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Development of Miniaturized Wearable Wristband Type Surface EMG Measurement System for Biometric Authentication

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Abstract: Personal authentication systems employing biometrics are attracting increasing attention owing to their relatively high security compared to existing authentication systems. In this study, a wearable electromyogram (EMG) system that can be worn on the forearm was developed to detect EMG signals and, subsequently, apply them for personal authentication. In previous studies, wet electrodes were attached to the skin for measuring biosignals. Wet electrodes contain adhesives and conductive gels, leading to problems such as skin rash and signal-quality deterioration in long-term measurements. The miniaturized wearable EMG system developed in this study comprised flexible dry electrodes attached to the watch strap, enabling EMG measurements without additional electrodes. In addition, for accurately classifying and applying the measured signal to the personal authentication system, an optimal algorithm for classifying the EMG signals based on a multi-class support vector machine (SVM) model was implemented. The model using cubic SVM achieved the highest personal authentication rate of 87.1%. We confirmed the possibility of implementing a wearable authentication system by measuring the EMG signal and artificial intelligence analysis algorithm presented in this study.

Keywords: personal authentication; electromyogram; wearable electromyogram; support vector machine



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1. Introduction

Biometric recognition is a technology that recognizes an individual based on the unique characteristics of their body. This technology authenticates the host by analyzing a person's physical characteristics and determining whether they match the host data stored in the database. For example, authentication systems analyze features such as the pattern of the fingerprint or iris [1,2] or the face shape of the host [3]. In addition, an individual can be authenticated by analyzing the gait using an accelerometer integrated to the user's smartphone [4], or by analyzing the characteristic frequency of the voice [5,6].

The most promising biometric technology is the use of unique signals, such as electrocardiogram (ECG) and electromyogram (EMG) signals [7,8]. This method analyzes the morphological characteristics of ECG and EMG signals and has a considerable potential for development in the field of biometrics technology because it enables real-time authentication and prevents hacking.

However, the configuration of an authentication system using ECG signals is complicated [9]. In addition, incorrect authentication or errors due to changes in the signal may occur depending on the user's health condition, for instance, when the user suffers from a disease [10]. In contrast, the EMG-based authentication systems are more suitable because they are not influenced by the surrounding noise or the health of the user. Therefore, authentication studies using EMG signals have been actively conducted in the recent years [11–14].

In a previous study, the user was authenticated through an artificial neural network by measuring the EMG signal of the thigh and extracting 10 feature points while walking. However, since the device used in this study was a stand-alone type system and was not wearable, there were temporal and spatial limitations when using it for authentication [15]. Moreover, in another study, an individual used an EMG signal measurement module composed of eight channels, which performed personal authentication through convolutional neural network (CNN) analysis [16,17]. However, in these studies, the size of the device used was large [9], the measurement area was in the thigh, which was very inconvenient, and an additional stand-alone type of equipment was required for bio-signal measurement and processing [18].

In previous studies that attempted to perform authentication using a surface electromyogram, similar to the system that we proposed, special hand gestures performed by a user were analyzed and classified with an SVM to recognize the host data [16]. In this study, the correlation coefficient and cross-correlation functions were used to improve the accuracy of the SVM method.

In a previous authentication study, changes in the EMG signal based on wrist movement were detected [12]. The EMG signal was measured using an 8-channel EMG module (MYO Armband, Thalmic Labs, Kitchener, ON, Canada), and characteristic points, such as band power and root absolute sum square, were extracted from the EMG signal. For signal analysis, ARM Cortex A-53 was used, and an accuracy of 92% was achieved through real-time data processing and analysis.

In a previous study, the EMG signal was used to unlock the pattern lock by drawing a pattern after attaching a wet electrode to the forearm, and data were classified using a one-class classification algorithm [13]. These previously proposed methods are inconvenient owing to the following reasons: The size of the motion must be large, and the sample signal must be set for each person.

In the present study, to implement a real-time EMG signal measurement and analysis system, a wearable EMG signal measurement module that can be worn on the forearm and an artificial intelligence (AI)-based algorithm for EMG signal analysis were developed. In particular, it is possible to flexibly adapt to the curvature of the human body by measuring the EMG signal using a flexible dry electrode. Moreover, unlike wet electrodes, dry electrodes can be reused; therefore, a system that can efficiently measure EMG without any additional cost has been implemented. In addition, the optimal algorithm was implemented using a multi-class support vector machine (SVM) that enables efficient hyperplane search according to kernel function change for accurate and fast authentication by classification of measurement data. Thus, the possibility of implementing a wearable type EMG personal authentication system was confirmed.

2. Materials and Methods

2.1. Module and Signal

Figure 1 shows the EMG module developed for personal authentication research using the EMG signal analysis. The module was manufactured as a minimized wearable device with a size of $15 \times 25 \times 2 \text{ mm}^3$ that can be worn on the forearm; it uses one channel consisting of two dry electrodes. The weight of the module is 5.8 g, and incorporates a 3.7 V 120 mAh lithium-ion battery, which has an operating time of approximately 24 h. The EMG measurement module consists of an analog circuit for signal processing, which allows for noise reduction. The analog circuit of the EMG signal module comprises a 2nd Sallen-key filter. The EMG module includes a potentiometer for gain control (gain: 10–100), and the output size of the EMG signal can be adjusted. The input power of the EMG measurement module was 3.3 V (single power).

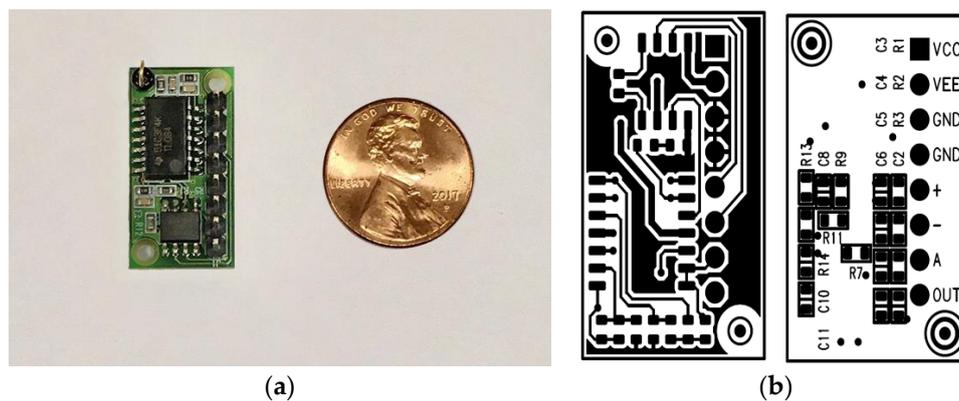


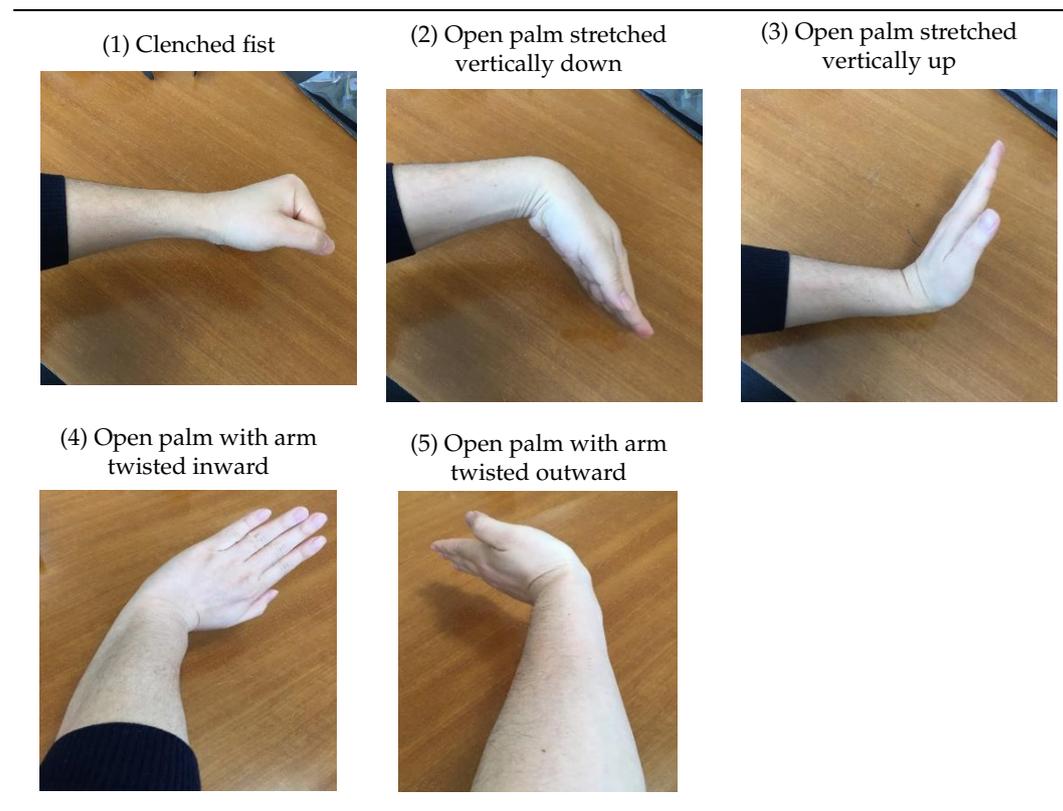
Figure 1. Development of electromyogram (EMG) detection system (a), top and bottom Gerber file (b). The manufactured module has a size of $15 \times 25 \times 2 \text{ mm}^3$ and can measure one channel signals at the same time.

Figure 2 shows the EMG signals measured using the developed EMG module. The EMG signal was measured when the subject clenched the fist. The normal signal indicates that the subject is not performing any action; the moderate force signal indicates the EMG signal measured when the subject slightly clenches their fist. The grasp signal is the waveform when the subject firmly clenches the fist. As can be seen in Figure 2, the peak-to-peak value of the EMG signal increased as the muscle strength increased. In the case of adult males in their twenties, the average EMG signal was approximately 1.3 V.

<p>Normal</p>		<p>V p-p(2)</p> <p>Current 77.98 mV Mean 76.051 mV Min 28.63 mV Max 77.98 mV</p>
<p>Moderate force</p>		<p>V p-p(2)</p> <p>Current 793.34 mV Mean 298.443 mV Min 35.03 mV Max 793.34 mV</p>
<p>Grasp</p>		<p>V p-p(2)</p> <p>Current 1.32960 V Mean 433.163 mV Min 31.79 mV Max 1.32960 V</p>

Figure 2. EMG signal according to muscle strength. EMG signal is output in proportion to the subject’s muscle force.

The excessive exercise was restricted to at least 5 h before starting the experiment. The subjects wore the wearable-type EMG signal measurement band produced in this study on their left wrist and then performed hand gestures according to five movements illustrated in Table 1. Each operation was repeated 10 times to acquire a signal. The EMG signal measured from the test participant was subjected to feature point extraction and classification using Matlab (2018a).

Table 1. Hand gesture for EMG data acquisition.

2.2. Data Acquisition

EMG signals from 50 subjects (41 males, 9 females) were measured. Figure 3 shows the watch-type wearable EMG system and the electrodes worn on the subject's left arm. The film-type dry electrode was manufactured to fit the curve of the forearm to measure the EMG signal. Two types of patterns were created using copper on a thin film layer. The size of the electrode was $2.1 \times 3.8 \text{ cm}^2$, and it was manufactured in types A and B to check the performance by various patterning. To use the square film area efficiently, a pattern was formed, as shown in Figure 3C. Type A is the active electrode, and Type B is the ground electrode. The EMG system developed in this study uses one channel but can add additional channels, if required.

2.3. Pre-Processing

The EMG signal contains various noises, such as impedance noise between the skin and electrodes, motion artifacts, and electrical noise inside the module. These noises degrade authentication accuracy; therefore, they must be minimized through pre-processing. In this study, a digital filter was designed in MATLAB and applied to the EMG signal. In general, the EMG signal is distributed in the frequency band of 5–450 Hz [19]. Butterworth-type high-pass and low-pass filters were designed, and a band pass filter was applied to reduce noise at 60 Hz. Figure 4 shows the noise reduction by the designed filter, and the top and bottom graphs show the raw and filtered signals of the EMG signal, respectively. The filtered signal has a noise reduction of approximately 40% compared to the raw signal.

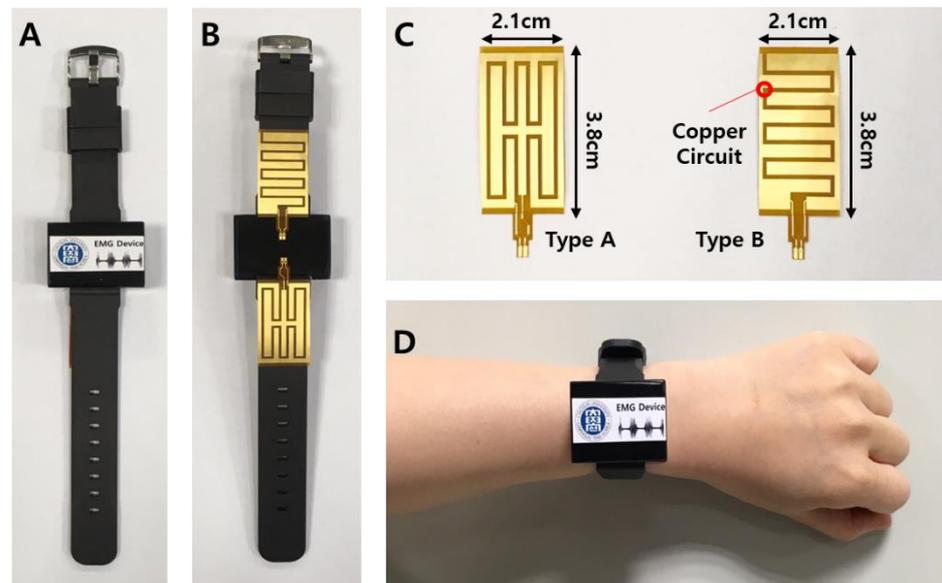


Figure 3. (A,B) Wearable EMG detection module. (C) Two types of flexible dry electrodes. (D) EMG system worn on wrist.

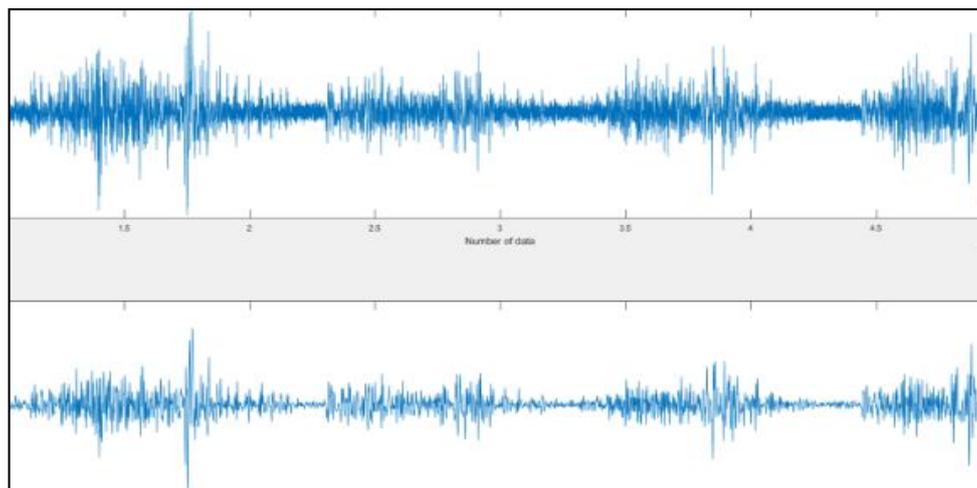


Figure 4. (Top) raw data, and (bottom) filtered data. The filtered EMG signal reduced noise by about 40% compared to the raw signal.

2.4. Feature Extraction

Various parameters such as signal length, mean frequency, and peak-to-peak value can be extracted from the EMG signal. The parameters applied to EMG authentication include root mean square (RMS), waveform length (WL), integral EMG (IEMG), simple square integral (SSI), and variance (VAR) [20,21].

$$\text{RMS} = \sqrt{\frac{1}{N} \sum_{n=1}^N x_n^2} \quad (1)$$

The RMS parameter (Equation (1)) is mostly used in EMG-related studies and can be extracted by performing square * mean * square root operation on the EMG signal. RMS is

a parameter related to muscle strength and contraction, and its value significantly increases as the strength of the subject increases.

$$WL = \sum_{n=1}^{N-1} |x_{n+1} - x_n| \quad (2)$$

WL (Equation (2)) is a parameter that indicates the complexity of EMG signals. This parameter is related to the amplitude, frequency, and time of the EMG signal and can be defined as the length of the surface EMG signal measured over a certain period of time.

$$IEMG = \sum_{n=1}^N |x_n| \quad (3)$$

IEMG (Equation (3)) is a parameter related to the subject's muscle strength, and it is extracted by calculating the area under the graph when the EMG signal is graphed in the time domain. The IEMG value is the same as the RMS parameter, and its value increases as the muscle strength increases.

$$SSI = \sum_{n=1}^N |x_n|^2 \quad (4)$$

SSI (Equation (4)) is extracted by squaring the amplitude of the EMG signal in the time domain. The method of calculating the SSI is similar to that of calculating the IEMG.

$$VAR = \frac{1}{N-1} \sum_{n=1}^N x_n^2 \quad (5)$$

VAR (Equation (5)) is a parameter that indicates the variance value of the EMG signal and quantifies the difference between the EMG signal and the average value in the time domain. Similar to the IEMG parameter, VAR is related to the subject's muscle strength [22].

2.5. Data Classification

In previous authentication algorithm studies using the CNN, when the difference between aspects (signal size, and signal shape) of the pre-trained EMG signal and the newly measured data was large, the authentication performance degraded. Wearable systems require measurement in various environments and real-time analysis. However, the large deviation of EMG signals according to the measurement environment hinders authentication by signal analysis. To overcome this limitation, in this study, we implemented a classification algorithm using multi-class SVM that can flexibly change the hyperplane structure according to the given data.

Figure 5 shows the distribution of the EMG signals the classification results obtained using the proposed algorithm. Multi-class SVM is an algorithm that classifies EMG signals using multiple decision boundaries. If there are N classes and all classes except to the i-th class are binary, the i-th class is +1, and the remaining classes are -1.

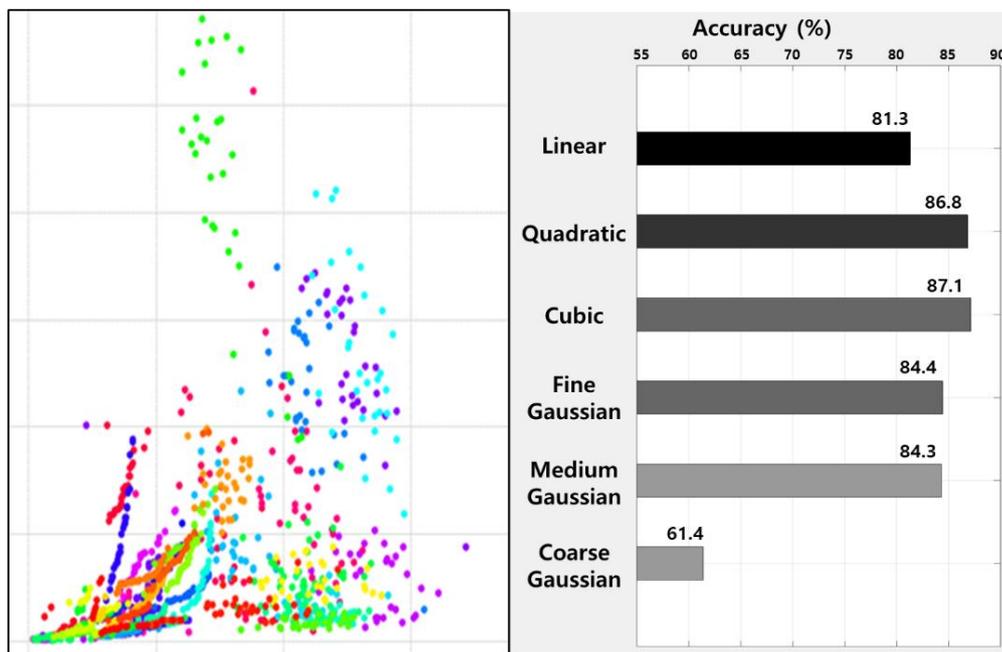


Figure 5. Classification results of EMG signal by using multi-class support vector machine (SVM). The SVM showed an average accuracy of 80.9%, Cubic SVM showed the highest accuracy of 87.1%.

The EMG signal features were extracted using six SVM methods, and personal authentication experiments were conducted. Figure 6 shows the personal authentication results of the cubic SVM and coarse Gaussian SVM. Authentication with the cubic SVM method exhibited the highest authentication rate of 87.1%, whereas that with the coarse Gaussian SVM was 61.4%. All SVMs adopted a one-to-one matching method, and the training was completed within a maximum of 3 min.

Cubic SVM	Coarse Gaussian SVM
Accuracy: 87.1%	Accuracy: 61.4%
Training Time: 156.7s	Training Time: 145.53s
Kernel function: Cubic	Kernel function: Gaussian
Kernel scale: Automatic	Kernel scale: 8.9
Multiclass method: One-vs-one	Multiclass method: One-vs-one
Feature point: 5	Feature point: 5

Figure 6. Classification results using Cubic SVM and Coarse Gaussian SVM, Cubic SVM represents the best case, and Coarse Gaussian SVM represents the worst case.

The SVM algorithm has different classification speeds and structural flexibilities depending on the classifier type. Linear SVM is the simplest SVM that uses a linear-type hyperplane. Simple distributed data can be easily classified, but complex data cannot be accurately classified.

$$k(x_i, x_j) = (x_i, x_j + 1)^2, \tag{6}$$

Quadratic SVM uses a second-order polynomial to construct a hyperplane; thus, it has a better classification performance than the linear SVM.

$$k(x_i, x_j) = (x_i, x_j + 1)^3. \quad (7)$$

Cubic SVM has a hyperplane based on a three-order polynomial; thus, data classification is possible through a relatively flexible hyperplane.

Fine, medium, and coarse Gaussian SVMs are classifiers to which the square root function is applied, such that the hyperplane can be created in a flexible structure. Because all SVM classifiers other than linear SVM have a complex hyperplane structure, the binary classification speed is high, but the multi-class classification speed is low. If data cannot be separated using a linear SVM, an SVM using a high-dimensional hyperplane should be applied. For example, quadratic or cubic SVM builds a hyperplane using two- or three-order polynomials. If a quadratic or cubic SVM is used, better classification results than those with a linear SVM can be obtained.

A polynomial kernel can be applied to train nonlinear models. Table 2 shows the accuracies of different types of SVMs. Training with cubic SVM requires more training time than a quadratic SVM but provides a more accurate data classification [23]. The personal authentication algorithm using multi-class SVM showed the highest accuracy of 87.1% when using cubic SVM.

Table 2. Accuracy by applying a polynomial kernel.

Classifier Type	Title 2	Title 3
Linear	81.3	Auto
Quadratic	86.8	Auto
Cubic	87.1	Auto
Fine Gaussian	84.4	0.5
Medium Gaussian	84.3	2.2
Coarse Gaussian	61.4	8.9

Algorithm 1 represents the operation procedure of the SVM classifier. The parameters extracted from the EMG signal were stored in the predictor variable. Label data of the EMG signal were saved in the response variable. Fifty EMG signals were classified using six types of SVM classifiers. The EMG signal classification process proceeds with one-to-one matching; if the EMG signal does not match the response data, it performs matching with other response data.

Algorithm 1 SVM based on EMG data classifier

```

Step 1: Create function SVM_classifier
Step 2: Predictor = InputData(Feature Extraction)
Step 3: Response = InputTable(EMG data)
Step 4: Classification SVM
Step 5: for n = 1; n > 50; n++
Step 6: if Predictor = Response //One-vs-one matching
Labeling
Step 7: else
Another matching
END
END function

```

To apply the SVM classifier, K-fold cross-validation was performed. This can improve training efficiency when the amount of data is small. In addition, it can prevent overfitting and underfitting problems [24]. The K-fold cross-validation procedure was performed as follows.

Figure 7 shows the data segmentation method used for cross-validation. To maximize the training efficiency with a small dataset, the dataset was divided by K. The first section of the data was used as test data, and the remainder was used as training data to proceed with learning. Cross-validation was completed by repeating this procedure K times. In the authentication experiment using EMG signal analysis, the K value of the K-fold cross-validation was set to 10. Table 3 shows the accuracy values according to the change in K value from 2 to 12.

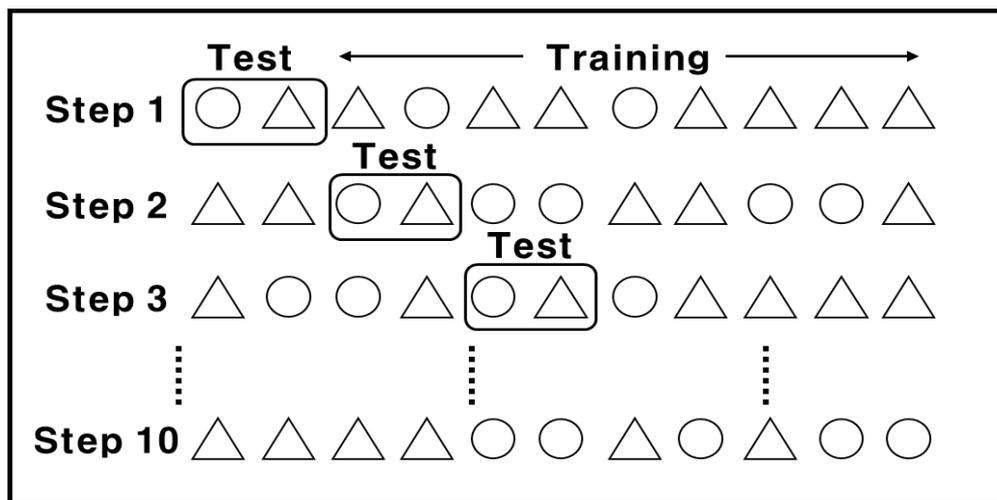


Figure 7. K-fold cross-validation. In this study, the EMG dataset used for learning was divided into ten.

Table 3. Result by K value.

K-Fold	Accuracy
K = 2	85.1%
K = 3	85.3%
K = 4	85.4%
K = 5	86.1%
K = 6	86.2%
K = 7	86.8%
K = 8	87.0%
K = 9	86.9%
K = 10	87.1%
K = 11	87.0%
K = 12	86.8%

Figure 8 shows the results of the EMG authentication using the K value of cross-validation. The personal authentication rate increased as the K value increased, and the highest accuracy was obtained when K was 10. When the K value was 11 or more, the personal authentication results decreased.

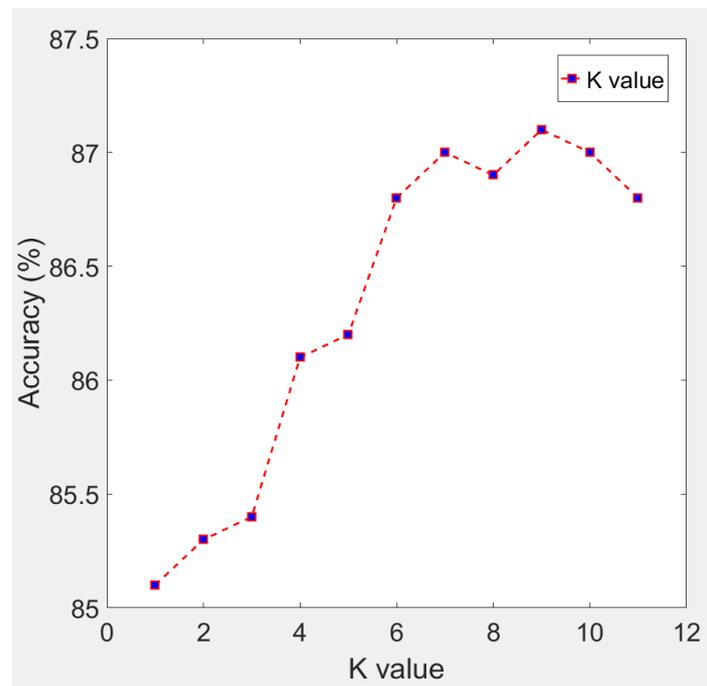


Figure 8. Cross-validation result. Multi-class SVM showed the highest accuracy when K value was 10.

3. Results

In this study, we developed a miniaturized wearable EMG measurement system that can be worn on the forearm. The dry electrode was manufactured in a flexible shape and applied to the watch strap to adapt to the curve of the forearm. The dry electrode size was $2.1 \times 3.8 \text{ cm}^2$ and comprised two patterns. We implemented a personal authentication algorithm that is optimal for EMG signal classification using six multi-class SVMs that enable an efficient hyperplane search according to the kernel function value change. Linear SVM using a first-order polynomial showed a poor personal authentication rate of 81.3% owing to the simple hyperplane structure. The quadratic SVM was relatively well adapted to the EMG signal when using a quadratic polynomial-based hyperplane, and an authentication rate of 86.8% was obtained. In addition, cubic SVM, which forms a hyperplane using a third-order polynomial, achieved the highest personal authentication rate of 87.1% in this study. The results indicate that the flexible classification structure of the cubic SVM provided a better performance when applied to EMG signals with a complex distribution. Fine, medium, and coarse Gaussian SVMs, in which the kernel function changes according to the amount of data to be classified, are considered to have a lower personal authentication rate because overfitting occurs.

Table 4 shows the false positive rate (FPR) and true positive rate (TPR) values of the multi-class SVM. FPR is the probability of classifying host data as data from other people. Thus, a lower FPR indicates a higher personal authentication rate. TPR is the probability of correctly classifying the host data among all host data and indicates accuracy; therefore, a higher TPR indicates better accuracy. It was confirmed that the cubic SVM method has superior FPR and TPR values compared to the other SVMs analyzed.

Table 4. False positive and true positive rate.

Classifier Type	False Positive Rate	True Positive Rate
Linear	0.0032	0.813
Quadratic	0.002	0.8682
Cubic	0.002	0.8718
Fine Gaussian	0.0024	0.8436
Medium Gaussian	0.0022	0.8428
Coarse Gaussian	0.0076	0.614

To improve the training efficiency of the multi-class SVM, cross-validation efficiency according to K change was tested. The value of K increased by one from two, which is the smallest unit that can be divided into the dataset. For a K value of 10, the highest personal authentication rate of 87.1% was obtained, which decreased with a further increase in the K value.

4. Discussion

This study was conducted to classify EMG signals using a wearable type authentication system that can be worn on the wrist. The possibility of constructing a system that can authenticate simple hand gestures in daily life is suggested.

The main advantage of this study is that it has relatively little influence on the surrounding brightness, noise, and health of users. Flexible skin problems and pain may be caused by the adhesion substance surrounding the wet electrode, and the signal may be distorted owing to the effect of the gel when a long-term measurement is taken. However, the dry electrode developed in this study has the advantage of being easily attached to the body in a flexible form and can be reused.

The application of flexible dry electrodes in our system is advantageous in that it allows for the manufacture of electrodes that are suitable for the body, with different characteristics for each person, through the formation of a desirable copper pattern.

In general, epidermal electronics are used as electrodes to which EMG/ECG sensors, strain gauges, power coils, and wireless antennas are attached on the skin. The previous research cases that applied biosignal using epidermal electronics are as follows.

Carolina Miozzi et al. [25] proposed a wireless electronic skin with a size of $3 \times 3 \text{ cm}^2$ suitable for acquiring EMG signals conveniently in the field of sports or healthcare.

Kim et al. [26] developed a stretchable, ultrathin, transparent electronic skin. And the function was tested with ECG sensing and strain sensor.

Lee et al. [27] developed a metal-based stretchable epidermal electrode by micro-fabrication. This electrode was made of polyimide, gold, titanium, PDMS, etc., and its performance as an electrode was tested through an EMG signal measurement experiment.

However, the epidermal electronics mentioned above should also be supplemented with adhesion to the skin in order to obtain signal acquisition performance and to minimize noise generated by movement. Since the flexible dry electrode that we proposed is fixed by the strip, noise generation could be minimized.

The personal authentication method using EMG signals is expected to contribute to establishing a more secure authentication system by enhancing the level of personal authentication through fusion with other biosignals such as ECG and PPG.

In a recently conducted study, authentication was performed through the evaluation of six motions 10 times by five experimenters [28]. As a result of the experiment using SVM by gesture, 66.7% accuracy was achieved. In addition, a recognition rate of 80% was achieved when a random forest was used. The use of multiple channels to improve authentication has been researched.

In another previous study, a team of researchers obtained EMG signals from 56 experimenters and extracted 18 feature points. KNN and LDA were combined to form an ensemble model, and an accuracy of 97% was achieved [29].

There is data that discloses the FPR value to indicate the performance of the previous study results related to personal authentication. Previous studies showed the FPR values ranging from 0.08 to 0.167 [30–32].

In this study, the FPR value was 0.0032. Although it is not far behind the previous research results, it is expected that it can be improved if the model and device performance are optimized. However, this study has limitations. In the EMG signal analysis and authentication experiment, a maximum accuracy of 87.1% was obtained, but the research trend in the personal authentication field requires an accuracy of more than 90%. Therefore, a personal authentication system using EMG signals needs to improve the performance. To ensure the reliability of the proposed system and authentication method, additional studies such as additional extraction of parameters and redesign of EMG signal classifier are required.

In addition to improving the performance of the algorithm, additional research on electrodes is required to improve the characteristics of the hardware system. In particular, when an electrode is fabricated using laser induced graphene technology, the contact resistance can be reduced by improving the skin adhesion of the electrode [33,34]. Thus, higher quality EMC signals can be obtained. Moreover, when applied to an improved algorithm, the classification accuracy is can be further improved.

5. Conclusions

In this study, to implement a real-time EMG signal measurement and analysis system, a small wearable EMG detection system that can be worn on the forearm was developed. A flexible type of dry electrode was employed to easily measure the EMG signal. By analyzing the acquired signals, we developed an SVM-based AI algorithm that enables personal authentication. In particular, the optimal algorithm was implemented using multi-class SVM, which enables efficient hyperplane search according to kernel function change for accurate and fast authentication through classification of measurement data. The personal authentication result by EMG signal analysis demonstrated the best result of 87.1% when using cubic SVM. Additional investigations, such as miniaturization of the wearable system, kernel function change, and SVM structure improvement, confirmed the possibility of implementing the wearable EMG authentication system. If the developed wearable EMG measurement system is further miniaturized and combined with an ECG system, it can be used as a healthcare system or disease prediction system to manage health in daily life.

Author Contributions: S.S. constructed the EMG detection system and suggested the concepts for the work; M.K. performed the experiments; J.J. analyzed the data; Y.T.K. supervised the writing of the article. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflict of interest.

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