co. Ltd. to measure the pressure between the ground and the foot when the human subject walks. This can be additional information to find the moment to separate two consecutive gait phases.

Figure 6 illustrates real examples of the implemented physical data acquisition subsystem and receiving subsystem. The acquisition subsystem attaches sensors and Zigbee module and uses a band to hang at the limb at measure time. The receiving subsystem consists of Zigbee module and analog output and 2.5 phi stereo jack is used as connector between analog output and input of UIM100C of MP150CW.



(a) Acquisition subsystem (b) Receiving subsystem

Fig. 6. Implemented physical data acquisition modules.

Equation 15 derives the classification accuracy. The statistical performance of the classification methods was evaluated through a bootstrap method when the classification was repeated 100 times ($T$=100) for the various training samples ($N$=1 through $N$=15).

$$\text{Accuracy} = \frac{\text{Number of correctly classfied testing samples}}{\text{Total number of testing samples}}. \quad (15)$$

The parameters shown in Table 1 are used to verify the validity of the subcorrelation filter weighting according to the importance of the TD feature based on different movements. The accuracy of the proposed method using a single feature ranks *WL*(B), *MAV*(A), *WAmp*(F), *VAR*(C), *SSC*(E), and *ZC*(D) in descending order. Among the six features, the accuracy of the proposed method using *WL*, *MAV*, or *WAmp* is consistently higher than it is when using the other single features in each movement. Additionally, the accuracy and stability of the proposed method using weighting parameters (WPs) H through L after choosing *WL*(B), *MAV*(A), and *WAmp*(F) are better than the accuracy and stability achieved when using only *WL*(B). In particular, the accuracy of K in all movements is consistently higher than that of WPs H, I, J, and L. In addition, the analysis of variance (ANOVA) results indicate that the WPs can affect the performance ($F$=37.29, $p$<0.05).

Figure 7 shows the classification accuracy of PCA, LDA, and the proposed method in the case that the number of training samples varies from 1 to 15. The proposed method shows better performance in accuracy and stability than PCA and LDA when a small number of training samples is used. It is because the proposed method produces adaptive correlation subfilters, assigning weights according to the importance of TD features sensitive to the signal detection of correlation analysis. This means that the proposed method represents characteristics of an EMG signal better than other methods. The classification accuracy of the proposed method slightly increases and remains almost unchanged when 15 or more training samples are used.

Figures 8 and 9 show classification accuracies of the

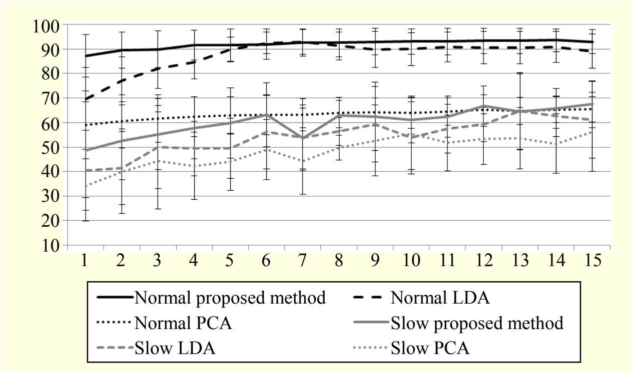



Fig. 7. Classification accuracy according to number of training samples ($N$=1-15, $T$=100, and WP=K).

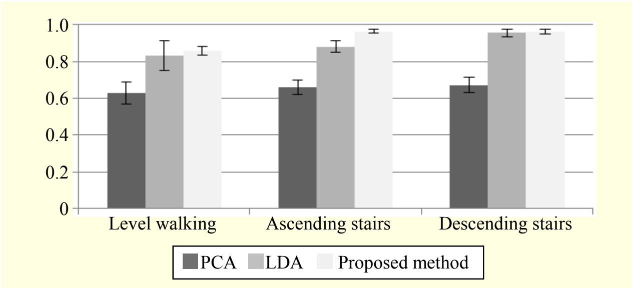



Fig. 8. Average classification accuracy for three locomotion modes (normal speeds, $N$=1-15, $T$=100, and WP=K).

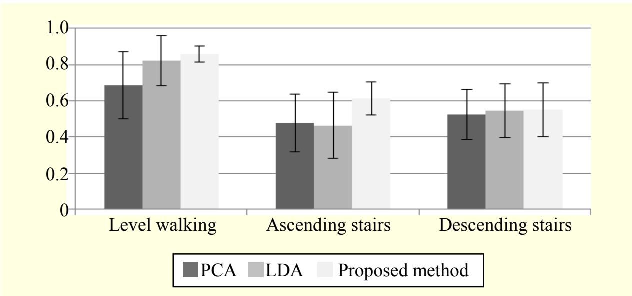



Fig. 9. Average classification accuracy for three locomotion modes (slow speeds, $N$=1-15, $T$=100, and WP=K).

proposed method, PCA, and LDA for three locomotion modes for the case in which the walking speed is normal and for the case in which the walking speed is slow, respectively. As shown in Fig. 8, the normal walking speed for level walking, ascending stairs, and descending stairs is 0.8 m/s, 0.77 m/s, and 0.77 m/s, respectively. The accuracies and stabilities of the proposed method are 85.89% (±2.5) for level walking, 96.47% (±0.9) for ascending stairs, and 96.37% (±1.3) for descending stairs. The result shows that the accuracy and stability of the proposed method is better than that found for the LDA method in all movements.

In Fig. 9, the slow walking speed for level walking, ascending stairs, and descending stairs is 0.57 m/s, 0.88 m/s, and 0.88 m/s, respectively. The result shows that accuracies and stabilities of the proposed method are still higher than those of LDA and PCA. However, we can see that the recognition rates of the proposed method, LDA, and PCA become lower because the distinction of the gait phase in slow movement is more difficult than in normal movement. According to the ANOVA results, the variation in accuracy between the proposed method and LDA over all movements is significant ($F$=217.4 and $p$<0.05 for normal speed; $F$=55.28 and $p$<0.05 for slow speed).

Using an Intel core i-5 3.3-GHz system, the proposed method took an average of 8.49 ms to calculate the features and classify the locomotion mode over tens of repetitive executions. Therefore, the proposed method can be applied to real-time EMG pattern recognition since the method can be completed within 264.49 ms, including the 256 ms needed for the EMG signal collection.

Table 2. Time performance for recognition and training.

| Method | LDA | Proposed method |
|---|---|---|
| Recognition time | 1.37 µs | 8.46 ms |
| Training time | 41.39 ms | 4.15 ms |

Table 2 shows the recognition time and the training time performance for both LDA and the proposed method. The proposed method takes more time than LDA in terms of the recognition process, whereas its training time is shorter than that of LDA. The reason is that the proposed method includes the FFT and IFFT process. This issue can be improved by using additional elements, such as a field-programmable gate array and a digital signal processor.

LDA performs dimensionality reduction while preserving as much of the discriminatory information of class as possible. Therefore, it has a problem finding the optimal discriminant projection vector, whereas the proposed method does not have that problem. The training step is simply performed by calculating the average of the features relative to the training samples. Therefore, the proposed method shows high performance compared to LDA in terms of the training process.

## V. Conclusion

In this paper we presented a new EMG pattern recognition method, which applies weights to the six subcorrelation filters according to the importance of TD features based on the movements. To apply the tracking ability of correlation analysis usually used for visual object tracking to EMG pattern recognition and construct a detection filter, the proposed method uses six TD features, all of which have been verified in existing studies and can determine the importance of the features based on a human subject's locomotion mode.

The method proposed in this paper was able to make a more efficient classifier through fewer training samples by using MOSSE sensitive to signal change. The method uses the feature of conventional TD attested in many other experiments. By combining the way to assign the weights according to the importance with features sensitive to signal detection of correlation analysis, it can recognize EMG signals efficiently.

In this study, we proposed a new method by which correlation analysis can be used with EMG pattern recognition. We verified that this method can be a suitable solution for the recognition of EMG signal patterns. Therefore, this research opens up the possibilities of using the filter update ability in further research. The filter update ability will work well in improving EMG signal recognition. Even the same movements can show slight differences whenever they are observed. The method proposed in this paper can cover up such differences. In reality, the proposed method can be applied to rehabilitation and to clinics using prosthetic leg systems, since the correlation feature analysis outperforms other classification techniques in terms of accuracy and stability.

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**Deok-Hwan Kim** received his MS and PhD degrees in computer engineering from the Korea Advanced Institute of Science and Technology. He is a professor in the School of Electronics Engineering at Inha University, Incheon, Rep. of Korea. His research interests include embedded systems, storage systems, multimedia systems, and bio-inspired systems.

**Chi-Young Cho** received his MS and PhD degrees in electronics computer engineering from Busan University of Foreign Studies. He is an invited professor in the Department of Japanese Business (IT Convergence) at Busan University of Foreign Studies, Busan, Rep. of Korea. His research interests include pattern recognition, computer vision systems, multimedia systems, and bio-inspired systems.

**Jaehwan Ryu** received his MS degree in electronics engineering from Inha University. He is a PhD student in the School of Electronics Engineering at Inha University, Incheon, Rep. of Korea. His research interests include bioengineering, embedded systems, signal processing, hyperspectral imaging, geographic information systems, and bio-inspired systems.