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Hand Gesture Recognition Suitable for Wearable Devices using Flexible Epidermal Tactile Sensor Array

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Abstract – With the explosion of digital devices, interaction technologies between human and devices are required more than ever. Especially, hand gesture recognition is advantageous in that it can be easily used. It is divided into the two groups: the contact sensor and the non-contact sensor. Compared with non-contact gesture recognition, the advantage of contact gesture recognition is that it is able to classify gestures that disappear from the sensor's sight. Also, since there is direct contacted with the user, relatively accurate information can be acquired. Electromyography (EMG) and force-sensitive resistors (FSRs) are the typical methods used for contact gesture recognition based on muscle activities. The sensors, however, are generally too sensitive to environmental disturbances such as electrical noises, electromagnetic signals and so on. In this paper, we propose a novel contact gesture recognition method based on Flexible Epidermal Tactile Sensor Array (FETSA) that is used to measure electrical signals according to movements of the wrist. To recognize gestures using FETSA, we extracted feature sets, and the gestures were subsequently classified using the support vector machine. The performance of the proposed gesture recognition method is very promising in comparison with two previous non-contact and contact gesture recognition studies.

Keywords: Flexible epidermal tactile sensor array, Hand gesture recognition, Wearable device, Wearable sensor.

1. Introduction

With the explosion of digital devices, interaction technologies between human and devices are required more than ever. Among them, gesture recognition technologies have gained a great deal of attention with their simpler interface [1 - 5]. In particular, hand gesture recognition is advantageous in that it can be widely used. Essentially, hand gesture recognition is divided into the two groups: the contact sensor and the non-contact sensor. The non-contact sensor is mostly based on visual technology [6, 7]. It extracts information on the shape and movements of the hand from a momentarily image through various techniques and then recognizes the hand gestures from this information. Wei Lu et al. (2016) [8] proposed a novel feature vector which is suitable for representing dynamic hand gestures, and presented a solution to recognize such gestures using the feature vector with just a Leap Motion controller (LMC). Guillaume Plouffe et al. (2015) [9] proposed a natural user interface that recognizes and tracks hand gestures based on depth data acquired by a Kinect sensor in real time. Alternatively, for the contact sensor, the user directly wears the sensor. Such sensors include the inertial sensor, the magnetic sensor, the gyro sensor and the electromyography (EMG) sensor. Wrapping the sensor around the user's forearm or wrist and wearing a glove attached to the sensor are examples of gesture recognition [10 - 12]. In these technologies, the most commonly used method of recognizing gestures by the sensors is to detect the user's muscular activities according to hand movements. For this, EMG sensor is commonly used to measure the muscular activities because it measures the electric potential to activate the muscle by electrodes attached on the skin [13]. There are many studies for gesture recognition using EMG sensor as an input [14-16]. However, the electric potential of muscles is, in general, too sensitive to electric noise, because the magnitude of the electric potential is in the range of sub millivolts, which is significantly small compared to the electric noise induced by wall-electricity. In addition, it requires an amplifier circuit that includes a voltage follower and a differential amplifier, which makes the electrodes or peripherals slightly bulky. Another drawback is that it needs to be directly attached on the skin. These factors make the application of EMG challenging to mobile devices [17].

Another way to recognize the human intention is force-sensitive resistors (FSRs) [18, 19]. The recognition mechanism of FSRs is to detect the muscular activity by monitoring change of resistors according to the swelling of muscles. FSRs is generally known for it is robust to noise compared to the other sensors, but it has the drawback that the output voltage of FSRs sensors is nonlinear because of the relationship between an output voltage and the resistance [20].

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To improve the problems with EMG and FSRs sensor, many researchers proposed a new sensor. Pyeong-Gook Jung et al. proposed the sensor for recognizing the muscular activities based on air-pressure sensors and air-bladders [17]. It detects the muscular activity by measuring the change of the air pressure in an air-bladder contacting the interested muscles. They verified the performance of the air-pressure sensors are better than EMG sensor in terms of wear-comfort, reliability, linearity, and durability.

In this paper, we propose a novel contact gesture recognition method based on Flexible Epidermal Tactile Sensor Array (FETSA) that is used to measure electrical signals according to movements of the wrist. The detection mechanism of FETSA is similar to FSRs sensors, but we provide enhanced usability in terms of wearing the sensor due to flexible characteristic. For verifying the performance of the sensor, we accomplish comparison test between a commercial EMG sensor and FSRs sensor, and we compare the performance of the proposed system with two previous non-contact and contact gesture recognition studies. For the comparison, we set experimental conditions equal to the previous studies. Furthermore, we accomplish another recognition experiments using gestures we define in this research. To recognize gestures using the FETSA, we remove an artifact through a preprocessing method and then extract feature sets, such as stochastic values.

The rest of this paper is organized as follows. Section 2 explains the FETSA. Sections 3 and 4 present the recognition method that is proposed in this research and the experiments performed, respectively. Section 5 presents summaries and conclusions.

2. Flexible Epidermal Tactile Sensor Array

In this research, the Flexible Epidermal Tactile Sensor Array (FETSA) is used for measuring the physical deformation of the sensor according to the movement of the wrist. Therefore, the sensor acquires data in the form of a change of electrical resistance following the muscle's movement. A design that optimizes suitable positions and the number of sensors for the movement in the wrist muscles is a necessary part of developing the flexible sensor array. The sensor array was experimentally designed with an array of 16 sensors by focusing on the extensor pollicis longus for the wrist movement and the flexor pollicis longus for the finger movement. Fig. 1 shows the logical model of the Flexible Epidermal Tactile Sensor Array.

The gesture recognition sensor array was fabricated on a flexible polyimide to improve the fit for the surface of the body of the user. Firstly, metal deposition was performed with Ni-Cr and Cu in order to make a resistor whose resistance changes according to the movement of the wrist on a flexible substrate (polyimide). In the following, a coating was made using DFR (dry film photoresist) to

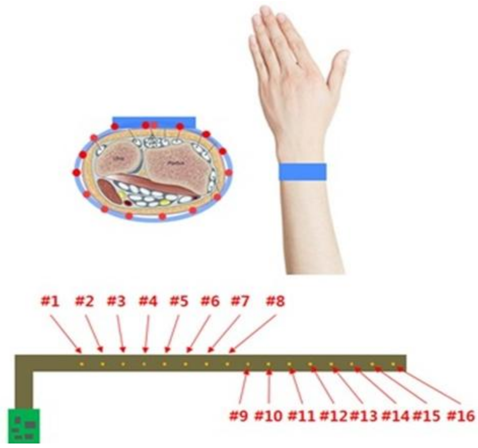


Fig. 1. The logical model of the Flexible Epidermal Tactile Sensor Array

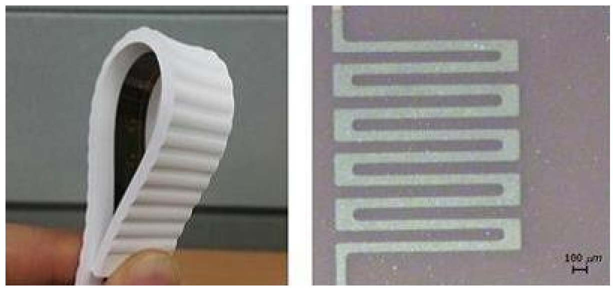
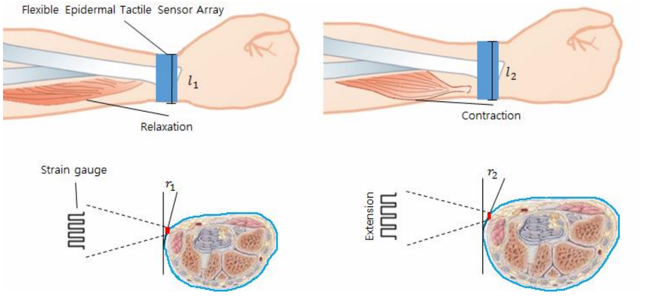


Fig. 2. Fabricated Flexible Sensor Array and sensor image taken with an optical microscope (Scale bar, 100 μm)

achieve a uniform PR (photoresist) coating. After the exposure process, PR developing and Cu etching were sequentially performed. After etching, the DFR coating, exposure, and development were performed one more time, and the Ni-Cr was etched. Finally, a cover layer was formed on the exposed metal to protect the sensor. The fabricated sensor was packaged with silicone to protect the sensor and induce an improved wrist movement (KE-12, Shin-Etsu Co.). The fabricated flexible sensor array showed bending characteristics up to a curvature radius of 5 mm. Depending on the movement of the wrist, the resistance value of the flexible array sensor is processed using a circuit and converted into a digital code (analog-to-digital) value. This coded value is then used for gesture recognition. The sensitivity of the sensor measured about 0.05143 Ω/g. Fig. 2 shows a flexible sensor array that has been manufactured using the above process, with the image taken using an optical microscope.

2.1 Detection mechanism of FETSA

In order to detect the deformation of the sensor according to the movement of the wrist in a reliable way, the FETSA consists of a strain gauge whose resistance is able to change according to the movement of the wrist on a



(a) (b)

Fig. 3. Example of deformation of a tactile sensor with relaxation and contraction of wrist muscles. (a) Relaxation. (b) Contraction

flexible substrate. Therefore, the FETSA measures the change of resistance with the relaxation and contraction of wrist muscles.

Various muscles under the wrist contract and relax while the wrist is moving. For example, the extensor carpi radialis longus muscle under the forearm contracts when the wrist is angled up. As shown Fig. 3, changes in the thickness of the wrist are caused by the expansion and contraction of the muscles according to the movements of the wrist. Therefore, the degree of crookedness of the sensor wrapped around the wrist changes and resistance changes because the strain gauge is expanded.

3. Gesture Recognition

Fig. 4 shows the overall flowchart of the proposed gesture recognition method.

3.1 Preprocessing

While a bio-signal is recorded, the mixing of signals sometimes occur. These artifacts are recorded by confusing a heartbeat with a movement of the wrist as an artery positioned under the wrist. It is necessary to remove such artifacts as it leads to a degradation of the quality of the signal. As shown Fig0 5(a), a stably recorded signal is periodically deformed by a heartbeat. As this can a cause reduction in the accuracy of gesture recognition, we use a median filter to remove these artifacts. The median filter is effective for removing impulse noises such as these artifacts while being able to preserve the existing property of the signal. Fig. 5(b) shows the results with the removed artifacts.

3.2 Feature extraction

In previous studies, bio-signals such as EMG have been analyzed in frequency domains using Fourier transform. However, Fourier transforms are not effective for computational complex problems and are not suitable for

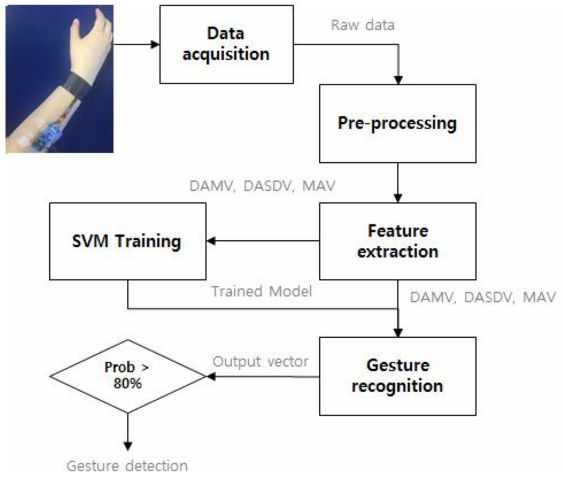


Fig. 4. The overall flowchart

(a) (b)

Fig. 5. (a) Signal varied by heartbeat. (b) The results with removed artifacts

non-stationary signals, such as bio-signals. Therefore, in this study, we extract time series features that are relatively simple in the frequency domain in terms of the computational complexity.

The difference absolute mean value (DAMV) feature vector is a measure of signal variation equal to the average absolute difference of two sequential values. The equation is as follows:

$$DAMV = \frac{\sum_{i=1}^{N-1} \left| X(i) - X((i+1)) \right|}{N-1} \tag{1}$$

The difference absolute standard deviation value (DASDV) is a feature that represents the standard deviation value of the difference between two sequential values. The feature is expressed by equation (2):

$$DASDV = \sqrt{\frac{\sum_{i=1}^{N-1} \left(X(i) - X((i+1)) \right)^2}{N-1}} \tag{2}$$

The mean absolute value (MAV) is a measure of signal power equal to the average absolute value of the signal. The equation is as following:

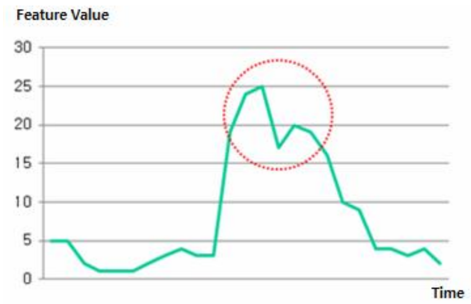


Fig. 6. Example of extracted DAMV feature

$$MAV = \frac{\sum_{i=1}^{N} |X(i)|}{N} \tag{3}$$

3.3 Support vector machine

A support vector machine with a polynomial kernel is used to classify gestures. We use Sequential Minimal Optimization (SMO) to optimize the machine learning algorithm. Generally, as SVM is not affected by noise data and does not generally cause overfitting, it is used in various fields. However, SVM requires optimization testing for optimal models and parameters. In order to resolve the XOR problem, we use the Radial Bias Function (RBF), with the parameters experimentally set.

3.4 Gesture detection

Using the preprocessing described in section 3.1, the artifacts of the recorded signal are removed. And then, three features are extracted from the signal after preprocessing. The period of the extraction is about 0.13 second in consideration of the time for making a gesture. Fig. 6 is an example of the extracted DAMV feature when a subject makes a gesture.

In order to train using only a feature when making a gesture, we picked the peak point of the signal. The peak point is extracted in order to train only the feature of the period when subjects make a gesture. We train SVM using the feature inside the red circle, as shown in Fig. 6. And then, the SVM classifies gestures from the signal of the sensor. Using the output of classification, the probability of each gesture is calculated. The equation can be expressed as:

$$\Pr obability = \frac{Outvector}{\sum Outvector} \tag{4}$$

Lastly, the gesture with the highest probability is detected. If the probability is under 80%, a gesture is not detected.

The gesture detection speed is computed using Visual Studio 2010 with Intel i7-4770 3.40GHz, 16 GB RAM and 64-bit Windows 7 operating system. The speed detecting a gesture was 750 milliseconds.

4. Experiments

In order to verify the performance of our proposed method, we accomplish comparison test between a commercial EMG sensor and FSRs sensor, and we compare with two previous non-contact and contact gesture recognition studies. To compare with previous studies, we set the conditions of the experiment equal to the previous studies [17, 21]. Furthermore, we perform a recognition experiment using the gestures we define in this research. Fig. 7(a) shows a test environment for the proposed gesture recognition. Subjects who participated in this experiment wear the FETSA sensor covered with a band, as shown in Fig. 7(b).

4.1 Comparison with EMG and FSRs sensor

To verify the reliability of FETSA, we compare the sensor with EMG and FSRs sensors which are most commonly used for detecting the user's muscular activities. For this, a commercial FSRs sensor, RA9P with Arduino, and a commercial EMG sensor and Muscle Sensor v3 kit are used.

Fig. 8 shows experimental results of the comparison.

(a) (b)

Fig. 7. (a) Test environment for the proposed gesture recognition. (b) FETSA sensory band

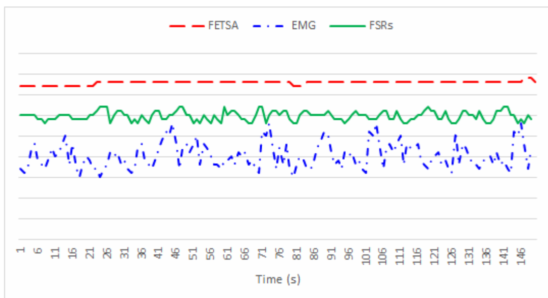


Fig. 8. Experimental results of comparison with EMG and FSRs sensor

The signal is acquired from the sensors while the subject who attaches each sensor remains motionless. For the quantitative comparison for the reliability of sensors, signal-to noise ratio (SNR) is calculated. To estimate a desired signal, low-pass filter is used. The SNR equation is as follows:

$$SNR = 10\log_{10}\left(\frac{P_{signal}}{P_{noise}}\right) \quad (5)$$

The SNR of FETSA signal is about 27.92, while the SNR of FSRs and EMG is 11.56 and 15.67 respectively.

4.2 Linearity

As described in section 2.1, the deformation of the sensor is measured by a change of resistance with the relaxation and contraction of wrist muscles. Therefore, it is expected that the change of resistance measurement is proportional to the angle of the wrist. However, because there are many factors that conflict with these assumptions, we performed an experiment for the verification of linearity. A subject was asked to fold their wrist while maintaining a constant angle while the signal was measured. In order to test linearity, we used six different wrist angles, consisting of 0, 15, 30, 45, 60 and 75 degrees.

Fig. 9 shows the linearity test results. Every sensor output was used to perform the linearity test, however, three representative channels are shown in Fig. 9 as examples. The subject repeated the same experiment 10 times, and the average and standard deviation values are shown in Fig. 9. According to the results, the outputs were close to linear, although the data show inflections, which might be due to different influences. Therefore, sensor output increases in proportion to the angle of the wrist.

4.3 Repeatability

It is important to show good repeatability with a sensor. Therefore, an experiment was carried out for the verification of repeatability. A subject was asked to clench and open their fists iteratively. This was repeated 25 times. Fig. 10 shows the experimental results as an example.

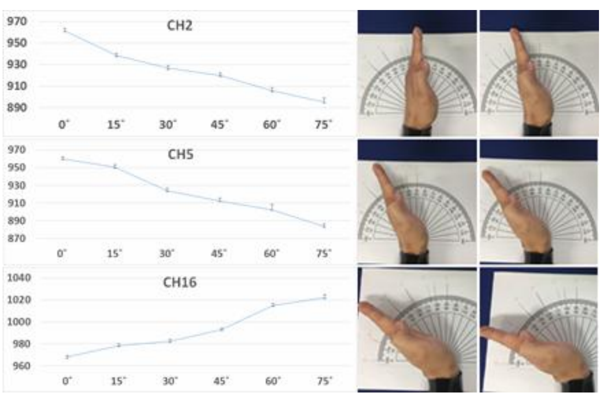


Fig. 9. Linearity test results

Every sensor output was used to perform the repeatability test, however, six representative channels are shown in Fig. 10 as examples. As shown in Fig. 10, the same signal pattern was observed for all moments. In addition, we measured the average and standard deviation of repeated signals at moments when the fist was clenched. For example, the channel 7 sensor shows an average value of 1029.1 and standard deviation of 8.04. The average value of all sensors was about 994.8, and the standard deviation value of all sensors was about 8.71. According to the results, the standard deviations were very small compared to the average value, which verifies that the FETSA is able to accurately measure muscle activity iteratively.

4.4 Comparison with non-contact gesture recognition

Seo Yul Kim et al [21] introduced a hand gesture recognition sensor using ultra-wideband impulse signals, which are reflected from the hand. In this study, six American Sign Language (ASL) hand gestures are defined for the experiment. In addition, to classify the gestures, a Convolution Neural Network (CNN), which extracts its own features and constructs a classification model, was

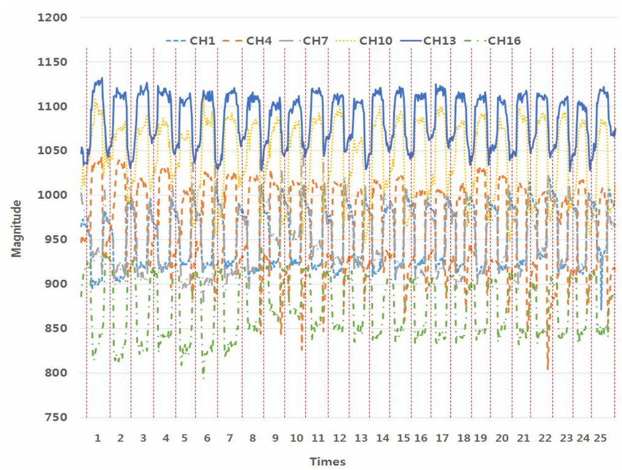


Fig. 10. Repeatability test results

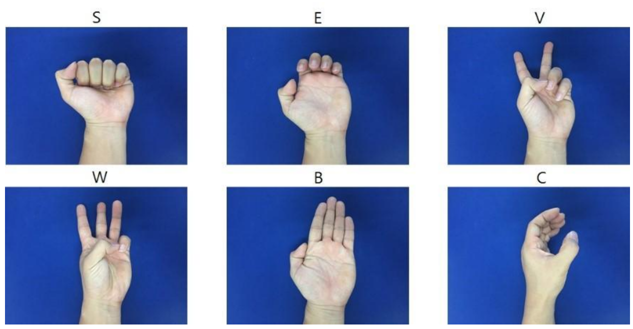


Fig. 11. The six gestures that were defined in previous research [21]

Fig. 12. Classification accuracy for the "S", "E", "V", "W", "B" and "C" gestures from the previous studies with CNN and SVM [21], and with proposed method

used. Fig. 11 shows the six gestures that were defined in the previous study.

A total of five people to part in this experiment. Each participant performed each of the six gestures in Fig. 11 100 times. The signal according to each of the six gestures is obtained from the FETSA sensor. Therefore, we constructed a 3000-point data set equal to the previous research. We randomly divided the data into two subsets: 80% for training and 20% for testing.

The experimental results are presented in Fig. 12. The results show that the average accuracy of the previous study with CNN is 91 % [21], the average accuracy of the previous study with SVM is 83.33% [21] and the average accuracy of the proposed method is 95.83%. In previous research, an accuracy of 100% for the five gestures ("S", "E", "V", "B", "C") was achieved. However, the "W" gesture shows a low accuracy as the gestures of "W" and "V" are similar. In contrast, the "W" gesture exhibits a high accuracy in the proposed gesture recognition method, although the "E" and "V" gestures have a slightly lower accuracy compared to the previous research.

4.5 Comparison with contact gesture recognition

Pyeong-Gook Jung et al [17] introduced a new method for recognizing the muscular activities based on air-pressure sensors and air-bladders. Muscular activity is detected by measuring the change of the air pressure in an air-bladder that is in contact with the interested muscle. The principle of measuring the muscular activity is similar to the method of FSRs. For gesture recognition, the rule base of fuzzy logic was used. The rule base was mainly determined from the muscle roles of each gesture and the air bladders corresponding to the muscles. Fig. 13 shows the six gestures that were defined in the previous research.

Each participant performed each set of experiments more than 10 times. The experimental results for the comparison between each subject are presented in Table 1.

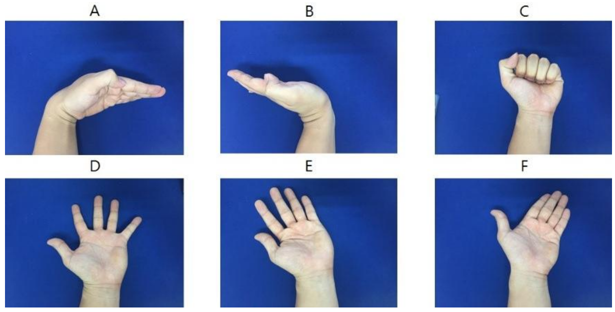


Fig. 13. The six gestures that were defined in previous research [17]

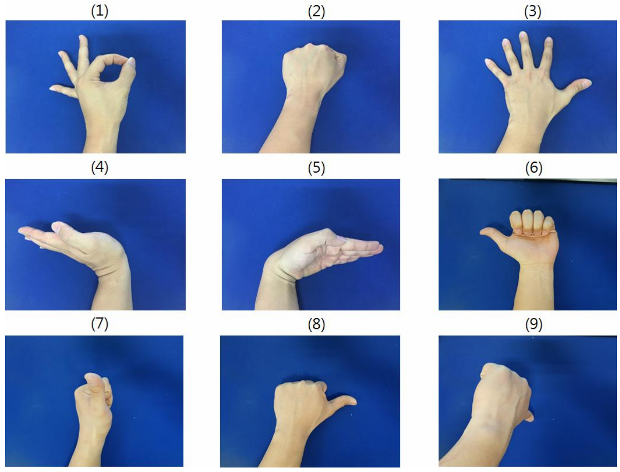


Fig. 14. The nine gestures defined in this research

From the results, the average accuracy of the proposed method was 98.15%, greater than the average accuracy of the previous research (95.35%) [17].

4.6 Hand gesture recognition with the FETSA sensor

The nine hand gestures that we defined in this research are shown in Fig. 14: The pinch of the finger [(1) in the figure]; the flexion and extension of the fingers [(2) and (3)]; the flexion and extension of the wrist [(4) and (5)]; the twist of the wrist [(6), (7), (8) and (9)].

Total 10 subjects are participated in this study. The subjects were composed of six males and four females. Before the experiments, the subjects trained the SVM to recognize the gestures for five seconds. The average of the training error rate was 4.24%. Each experiment is accomplished 30 times per gesture, with the gesture randomly selected by the experiment organizer. The subjects made a gesture according to the organizer's instructions. Therefore, the gesture recognition is accomplished for a total of 2700 times.

The experimental results are presented in Fig. 15. For the investigated nine gestures, the average classification accuracy was 97%. In general, the misclassification rate was broadly low. However, the misclassifications of the input

Fig. 15. Experimental results with confusion matrix (%)

of gesture 1 with the output gesture is 6, and the input of gesture 8 with the output of gesture 2 was observed relatively higher than other misclassifications.

5. Conclusion

In this research, we developed the Flexible Epidermal Tactile Sensor Array (FETSA), used for measuring the electrical signal according to the movement of the wrist. To recognize gestures using FETSA, we removed artifacts using a preprocessing method and we subsequently extracted feature sets. The gestures were classified using the support vector machine. The performance of the proposed gesture recognition method was verified with comparisons with two previous non-contact and contact gesture recognition studies. Furthermore, we performed a recognition experiment using gestures that we define in this research. Results showed that our proposed method performed better than the previous studies. Also, for the hand gesture recognition using the nine gestures defined here, the average classification accuracy was 97%.

In future work, we plan to measure many gestures from various human subjects to train a system for general-purpose hand gesture recognition.

Acknowledgements

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