An Elbow Motion Classification Approach Based on the MT System Using Mechanomyogram Signals

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Abstract: The objective of this paper is to propose a mechanomyogram (MMG)-based motion classification system comprised of a muscle-activity onset detector and a motion classifier. The detector identifies muscle-activity onset time using sampled time-series of MMG signals of biceps and triceps brachii of a human upper arm based on the Mahalanobis-Taguchi method. The classifier is based on the Recognition-Taguchi method and an AdaBoost ensemble learning technique, and distinguishes the flexion and extension of an elbow directly from time-series data of MMG signals of biceps and triceps brachii. We conducted an experimental comparison of the proposed classification system with our previous one based on discriminant analysis techniques to evaluate performance with research participants. Results verified the feasibility of the system and showed that the proposed system achieved higher classification performance than the previous one.

Key Words: mechanomyogram, muscle-activity detection, motion classification, Mahalanobis-Taguchi system, ensemble learning.

1. Introduction

Wearable robots designed as aids, such as wearable robotic exoskeletons and powered prostheses, have been gaining attention recently according to advances in robotic technologies [1]. For such robots involving direct and full-time human-robot interactions, user safety is critical.

In our previous paper [2], we developed a wearable assistive exoskeleton with a soft and lightweight artificial muscle actuator driven by the pressure of tap water. One of that system’s shortcomings, however, was that its responsiveness was lower than that of electric motor-driven exoskeletons. In order to address this issue, we turned to sophisticated human-robot interfaces and control strategies. Biosignals such as electromyogram (EMG) and mechanomyogram (MMG) signals are one effective remedy for improving responsiveness. Such signals grasp the user’s muscle activity directly. EMG signals, which reflect the electrical activity of muscles, are affected by changes of skin impedance due to perspiration and moisture. On the other hand, MMG signals, which indicate a muscle’s mechanical activity, are robust to changing skin impedance and sensor placement [3]. As with EMG signals, the amplitude of MMG signals increases according to the increase in a muscle’s contraction force [4],[5].

Figure 1 depicts our proposed MMG-based volitional control strategy for our exoskeleton. The strategy consists of a muscle-activity onset detector, a motion classifier, and an assist-torque controller with a joint-torque estimator. For muscle-activity onset detection, we presented a new approach by monitoring surface EMG signals and incorporating them into a pneumatically driven exoskeleton [6]. In [6], the mere use of a muscle-activity onset detector contributed to enhance the performance of the exoskeleton. Hence, we aimed to develop the detector separately from the classifier. In addition, we proposed an elbow-joint torque estimator based on a simplified musculotendinous model, together with MMG signals of the biceps and triceps brachii of a human upper arm [7]. We verified the accuracy of our estimator in comparison to an estimator using EMG signals. However, because the estimator employs a biomechanical approach, it requires computational effort, and its estimation performance is not yet good enough for classification [7]. One of our next steps will be the development of a high-accuracy motion classifier based on MMG signals.

Fig. 1 Concept of MMG-based volitional control for a wearable exoskeleton.
between the user’s intent to flex or extend. From the viewpoint of the practical application of a motion classification system to wearable robotic exoskeletons, it is desirable that higher classification performance be achieved with less training data in order to quickly adapt an exoskeleton to its user before operation initiation. However, some previous approaches demonstrated insufficient classification performance, while others required a lot of data and effort for system tuning to attain high accuracy. In our preceding paper [13], we proposed an MMG-based motion classification system comprised of a muscle-activity onset detector and a motion classifier. The system aimed to classify the flexion and extension of an elbow from a time series of MMG signals of the biceps and triceps brachii of the upper arm. The classifier was based on discriminant analysis techniques. In that paper, we introduced AdaBoost [14],[15], an ensemble learning technique, into the classification system, and experimental performance test results demonstrated its effectiveness.

In order to achieve higher classification accuracy, the aim of this paper is to develop a new elbow motion classification system based on MMG signals using the Mahalanobis-Taguchi system (MTS) [16],[17]. The MTS is diagnostic and pattern-recognition technology for multivariate data. In the MTS, a reference group is first constructed based on normal samples, and classification is then executed according to the distance between the center of the group and a new input analysis technique. The MTS exhibits higher performance with less training data and training time than ordinary neural networks [18]. It comprises several methods. In this study, we apply the Mahalanobis-Taguchi (MT) method [16],[19] to muscle-activity onset detection and apply the Recognition-Taguchi (RT) method [17],[20] to motion classification. The contribution of this paper is to propose a new MMG-based motion classification system based on the MTS approach as follows:

- We combine our previous muscle-activity onset detector using MMG signals [13] and the MT method and assess its performance.
- We develop a new motion classification algorithm by adapting the AdaBoost technique for the RT method, which is integrated with our proposed muscle-activity onset detector.

The remainder of this paper is organized as follows: Section 2 describes our muscle-activity detector using MMG signals and experimental results on its detection performance. Section 3 presents the elbow motion classification system combined with the muscle-activity detector based on MMG signals and classification experiment results. Section 4 provides our conclusions.

2. MMG-Based Muscle-Activity Onset Detection

2.1 Mechanomyogram

Muscle fibers generate minute oscillations as they contract longitudinally and expand radially. These travel to the skin surface. Such oscillation, which is the muscle’s mechanical activity, is referred to as an MMG (mechanomyogram) signal [4],[5]. Like EMG (electromyogram) signals, which reflect a muscle’s electrical activity, MMG signals can be detected noninvasively. The amplitude of both signals increases according to the increase in the muscle’s contractive force.

The advantages of MMG over EMG signals in terms of their application to wearable robotic devices include the elimination of the need for direct skin contact, and robustness to sensor placement and changes in skin impedance [3],[21]. Accordingly, MMG signals are more suitable than EMG signals in humid and wet conditions, as water-resistant accelerometers are available. While high sensitivity to motion artifacts is a disadvantage, adequate filtering allows the separation of motion acceleration and MMG signals [9].

2.2 Muscle-Activity Onset Detection

We have experienced an insufficient response in the use of pneumatic exoskeletons, especially in the activation of exoskeletons compared to electric motor-driven exoskeletons. In response, we first focused on the reduction of delay at the start of operation [6]. Voluntary human movement is caused by the activity of skeletal muscles. Muscle activity is induced by electric signals from the brain, measurable by EMG electrodes. MMG signals occur immediately following EMG signals. In this paper, we first describe an approach to detecting muscle-activity onset using MMG signals.

2.2.1 MT method

In the MT method [16], a reference group is created based on normal samples. This group is called the unit space (or Mahalanobis space), which is used as an evaluation reference database. Training in the MT method means the construction of that unit space. The Mahalanobis distance between the center of the unit space and a new sample to be classified is calculated, and based on the distance the new sample is classified according to whether it is normal or not. In other words, if the distance is within a predetermined threshold, it is classified as normal. Since normal is an evaluation criterion in the MT method, all the data that are far from normal are classified as anomalies. Therefore, the detection of an unknown anomaly is possible.

The MT method is executed as follows [16]:

1. For given training samples, the mean and standard deviation of each item are calculated, and then the samples are standardized.
2. Using the standardized samples, the correlation coefficients between items are calculated, and a correlation matrix is obtained.

Using the inverse of the correlation matrix, the Mahalanobis distance for a new sample for testing is calculated, and the sample is classified based on the distance.

2.2.2 Proposed detector

We previously developed a muscle-activity onset detector for EMG and MMG signals based on the least squares method [6],[13]. Experimental results demonstrated that the detector outperformed the generalized likelihood ratio (GLR) technique [22]. In this study, we propose an improved version of it by combining the previous detector and the MT method.

MMG signals of biceps and triceps brachii of a human upper arm are measured by accelerometers. Beforehand, MMG signals of the muscles in the rest state are acquired for the MT method, and the unit space is created.

In the detector, the output from an accelerometer is sampled at a constant time interval, $\Delta t$ (s), and recorded as a time series of MMG signals $z(i)$ (m/s²), where $i$ is the discrete-time
We create a moving window of width $w_a$ (s), which is equal to $n_a(=w_a/\Delta t)$ samples of $z(t)$. Inside the current window, $z_c(j)(j = 1, \ldots, n_a)$ is calculated by cumulatively adding the magnitude of $z(t)$ at intervals of $\Delta t$. For $n_a$ samples of $z_c(j)$, the least squares (LS) method is applied, and an approximated linear equation is determined. We focus on the inclination of the obtained equation. For $n_a$ MMG signal samples of biceps brachii in the current window, the inclination of an approximated linear equation $a_{bb}$ is found. Similarly, the inclination $a_{tr}$ is found for $n_a$ MMG signal samples of triceps brachii in the current window. The vector $(a_{bb}, a_{tr})$ is given to the MT method. If the distance resulting from the MT method exceeds a predetermined threshold level $h_{\text{MT}}$, then the first of the $n_a$ samples is used to determine the muscle-activity onset time. If not, the window moves forward by one discrete time step, and the above procedure is iterated. Figure 2 is a schematic view of our detector.

### 2.3 Detection Experiment

#### 2.3.1 MMG data acquisition

We measured MMG signals while human research participants flexed and extended their elbows. Figure 3 shows an overview of the measurement procedure. We used two 3-axis piezoelectric accelerometers to measure MMG signals. As shown in Fig. 3, one was affixed on the biceps brachii and the other on the triceps brachii of participants’ upper arm [23]. A goniometer was used to measure participants’ elbow-joint angle. All sensor outputs were recorded on a PC through an A/D converter. The sampling frequency was set at 4 kHz. Every measured acceleration signal, consisting of the $x$-, $y$-, and $z$-direction acceleration components, was filtered with a band-pass filter. The magnitude of acceleration was then calculated from the 3-axis acceleration components. In a preliminary experiment, we tested the detector’s performance with each of the 3-axis acceleration components, as well as the magnitude of acceleration. Use of the magnitude led to the highest performance. In this study, we deal with this magnitude of acceleration as an MMG signal.

We acquired MMG signals from the accelerometers affixed on the biceps and triceps brachii while participants raised and lowered a weight. Each participant was instructed to carry out the following steps:

1. To sit on a chair, place their elbow onto a table, and lightly grip the handle of the weight (2 kg)
2. To flex the elbow up to approximately 90° with the weight for 3 s
3. To maintain the position for 3 s
4. To extend the elbow back to a straight position for 3 s

Before the experiment, participants were fully informed about the experimental procedure, and provided informed consent for their participation.

#### 2.3.2 Results of detection experiment

To evaluate the muscle-activity onset detectors, we created testing datasets. Six healthy able-bodied research participants took part in the experiment. Each performed the above trial 10 times to create the datasets. One dataset corresponds to time-series data of MMG signals for one trial. In each trial, participants touched a button to record the onset time of elbow flexion and that of elbow extension.

Our previous muscle-activity onset detector [13] used only the output from an accelerometer affixed to the biceps brachii of the participant’s upper arm. The proposed detector uses acceleration information of both the biceps and triceps brachii. MMG signals in the rest state of the muscles were acquired for the MT method for 0.1 s in advance, and the unit space was created.

All the datasets were processed off-line using our proposed and previous detectors. Figure 4 shows an example of detection results with the proposed detector. Here we employ the following MAE (mean absolute error) in order to evaluate the detection accuracy of the two detectors: $\text{MAE} = \frac{1}{N_e} \sum_{i=1}^{N_e} |t_i - t_{Ni}|$, where $t_i$ is the muscle-activity onset time detected for a research participant by one of the two detectors; $t_{Ni}$ is the time when a participant touched a button in the abovementioned experiment, obtained from recorded data; and $N_e (= 10)$ is the total number of datasets per participant.

Figures 5 and 6 show box plots of the errors between $t_i$ and $t_{Ni}$ with the previous and proposed detectors, respectively, for
elbow flexion and extension for all research participants. Figures 7 and 8 show the MAEs obtained with the two detectors for elbow flexion and extension. Prior to the calculation of these errors, threshold levels were selected to minimize errors through trial and error. The width of a moving window was set at the same value (10 ms) for the two detectors. Dispersion for the proposed detector case in Fig. 6 and the MAEs using the proposed detector in Figs. 7 and 8 are lower for all participants than those using the previous detector. Note that while our previous detector \[13\] requires the tuning of a threshold level and does not need training, the detector proposed in this study requires both.

\[\text{Fig. 5} \text{ Errors of detected onset time with the previous detector.}\]

\[\text{Fig. 6} \text{ Errors of detected onset time with the proposed detector.}\]

\[\text{Fig. 7} \text{ MAEs of detected onset time for elbow flexion.}\]

\[\text{Fig. 8} \text{ MAEs of detected onset time for elbow extension.}\]

3. MMG-Based Motion Classification

3.1 Motion Classification

In our preceding study \[13\], we employed linear discriminant analysis (LDA), QDA, AdaBoost with LDA, and AdaBoost with QDA to classify the elbow flexion or extension from time-series data of MMG signals of two upper-limb muscles, and demonstrated classification accuracy. We here propose a new classification algorithm based on AdaBoost and the RT method.

3.1.1 RT method

The RT method is one of the MTS approaches \[17\],[20], suitable for pattern recognition, and is applicable to cases where training datasets have been divided into multiple classes beforehand, though the true value of each class is unknown. In the RT method, sensitivity and a standard signal-to-noise ratio of each of training samples are calculated first. Second, based on the sensitivity and the standard signal-to-noise ratio, the training samples are reconstructed. Finally, with the training samples, the unit space is created using the Mahalanobis-Taguchi-Adjoint (MTA) method, which is a revised version of the MT method. Similar to the MT method, the classification of a new input sample is performed by computing the distance between the center of the unit space and the new input sample. The RT method is executed as follows \[17\]:

1. For \(n\) given training samples, the mean of each item is calculated, and then the sensitivity \(\beta_i\) and the standard signal-to-noise ratio \(\eta_i\) are determined \((i = 1, \ldots, n)\).
2. By defining \(Y_i^1 = \beta_i\) and \(Y_i^2 = \frac{1}{\sqrt{\eta_i}}\), the variance-covariance matrix \(V\) of \((Y_i^1, Y_i^2)\) is computed.

By using the adjoint matrix of \(V\), the Mahalanobis distance for a new testing sample is calculated, and the sample is classified based on the distance.

3.1.2 AdaBoost

AdaBoost is an ensemble learning technique in which the combination of multiple base classifiers forms a strong classifier \[14\],[15]. When the training dataset \(X = [(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)]\) is given, AdaBoost randomly picks up training samples from the training dataset \(X\) according to a weight for each sample, and creates \(M\) base classifiers. \(n\) represents the number of training samples, \(x_i\) is the input vector, and \(y_i\) is the class label. To find base classifiers, AdaBoost first assigns an initial uniform weight to each training sample \((x_i, y_i)\) as \(w^1_i = \frac{1}{n}\).

1. At iteration \(m\), AdaBoost finds the base classifier \(f_m\) trained using training samples so as to minimize the weighted error \(e_m\) with \(w_m\). Then, \(e_m\) is calculated by \(e_m = \sum_{i=1}^{n} w_m y_i f_m(x_i)\).
2. A new training dataset \(X'\) is created by resampling from \(X\) according to \(w_m\). Then, \(f_m\) is trained with \(X'\). The weight for the training sample \(x_i\) is updated by

\[
\begin{align*}
    w_{(m+1)i} = \frac{w_{mi} \exp(-\alpha_m y_i f_m(x_i))}{Z_m}, \\
    \text{where} \alpha_m = \log \frac{1 - e_m}{e_m}, \text{ and } Z_m \text{ is the normalization factor.}
\end{align*}
\]

The weight \(w_{mi}\) is decreased when \(x_i\) is classified correctly by \(f_m\) and increased otherwise.
3. Procedures 1 and 2 are repeated for \( m = 1, \ldots, M \).

By these procedures, weights for correctly classified samples are decreased, and weights for incorrectly classified samples are increased. Therefore, at step 2 above, AdaBoost chooses a training sample with a higher weight preferentially. This allows AdaBoost to focus on difficult training samples.

With \( \alpha_m \) and \( f_m \), the resulting classifier of the AdaBoost algorithm becomes

\[
F(x) = \sum_{m=1}^{M} \alpha_m f_m(x),
\]

where \( x \) is a new input vector, \( f_m \) is the \( m \)th base classifier, \( \alpha_m \) is the weight for \( f_m \), and \( F(x) \) is the strong classifier.

3.1.3 Proposed classifier

We propose a new classifier based on the combination of the RT method and a revised AdaBoost algorithm. In the proposed classifier, since \( f_m \) in AdaBoost is trained by the RT method, \( f_m \) has the unit space for both elbow flexion \( U_f \) and elbow extension \( U_e \). The unit space for elbow flexion is constructed with training datasets for elbow flexion, and that for elbow extension is constructed with training datasets for elbow extension. For a new input vector, it calculates the distance from the center of \( U_f \) and that from the center of \( U_e \). For example, for a new input vector \( x \), if the distance for \( U_f \) is smaller than that for \( U_e \), then \( x \) is classified as flexion. Consequently, \( f_m \) produces the class label of flexion or extension.

In addition, we propose using the information of the distance obtained by the RT method for the modification of the weight \( w_{mi} \) in AdaBoost. The weight \( w_{mi} \) in AdaBoost is updated by Eq.(1) with the \( i \)th training dataset. At iteration \( m \) in the AdaBoost algorithm, for the \( i \)th training dataset, the distance for the unit space for elbow flexion \( U_f \) is defined as \( D_f \), and that for the unit space for elbow extension \( U_e \) is defined as \( D_e \). The standard deviation for the unit space for elbow flexion \( U_f \) is defined as \( \sigma_f \), and that for elbow extension \( U_e \) is defined as \( \sigma_e \). Although ordinary AdaBoost performs resampling only based on \( w_{mi} \) (at step 2 in the previous section), in our proposed classification algorithm, resampling is performed as follows:

- When updating the unit space for elbow flexion \( U_f \), resampling is performed based on the modified weight
  \[
  w_{mi} \left( \frac{D_f}{\sigma_f} + \frac{D_e}{\sigma_e} \right).
  \]

- When updating the unit space for elbow extension \( U_e \), resampling is performed based on the modified weight
  \[
  w_{mi} \left( \frac{D_f}{\sigma_f} + \frac{D_e}{\sigma_e} \right).
  \]

The first term of the modified weight becomes more than 1 if misjudgment occurs, and thus the weight is emphasized. The second term of the modified weight takes a large value if the distance is large, and therefore the weight is also emphasized. By using the resampled data, \( U_f \) and \( U_e \) are updated.

In a preliminary test, the classification performance of the AdaBoost with the RT method without the improvement was almost equivalent to that of the AdaBoost with QDA. By considering that the RT method is capable of quantifying a similarity level between patterns as a distance, we finally arrived at the above improvement.

3.2 Classification Experiment

3.2.1 Datasets creation

To train and evaluate the proposed MMG-based motion classifiers, we acquired MMG signals as research participants flexed and extended their elbows to create datasets. Four research participants were instructed to carry out the trial (lifting and lowering a weight) in the same manner as described in Section 2.3.1. Each repeated the trial 20 times. Three-axis acceleration components were measured from each of the two accelerometers affixed on the biceps and triceps brachii of the upper arm, as shown in Fig. 3. These were processed with a band-pass filter. The magnitude of acceleration was then calculated as an MMG signal from the measured acceleration components, and all the values were normalized with the maximum value into the interval \([0, 1]\).

Twenty datasets per participant were acquired from 20 trials. Please note that one dataset consists of time-series data for elbow flexion and elbow extension per one trial since each trial contained both. For the classification evaluation experiments, 10 of the 20 datasets were randomly selected as the testing datasets, and \( N_t \) datasets from the remaining datasets were selected as training datasets. Each dataset was comprised of a set of the samples \((x_i, y_i)\). An input vector \( x_i \) to the classifiers consisted of a pair of the sampled time-series of an MMG signal of the biceps and triceps brachii at a discrete time step \( i \), \( y_i \) is the correct class label (flexion/extension).

3.2.2 Results of the classification experiment

In the classification evaluation experiments, the proposed muscle-activity onset detector described in Section 2.2.2 was first applied to every dataset, and the necessary part of the dataset was automatically extracted. After this process, using randomly selected \( N_t \) training datasets, the classifiers (i.e., the proposed one, the AdaBoost with LDA, and the AdaBoost with QDA) were trained for comparison. Finally, using the 10 testing datasets, we executed motion classification tests by the three classifiers, and assessed their classification performance. Figure 9 illustrates a distribution plot of normalized acceleration for the biceps and triceps brachii for elbow flexion and extension classes in testing datasets and decision boundaries of LDA and QDA, obtained based on training datasets for a participant.

For the purpose of evaluating the classifiers’ performance, we employed the area under the ROC (receiver operating characteristic) curve as a criterion \([24],[25]\). This criterion is referred to as AUC hereafter. A ROC curve for each classifier was obtained with the true positive rate and false positive rate. AUC is a numerical value computed based on the ROC curve and takes between 0 and 1. For training, input vectors \( x_i (i = 1, \ldots, n_t) \) were created per training dataset from \( n_1 \) samples for a \( T_1 \) period right after muscle-activity onset. For testing, \( n_2 \) samples
per testing dataset for a \(T_2\) period were used right after muscle-activity onset as follows:

1. Each of the inputs \(x_i\) \((i = 1, \ldots, n_2)\) was classified.

2. If the ratio of the number of the correct answers to \(n_2\) exceeded the predetermined threshold level \(h_t\), the classification result was considered correct.

For all testing datasets, procedures 1 and 2 were iterated to find ROC curves. In the following experiments, for each of the classifiers, the computation of AUC was repeated 500 times offline for each participant, and we determined the mean AUC. This was because training and testing datasets were selected at random, and thus the AUC fluctuated slightly. The threshold level \(h_t\) was set at 0.9 from a preliminary test.

Figure 10 shows the relation between the AUC and the number of iterations of the AdaBoost algorithm \(M\). In this figure, the AUC denotes the average of all research participants. We here set \(N_t = 10\) and set the number of the testing datasets at 10. Based on our preceding study [13], \(T_1 = 2\) s and \(T_2 = 10\) ms were selected. The symbol \(\circ\) indicates the AUC of the proposed classifier, the symbol \(\triangle\) indicates that of the AdaBoost with LDA, and the symbol \(\square\) indicates that of the AdaBoost with QDA. The case without utilizing the AdaBoost algorithm corresponds to \(M = 1\). From this result, the AUC of the proposed classifier becomes almost constant at the highest level over \(M = 30\). Therefore, we fixed \(M\) at 30 hereafter.

Figure 11 shows the relation between the AUC and the number of elbow flexion and extension trials \(N_t\) for training. Parameters other than \(N_t\) were the same as in the experiment above. \(N_t\) was increased from 2 to 10, and the number of the testing datasets was fixed at 10. The symbol \(\circ\) indicates the AUC of the proposed classifier, the symbol \(\triangle\) that of the AdaBoost with LDA, and the symbol \(\square\) that of the AdaBoost with QDA. In this result, the proposed classifier provides the highest AUC among the three classifiers for all \(N_t\), and at \(N_t = 10\), the AUC of the proposed classifier becomes the highest. In comparison with the other two classifiers, the AUC of the proposed classifier tends to be higher even when \(N_t\) is small.

The AUC values for the three classifiers are summarized in Fig. 12 for each research participant under \(M = 30\), \(N_t = 10\), \(T_1 = 2\) s, and \(T_2 = 10\) ms. In all experimental results, the results using the proposed classifier demonstrated the highest classification performance for all research participants, although our classifier took slightly more time than the AdaBoost with QDA. These results suggest that our proposed classification system based on the MTS is applicable for elbow motion classification based on MMG signals, and can attain high classification accuracy.

4. Conclusions

We developed a new elbow motion classification system using MMG signals and based on the MTS. The results obtained in this study can be summarized as follows:

- We proposed a muscle-activity onset detector that is an enhanced version of our previous detector using the MT method. Although it requires advance training with MMG signals of the rest state of muscles, its accuracy considerably outperformed the previous one in experiments.

- We also proposed a motion classification system composed of the muscle-activity onset detector and the RT method-based classifier based on the revised AdaBoost algorithm to distinguish flexion and extension of a human elbow from time-series data of MMG signals of biceps and triceps brachii. The classification accuracy of the proposed classification system is superior to the AdaBoost with LDA and with QDA.

Our future work will be the development of the integrated MMG-based volitional control system shown in Fig. 1 for an exoskeleton.

References

[1] J.L. Pons: Wearable Robots: Biomechatronic Exoskeletons, John Wiley & Sons, 2008.

[2] T. Kosaki, A. Nitanda, K. Atsuumi, and S. Li: Development of an elbow power assist device with a water-hydraulic muscle actuator, Transactions of the JSME, Vol. 82, No. 841, DOI:10.1299/transjsme.16-00174, 2016 (in Japanese).

[3] J. Silva, W. Heim, and T. Chau: A self-contained mechanomyography-driven externally powered prosthesis, Archives of Physical Medicine and Rehabilitation, Vol. 86, pp. 2066–2070, 2005.
[4] C. Orizio, R. Perini, and A. Veicsteinas: Muscular sound and force relationship during isometric contraction in man, European Journal of Applied Physiology, Vol. 58, pp. 528–533, 1989.

[5] I. Stokes, M. Moffroid, and S. Rush: Comparison of acoustic and electrical signals from erectors spiniae muscle, Muscle Nerve, Vol. 11, No. 4, pp. 331–336, 1988.

[6] T. Kosaki, K. Atsuumi, Y. Takahashi, and S. Li: A pneumatic arm power-assist system prototype with EMG-based muscle activity detection, Proc. 2017 IEEE International Conference on Mechatronics and Automation, pp. 793–798, 2017.

[7] T. Kosaki, A. Tochiki, S. Li, and R. Kanazawa: Torque estimation of elbow joint using a mechanomyogram signal based biomechanical model, Proc. 12th France-Japan and 10th Europe-Asia Congress on Mechatronics, pp. 254–259, 2018.

[8] J. Silva, W. Heim, and T. Chau: MMG-based classification of muscle activity for prosthesis control, Proc. 26th Annual International Conference of the IEEE EMBS, pp. 968–971, 2004.

[9] K. Shima and T. Tsuji: An MMG-based human-assisting manipulator using acceleration sensor, Proc. 2009 IEEE International Conference on Systems, Man, and Cybernetics, pp. 2433–2438, 2009.

[10] V.P. Vidhya, K. Shalu George, and K.S. Sivanandan: Speed based classification of mechanomyogram using fuzzy logic, Proc. International Multi-Conference on Automation, Computing, Communication, Control and Compressed Sensing, pp. 569–573, 2013.

[11] K.H. Ha, H.A. Varol, and M. Goldfarb: Volitional control of a prosthetic knee using surface electromyography, IEEE Transactions on Biomedical Engineering, Vol. 58, No. 1, pp. 144–151, 2011.

[12] G.J. McLachlan: Discriminant Analysis and Statistical Pattern Recognition, Wiley, 1992.

[13] A. Tochiki, T. Kosaki, and S. Li: Classification of elbow motion based on mechanomyogram signals using discriminant analysis approaches, Proc. SICE Annual Conference 2019, pp. 689–694, 2019.

[14] Y. Freund and R.E. Schapire: A decision-theoretic generalization of on-line learning and an application to boosting, Journal of Computer and System Sciences, Vol. 55, No. 1, pp. 119–139, 1997.

[15] K. Okada, A. Flores, and M.G. Linguraru: Boosting weighted linear discriminant analysis, International Journal of Advanced Statistics and IT&E-C for Economics and Life Sciences, Vol. 2, pp. 1–10, 2010.

[16] W.H. Woodall, R. Koudelik, K.-L. Tsui, S.B. Kim, Z.G. Stoumbos, and C.P. Carvounis: A review and analysis of the Mahalanobis-Taguchi system, Technometrics, Vol. 45, No. 1, pp. 1–30, 2003.

[17] Y. Nagata: Several properties of MT system and improved procedures, Japanese Journal of Applied Statistics, Vol. 42, No. 3, pp. 93–119, 2013 (in Japanese).

[18] E.A. Cudney, J. Hong, K. Paryani, K.M. Ragsdell, and G. Taguchi: An evaluation of Mahalanobis-Taguchi system and neural network for multivariate pattern recognition, Journal of Industrial and Systems Engineering, Vol. 1, No. 2, pp. 139–150, 2007.

[19] S. Ishida, T. Tabaru, W. Iwasaki, and H. Miyamoto: Estimation of wire bonding states by ensemble based on MT method and thin AE sensor method, Transactions of The Japan Institute of Electronics Packaging, Vol. 9, E16-002-1–10, 2016.

[20] T. Nishikawa, T. Kamoshita, and H. Yano: Research of introduction recognition system (RT method) in individual voice control, Quality Engineering, Vol. 17, No. 5, pp. 41–46, 2009 (in Japanese).

[21] D.T. Barry, J.A. Leonard Jr, A.J. Gitter, and R.D. Ball: Acoustic myography as a control signal for an externally powered prosthesis, Archives of Physical Medicine and Rehabilitation, Vol. 67, No. 4, pp. 267–269, 1986.

[22] S. Micera, G. Vanozzi, A.M. Sabatini, and P. Dario: Improving detection of muscle activation intervals, IEEE Engineering in Medicine and Biology, Vol. 20, No.6, pp. 38–46, 2001.

[23] D.A. Neumann: Kinesthology of the Musculoskeletal System, 3rd ed., Mosby, 2016.

[24] F. Provost and T. Fawcett: Robust classification for imprecise environments, Machine Learning, Vol. 42, pp. 203–231, 2001.

[25] C. Seiffert, T.M. Khoshgoftaar, J.V. Hulse, and A. Napolitano: Resampling or reweighting: A comparison of boosting implementations, Proc. 2008 20th IEEE International Conference on Tools with Artificial Intelligence, pp. 445–451, 2008.

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