Abstract: In this paper, we propose an unbiased difference power that is robust against noise as a feature for electromyography (EMG)-based gesture recognition. The proposed unbiased difference power is obtained by subtracting the noise-biased part from the difference power. We derive the difference power equation and discover that the difference power is biased by twice the noise power. For noise power estimation, we utilized the characteristics of the EMG signal and estimated the noise power from the resting period. For performance evaluation, we used EMG signals provided by the open source Ninapro project database. We used the recognition accuracy as an evaluation index. We compare the recognition accuracy of the case using the proposed unbiased feature with those of two conventional cases. Experimental results show that the proposed unbiased difference power improves the accuracy compared with conventional ones. As the noise level increases, cases where the proposed unbiased difference power is used show a clear improvement in accuracy compared with the two conventional cases. For the signal-to-noise ratio (SNR) of 0 dB, the proposed unbiased difference power improves the average accuracy by more than 12%.

Keywords: EMG; gesture recognition; feature extraction; difference power; unbiased difference power; linear discriminant analysis

1. Introduction

Electromyography (EMG) is an electrical signal observed from muscle fibers related to gestures or movements. For activating movements, the brain generates electrical signals and transmits signals to muscle fiber through spinal cord and nerve fiber. The electrical signal called electromyography controls the contraction and extension of muscles. EMG-based researches for medical aids and smart devices have been actively conducted, such as prosthetic limbs for amputated patients [1,2] and armband-type controllers for human control interfaces [3,4]. To make this research successful, a high accuracy of gesture recognition is necessary.

EMG-based gesture recognition involves classifying unknown observed data into the most likely gesture which belongs to target gestures. Gesture recognition generally comprises two aspects: feature extraction and classification [5]. Research works on feature extraction and classification have been studied to improve the recognition accuracy [6–8]. Feature extraction is the process of computing vectors representing signal characteristics. Moreover, the feature extraction is the basis for EMG-based gesture recognition [9]. Because the feature extraction is crucial in EMG-based gesture recognition, various features in the time-frequency domain have been studied [10–13]. Rafiee et al. introduce the feature extraction method using continuous wavelet coefficient which enables continuous wavelet coefficients which enable to distinguish complicated gestures for classification [10]. Ju et al. introduce nonlinear features and find best combination with the outstanding recognition accuracy in fourteen features [11]. Altin compares the elbow gesture recognition accuracy using fifteen time-frequency domain features [12]. Arief et al. also compare 5 kinds of time series features [13].
Most EMG features are deteriorated by inevitable noise added during the recording. To handle the problem, various studies have been conducted to reduce the effect of noise [14–17]. Several studies have been conducted to identify features that are robust to noise problems [14,15]. These studies mainly compare the accuracies using different features in various noise levels, and confirm which features are relatively robust to noise. In some studies, denoising algorithms are introduced to reduce noise contamination in EMG signals [16,17]. These studies remove the noise by thresholding wavelet coefficients. Denoising algorithms may induce the information loss [18]. The feature selection is not a fundamental solution for making the gesture recognition robust against the noise.

The difference power is a feature frequently used in EMG-based gesture recognition [19–22]. However, the difference power is biased by the noise contaminated in the EMG signal. Because of the noise bias, the difference power varies greatly depending on noise levels. Therefore, the noise bias must be removed from the extracted difference power for the robust gesture recognition against noise. In this paper, we propose a feature known as “unbiased difference power” for the robust gesture recognition of noise. The unbiased difference power is extracted by excluding the noise-biased part from the difference power. To determine the noise-biased part, we derive the difference power mathematically. For the performance evaluation, we use the recognition accuracy. In addition, the recognition accuracy based on the proposed unbiased difference power is compared with the accuracy of the two conventional cases. Only when the proposed unbiased difference power is used as a feature was the recognition accuracy maintained, even when the signal-to-noise ratio (SNR) decreased.

2. Materials and Methods

2.1. Database Information

In this study, the publicly-released Ninapro project database 2 [23,24] is used. The database has been widely used for EMG-related research because of its experimental reliability, EMG data for various gestures, and good data quality with low noise. Exercise A in database 2 contains data on 17 gestures from 40 subjects. EMG was recorded from forearm, triceps, and biceps. Also, hand kinematics and dynamics are recorded simultaneously. Eight electrodes are located on forearm at even interval, two electrodes are placed on main activity spots of flexor and extensor, and two electrodes are placed on the triceps and biceps. Subjects are asked to imitate the motions shown on the screen of the laptop with their right hand. The motions are selected from the hand taxonomy as well as from hand robotics literature. Subjects are asked to perform 6 consecutive repetitions for each motion. Each motion repetition lasted around 5 s and was followed by a 3-s resting period. The whole exercise A lasted around 23 min. Detailed information about the database can be found in the research of Atzori et al. [23]. We calculate the SNR of every recorded signal, and averaged them by subject, motion, and channel. The subjects, motions, or channels with average SNR lower than 20 dB are excluded from the study. Ten motions of 14 subjects in the Ninapro database 2 exercise A are used for the evaluation. Table 1 lists 10 motions used for the evaluation.
Table 1. Synthetic descriptions of 10 gestures.

| #  | Description                                           |
|----|-------------------------------------------------------|
| 1  | Flexion of ring and little finger                     |
| 2  | Thumb opposing base of little finger                  |
| 3  | Abduction of the fingers                              |
| 4  | Fingers closed together                                |
| 5–6| Wrist supination and pronation (rotation axis through the middle finger) |
| 7–8| Wrist supination and pronation (rotation axis through the little finger) |
| 9  | Wrist radial and ulnar deviation                       |
| 10 | Wrist extension with closed hand                       |

2.2. EMG Gesture Recognition

Many EMG gesture recognitions are based on signal representation and classification [5]. In various studies, feature extraction is used for signal representation. In this study, the difference power is used as the feature. Let $x[n]$ be the input signal, then the difference power is expressed as

$$E[\Delta x[n]] = E[(x[n] - x[n-1])^2].$$

Classification is a stage for inferring the class of an unknown observation (test data) using information from earlier observations (training data). In this study, we use linear discriminant analysis (LDA) as a classifier. Although LDA may not be the most efficient classifier, LDA is a commonly-used and basic method due to its simplicity, robust classification to long-term usage, and its reasonable performance in gesture recognition [25–27]. Considering the main contribution of the paper is to propose the unbiased difference feature, we tested the proposed feature using the LDA classifier. However, for more rigorous performance evaluation and practical usage, it would be necessary to evaluate the performance using various classifiers. For LDA, we use a discriminant function with the mean value and pooled covariance of the training data to predict the test data class. For the performance evaluation we use classification accuracy. The classification accuracy is calculated as

$$\frac{100Nc}{N},$$

where $Nc$ is the number of correct trials and $N$ is total number of trials. We use the leave-one-out validation 100 times and we set $N$ at 100.

One reason for the deterioration in classification performance is the noise added to the signals. Figure 1 shows the feature variation for different noise levels. SNR, a measure of noise level in Figure 1 is $SNR = 10 \log_{10} \frac{P_{signal}}{P_{noise}}$, where $P_{signal}$ and $P_{noise}$ is power of noiseless signal and noise respectively. It is observed in Figure 1 that the difference power feature is highly deteriorated by noise and increased as SNR decreases.
Figure 1. Change in raw data and feature related to signal-to-noise ratio (SNR). (a–c) Noisy signals with corresponding feature. SNR of each noisy signal is (a) 20, (b) 10, and (c) 0 dB. (d) Difference power based on SNR.

3. Proposed Method

In this paper, we propose a feature called the unbiased difference power for robust classification through various noise levels. We preclude a noise-biased part from the noisy feature to extract the proposed unbiased difference power. The degree of noise bias is
confirmed by deriving the equation of the difference power. To preclude the noise-biased part, noise power estimation is necessitated. The noise power is estimated using the characteristics of the EMG signal.

3.1. Unbiased Difference Power

To extract the unbiased difference power, we subtract the noise-biased part from the noisy feature. By deriving the noisy features, we demonstrate the degree of noise bias. The recorded signal $x[n]$ can be expressed using the noiseless EMG signal $s[n]$ and noise signal $v[n]$ as

$$x[n] = s[n] + v[n]. \tag{2}$$

Let $\Delta x[n]$ be

$$\Delta x[n] = (x[n] - x[n - 1])^2. \tag{3}$$

Taking the expectation of defined $\Delta x[n]$, we can obtain difference power as

$$E[\Delta x[n]] = E[s^2[n] + s^2[n - 1] + v^2[n] + v^2[n - 1]
- 2s[n]s[n - 1] - 2v[n]v[n - 1]]. \tag{4}$$

Assuming that both the noiseless EMG, $s[n]$, and the noise, $v[n]$, are uncorrelated, Equation (4) is reduced to

$$E[\Delta x[n]] = E[s^2[n] + s^2[n - 1] + v^2[n] + v^2[n - 1]]
= 2\sigma^2_s + 2\sigma^2_v, \tag{5}$$

where $\sigma^2_s = E[s^2[n]]$ and $\sigma^2_v = E[v^2[n]]$.

As can be seen in Equation (5), the difference power feature is biased by $2\sigma^2_v$. Thus, the feature becomes more contaminated as the noise power, $\sigma^2_v$, increases more.

Intuitively, the simplest method to remove the noise effect on the difference power is to subtract the noise power as

$$\overline{\Delta x}[n] = \Delta x[n] - 2\sigma^2_v. \tag{6}$$

Subsequently, we obtain

$$E[\overline{\Delta x}[n]] = E[\Delta x[n] - 2\sigma^2_v] = E[\Delta x[n]] - 2\sigma^2_v. \tag{7}$$

In addition, Equation (7) expresses the unbiased difference power.

Figure 2 shows the difference between the difference power and unbiased difference power. The value of the difference power increases as the SNR decreases. As mentioned above, the increase in the difference power as the SNR decreased is due to noise bias. However, using the proposed unbiased difference power, the feature value stabilizes, although the SNR decreases. It is observed that the noise bias is removed in the unbiased difference power.
3.2. Noise Power Estimation

To extract the unbiased difference power, information regarding the noise power is required. Although the Ninapro project database 2 has good data quality with low noise, it is impossible to know and control SNR in EMG signals since there are countless noise sources, which are unknown and cannot be controlled. The best way to estimate SNR in EMG is to use the resting period when target muscles are fully relaxed without any motion activity and force since ideally EMG signals are not supposed to be observed in the resting period, i.e., signals observed in the resting period are only noise components [28,29]. Assuming the resting period is totally composed of noise signals, we can estimate the noise power. We used the concept of minimum statistical noise estimation method [30,31]. Since the minimum statistical method basically tracks the minimum noisy signal by continuously averaging past power spectral values, it shows good performance and is suitable to apply to the EMG signal. Figure 3 shows the recorded EMG signals. The dashed lines represent the start and end points of the gestures. In Figure 3, it is clear that the amplitude of the signal in the resting period is minute compared with that of the acting period. Using the characteristics, we can estimate the noise power as

\[
\hat{\sigma}^2 = \frac{1}{N} \sum_{k=1}^{N} (x[n-k])^2, \tag{8}
\]

where \(k\) denotes the resting period of the EMG signal, \(N\) is the length of the resting period, and \(n\) stands for the time just before the start point of gestures. Figure 4 compares the unbiased difference power using two different noise powers. The unbiased difference power using the estimated noise power shows a similar value with the unbiased difference power based on the ideal noise power case. This means that the noise power is estimated well using the proposed noise power estimation method.
Figure 4. Feature variation based on SNR. Black solid line shows unbiased difference power obtained using ideal noise power. Gray dashed line shows unbiased difference power obtained using estimated noise power.

4. Result

We generated a noise signal using raw signal information. To add noise to the raw signal, which is known as noisy signal, we added additive Gaussian noise with zero mean and $\sigma^2_{\text{noise}}$ variance to the raw signal. The variance of noise signal, $\sigma^2_{\text{noise}}$, is calculated as

$$\sigma^2_{\text{noise}} = \begin{cases} \frac{\sigma^2_s}{10^{\frac{\text{SNR}}{20}}} - \sigma^2_{\text{raw}}, & \text{for } \text{SNR}_{\text{raw}} \geq \text{SNR} \\ \epsilon, & \text{otherwise} \end{cases}$$

(9)

where $\sigma^2_s$ is variance of activated signal, and $\sigma^2_{\text{raw}}$ is the resting period variance of raw signal. $\epsilon$ is a small value, which is set $10^{-5}$ in this study. $\text{SNR}_{\text{raw}}$ is a SNR of the raw signal, which is calculated as $\text{SNR}_{\text{raw}} = 10 \log_{10}(\sigma^2_s/\sigma^2_{\text{raw}})$. We set five different SNR levels between 0 and 20 dB.

First, we confirm the classification rate of the raw data. Figure 5 shows the classification accuracy of the raw data. In this case, both the training and test data are selected from the raw data. Because these results confirm the accuracy of the raw data, we only used the difference power as a feature. All subjects showed an average classification accuracy of more than 60%.

For the performance evaluation, we compare the results using the proposed unbiased difference power with two different conventional cases: applying no denoising algorithm or unbiased feature (None) and conventional denoising algorithm based on wavelet reconstruction (denoising) [17]. The proposed unbiased difference power is divided into two categories based on the method used to obtain the noise power.

Leave-one-out validation is used for the performance evaluation. Moreover, we repeated the validation for 100 times to ensure the evaluation result. For the classification using the proposed unbiased difference power, noiseless feature, $E[\Delta x[n]] = E[\Delta x[n]] - 2\sigma^2_{\text{raw}}$, is used for training set, whereas calibrated noisy features, $E[\Delta x[n]] = E[\Delta x[n]] - 2\sigma^2_{\text{noise}}$, is used as test data. For the $\sigma^2_{\text{noise}}$, we use the ideal noise power and estimated noise power.
Figure 5. Classification result of raw data. (a) Confusion matrix of subject two. (b) Average accuracy of 14 subjects.

Figure 6 shows the confusion matrices of subject 1 which shows the best performance in classification of raw data. For the case none shown in Figure 6a, the diagonal, which represents the accuracy, decreases with the SNR. This phenomenon, however, is improved by applying denoising or using the unbiased difference power. In particular, the confusion matrices of the cases using the unbiased difference power in Figure 6c,d show outstanding improvement, i.e., low SNRs, compared with those of the denoising case in Figure 6b.
Then, to expand the confirmed results in single subject, we confirm the classification results of all subjects used for evaluation. Figure 7 shows the changes in the recognition accuracy of 14 subjects in four different situations. For the none case, the accuracy decreases rapidly with the SNR regardless of the subject, as shown in Figure 7a. The accuracy decrease associated with the SNR occurs even in the denoising case, as shown in Figure 7b. However, using the proposed unbiased feature, the accuracy is maintained even when the SNR decreases. As shown in Figure 7c,d, even when the SNR is 5dB, the accuracy of all subjects is maintained. When the SNR is 0dB, a slight decrease in accuracy appears in most of the subjects, but the result remained the highest. These results indicate that the proposed unbiased difference power enables robust gesture recognition against noise.
Finally, to summarize the results shown in Figure 7, we calculate the average accuracy through subjects. The subject averaged recognition accuracy graph shown in Figure 8 shows the effect of the proposed unbiased feature. Figure 8 shows a comparison of the subject average accuracy of the four cases. For an SNR exceeding 15dB, four cases indicate similar recognition accuracies. However, for 10dB, the accuracy of two conventional cases begins to decrease whereas the two cases using the proposed unbiased difference power maintain similar accuracies to that of the higher SNR. As the SNR decreases, recognition accuracy decreases in all cases in general, but the recognition accuracy using the proposed unbiased feature remains the highest. Comparing the recognition accuracies of the noiseless and 0 dB cases, it was discovered that the accuracy of the the none case decreased by approximately 39%, whereas it decreased by 27% for the denoising case. However, for the two cases
using the proposed unbiased difference power, only approximately 15% and 9% decrease is observed for the estimated and ideal noise cases, respectively. These results show that the proposed unbiased difference power is extremely effective for gesture recognition in noisy situations.

Figure 8. Subject-averaged accuracy comparison. Colored bar represents average accuracy using each method explained in legend; white bar above colored bar represents corresponding standard deviation.

5. Conclusions

In this study, we propose an effective unbiased feature for robust gesture recognition of noise. We extract an unbiased difference power by subtracting twice the noise power, which is a noise bias for the difference power. The validity of the proposed unbiased feature is confirmed by deriving an equation using the feature. For the noise power, we use the ideal and calculated values to confirm the difference between the real and ideal situations. The noise power estimation was simply obtained by calculating the power of resting period. Due to the characteristics of EMG and background noise, it is possible to simplify the noise estimation process. For performance evaluation, the recognition accuracy is used as an index. Moreover, we compared the results using the proposed unbiased feature with the results of the other two cases. None of the denoising algorithms were used in the first case, whereas a denoising algorithm based on wavelet reconstruction was used in the second case. The recognition accuracy by not applying any denoising algorithms decreases significantly as the SNR decreased. By applying the denoising algorithm, the rapid decrease in the previous case is alleviated. However, the results obtained using the proposed unbiased difference power indicate that the decoding accuracy is maintained, although the SNR decreases. The reason why the decoding accuracy is maintained although the SNR decreases is that the proposed unbiased feature maintains a similar value even under different noise situations, whereas difference power varies greatly. The results indicate that the proposed unbiased difference power effectively overcomes the interference caused by noise in the gesture recognition.

For future work, it is necessary to apply the proposed unbiased difference power to a recorded noisy signal. Recording the EMG signal from various noisy situations and confirming the performance of the unbiased difference power should be done for practical uses. The evaluation with various classifiers is also needed for more rigorous performance evaluation. Moreover, more unbiased features should be derived. Since we only introduced an unbiased difference power, more unbiased features could be introduced.
in similar methods. These unbiased features would help EMG-based gesture recognition to be more robust to noise.

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**Abbreviations**
The following abbreviations are used in this manuscript:

- **EMG** Electromyography
- **SNR** Signal-to-noise ratio
- **LDA** Linear discriminant analysis

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