A Study of Personal Recognition Method Based on EMG Signal

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***Abstract*—With the increasing development of internet, the security of personal information becomes more and more important. Thus, variety of personal recognition methods have been introduced to ensure persons' information security. Traditional recognition methods such as Personal Identification Number (PIN), or Identification tag (ID) are vulnerable to hackers. Then the biometric technology, which uses the unique physiological characteristics of human body to identify user information has been proposed. But the biometrics widely used at present such as human face, fingerprint, iris, and voice can also be forged and falsified. The biometric with living body features such as electromyography (EMG) signal is a good method to achieve aliveness detection and prevent the spoofing attacks. However, there are few studies on personal recognition based on EMG signal. According to the application context, personal recognition system may operate either in identification mode or verification mode. In the personal identification mode, the system recognizes an individual by searching the templates of all the users in the database for a match. While in the personal verification mode, the system validates a person's identity by comparing the captured features with her or his own template(s) stored in the system database. In this paper, both EMG-based personal identification method and EMG-based personal verification method are investigated. First, the Myo armband is placed on the right forearm (specifically, the height of the radiohumeral joint) of 21 subjects to collect the surface EMG signal under hand-open gesture. Then, two different methods are proposed for EMG-based personal identification, i.e., personal identification method based on Discrete Wavelet Transform (DWT) and ExtraTreesClassifier, and personal identification method based on Continuous Wavelet Transform (CWT) and Convolutional Neural Networks (CNN). Experiments with 21 subjects show that the identification accuracy of this two methods can achieve 99.206% and 99.203% respectively. Then based on the identification method using CWT and CNN, transfer learning algorithm is adopted to solve the model update problem when new data is added. Finally, an EMG-based personal verification method using CWT and siamese networks is proposed. Experiments show that the verification accuracy of this method can achieve 99.285%.**

***Index Terms*—Electromyography, personal identification, personal verification, discrete wavelet transform, ExtraTreesClassifer, continuous wavelet transform, convolutional neural networks, transfer learning, siamese network.**

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I. Introduction

With the increasing development of the internet, the security of personal information becomes more and more important. Thus, a variety of personal recognition methods have been introduced to ensure persons' information security. Traditional methods of personal identification such as Personal Identification Number (PIN), Identification tag (ID) or signature are not sufficiently reliable to satisfy the security requirements due to the risk of PIN/ID leakage, theft, imitation and forgery [1]. Then, the biometric technology which uses the unique physiological characteristics of the human body to identify user information is proposed to eliminate the risk of traditional recognition methods. At present, the morphological biometrics such as the human face, fingerprint, iris, and voice have been widely used in the identification system. For example, in the study of [2], researchers propose a personal recognition system based on both face feature and voice feature. The study in [3] proposes a new personal recognition system using multimodal biometrics including face recognition, fingerprint recognition, and speech recognition to improve the performance and robustness against fraudulent attacks. Although these biometric recognition systems eliminate the risk of traditional recognition methods, they also have some other weaknesses. For example, the human face can be counterfeited by 3D model, the fingerprint is easy to be recreated with latex, the voice can be easily recorded by recording equipment, and iris can be falsified by printing its features on contact lenses [4]–[6].

Biometric with living body features such as electrocardiogram (ECG), electroencephalogram (EEG) or DNA is a way to make up for the shortcomings of traditional biometric technology. These biometric features have some common characteristics, of which the most important ones are: universality-they exist in all the living creatures; distinguishability-there are no two identical DNA/EEG/ECG in the world; invisibility it is extremely difficult to be forged [7]. Thus personal recognition systems based on the biometircs with living body features can achieve aliveness

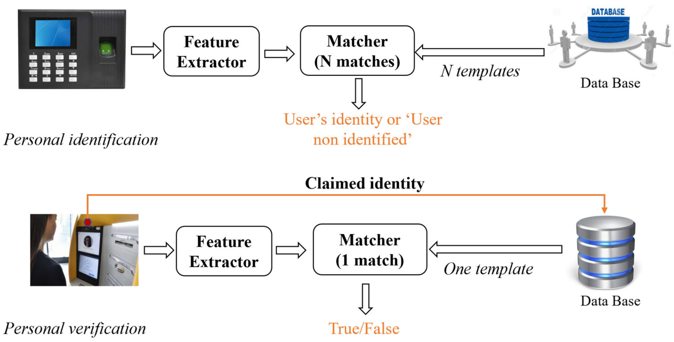

Fig. 1. Block diagrams of personal identification mode and personal verification mode.

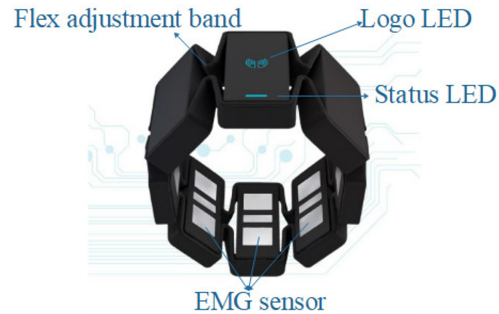

Fig. 2. MYO armband.

detection and prevent the spoofing attacks. The study in [8] presents a ducial point independent method for ECG-based personal identication, and its identication accuracy is about 99.4%. The study in [9] adopts deep learning algorithm to identify the EEG signals in different emotional states. It can achieve an accuracy of 99.90-100%. A new method of EEG-based person authentication using deep learning is investigated in [10], which demonstrates a relatively high verification accuracy of 91.44%. In [7], ECG signals are used in a personal identification system with CNN algorithm, and the accuracy is 98.7%. Nevertheless, it is inconvenient to collect ECG or EEG signal.

The electromyography (EMG) signal can also be used in a personal recognition system. EMG is a complex signal controlled by the nervous system [11], [12]. It depends on the anatomy and physiological characteristics of the muscle [11]–[17]. Since the direct link between intact muscle, intact central nervous system, and the brain is individual and directly related to each person's physiology, the EMG signal from forearm muscle group is unique, stable, and difficult to be forged and modulated [12], [18]–[21]. Thus, it is possible to use the EMG signal to do personal recognition. Besides, the acquisition of EMG signal is more simple and convenient than ECG or EEG due to the reason that the collection device of EMG can be worn on arm/leg or any other part of the body. Currently, there are few studies on the personal recognition based on EMG signals. The author in [22] presents a personal identification method by analyzing gait habit using EMG signals from the low-limb muscles. This experiment obtains an average identification accuracy of 93%. However, this recognition method has a limitation in the applicable population, such as disabled people with inconvenient legs or feet may not apply. Also, the recognition accuracy is not optimistic. An EMG-based personal authentication method using artificial neural networks is presented in [23], which obtains an authentication accuracy of 81.6%. In the study of [2], the researchers construct a personal authentication system based on the wrist EMG signal. By using a CNN model, the accuracy of personal authentication can achieve 94.57%. However, the authentication accuracy is still not optimistic. According to the application context, personal recognition system may operate either in identification mode or verification mode, as shown in Fig. 1. In the identification mode, the system recognizes an individual by searching the templates of all the users in the database for a match. While in the verification mode, the system validates a person's identity by comparing the captured features with her or his own template(s) stored in the system database [24]. However, there are none work focus on both EMG-based personal identification mode and EMG-based personal verification mode.

In this paper, we give a study of personal recognition method based on EMG signal, which was first presented in [25]. The MYO armband is used to collect the EMG signal from the arm of 21 subjects under hand-open gesture. Based on the acquired EMG data, both EMG-based personal identification and EMG-based personal verification method are proposed in this work. In the study of EMG-based personal identification method, we first use Discrete Wavelet Transform (DWT) and ExtraTreesClassifier algorithm to identify subjects from their EMG data. But this method need to re-train the whole network model when new data is added to the system, which will consume a great deal of time and computation resources. Thus, the identification method using Continuous Wavelet Transform (CWT) and Convolutional Neural Networks (CNN) is proposed. The network structure used in this method is a self-built model which can be changed according to the requirement. Then we adopt transfer learning algorithm based on this network to solve the model update problem. Finally, an EMG-based verification technique using CWT and siamese networks is proposed.

The rest of this paper is organized as follows. Section II introduces the hardware system. Section III gives the data acquisition method. In Section IV, two EMG-based personal identification methods are presented. Then the EMG-based personal verification method is described in Section V. Section VI concludes the paper.

II. Hardware System

The MYO armband from Thalmic Labs [26] is used to acquire EMG signal. It is a complete wireless motion and EMG sensing platform, as shown in Fig. 2. The armband comprises eight modules. Among them, the module with the logo includes a main processing board with an EMG sensor board. The other seven modules are all equipped with an EMG sensor board. The main board consists primarily a USB port, an ARM Cortex-M4 microprocessor, a low-energy Bluetooth and a 9-axis inertial measurement unit (IMU). The captured EMG and IMU data can be sent to other systems by using the Bluetooth link.

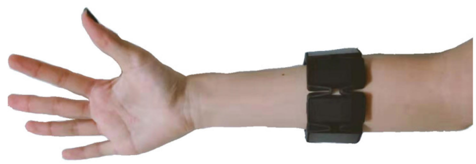

Fig. 3. Hand-open gesture.

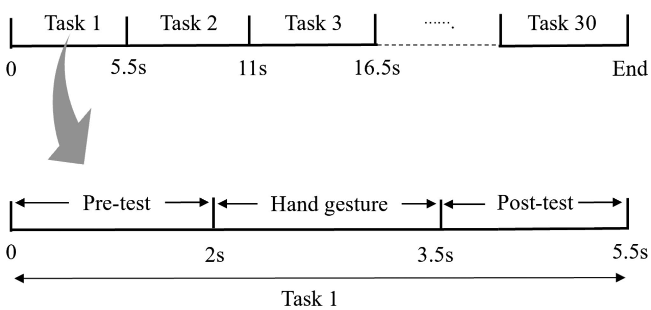

Fig. 4. Sequence diagram of each subject's EMG data acquisition trial.

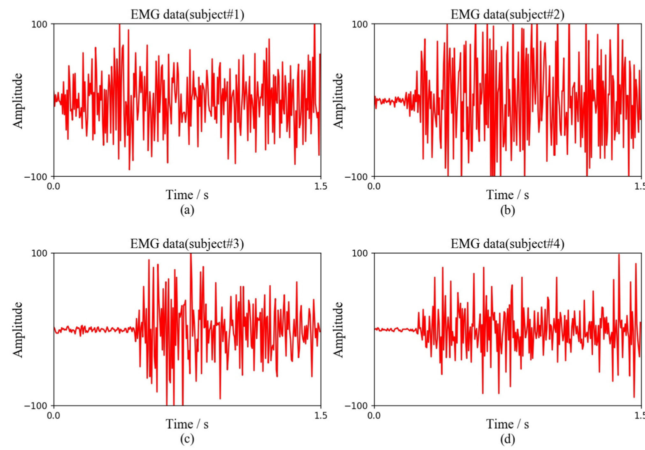

Fig. 5. Raw EMG signal of one channel captured from four subjects.

Fig. 6. Architecture of the personal identification method based on DWT and ExtraTreesClassifier.

III. Data Acquisition

The EMG signals are collected from a total of 21 healthy subjects of different ages, heights, and genders to ensure the reliability and extensiveness of the experimental data. The 21 subjects include five males and sixteen females. They are aged between 16 and 45 years old. Their heights are in the range of 155 cm and 175 cm. In the experiment, MYO armband is uniformly placed on the same position of each subject's right forearm to capture the EMG data. Specifically, the armband is placed on the height of the radiohumeral joint of each subject. Each subject is required to perform hand-open gesture, as shown in Fig. 3.

The sequence diagram of each subject's EMG signal acquisition trial is shown in Fig. 4. Each subject repeats a same task for 30 times. Each task comprises 2-seconds pre-test period, 1.5-seconds period for hand gesture, and 2-seconds post-test period. The experiment procedures are all instructed by the software automatically.

The sampling rate of EMG is 200 Hz. The acquisition time of EMG signals collected under hand-open gesture is 1.5 seconds. Thus the data length of each EMG channel is 300. Since the MYO armband has eight channels to collect EMG data, the data size of EMG data of each subject is 2400 points. Fig. 5 depicts the one channel EMG data captured from four randomly selected experimental subjects. From the results, it can be seen that the amplitude and frequency of EMG data are quite different from each other, indicating that it is possible to use the EMG signal to identify subjects.

IV. EMG-Based Personal Identification Method

In this section, two identification methods are proposed. First, an EMG-based personal identification method using discrete wavelet transform and ExtraTreesClassifier algorithm is investigated. Then, we use the continuous wavelet transform and convolutional neural network algorithm to identify subjects.

A. EMG-Based Personal Identification Using DWT and ExtraTreesClassifier

The architecture of the proposed personal identification method using DWT and ExtraTreesClassifier algorithm is shown in Fig. 6. First, the EMG signal is captured from the arm of the experimented subjects by MYO armband. Then, the collected data is pre-processed by DWT to extract features. Finally, the ExtraTreesClassifier is adopted to classify the experimented subjects. The detailed description is presented below.

1) Data Preprocessing and Feature Extraction: The DWT method is adopted to preprocess the raw EMG signals. DWT can be implemented as a filter-bank which can deconstruct a signal into its several frequency sub-bands [27]. If different types of signals exhibit different frequency characteristics, this difference in behavior has to be exhibited in one of the frequency sub-bands. Thus the features can be generated from each of the sub-band. And we can use the collection of features as an input for a classifier, such as Random Forest, Gradient Boosting, Logistic Regression, etc.

The DWT can be efficiently realized by decomposing the signal into approximation (low frequency) and detail (high frequency) coefficients. For the n-level decomposition, one approximation coefficients array and n details coefficients arrays can be obtained. Each coefficient array represents one sub-band, thus $n + 1$ sub-bands can be obtained in each EMG channel [28]. Based on the identification accuracy on the validation set, the level and wavelet of the decomposition are set to 4 and third-order Daubechies wavelet respectively. Thus, by applying DWT

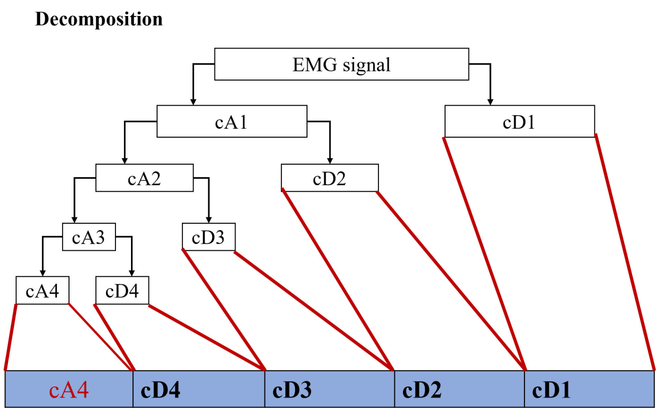

Fig. 7. Structure of 4-level wavelet decomposition.

TABLE I
THE FREQUENCY BANDS THAT EACH LEVEL CORRESPONDING TO

Coefficients Array	Frequency Bands
cA4	0-6.25Hz
cD4	6.25-12.5Hz
cD3	12.5-25Hz
cD2	25-50Hz
cD1	50-100Hz

to the raw EMG signal of each channel, 5 sub-bands will be obtained. The structure of 4-level wavelet decomposition and the frequency bands that each level corresponding to are shown in Fig. 7 and Table I respectively. Where cA represents approximation coefficients array and cD represents detail coefficients array.

Feature extraction is then adopted for each sub-band. Feature extraction is usually used to obtain representations and information embedded in the signal, which is necessary to minimize the complexity of implementation and reduce the cost of signal processing. In this paper, we adopt statistical method to extract features including variance, standard deviation, and root Mean Square value. Thus, each sub-band will generate 3 features. For 8 channel EMG signals of each subject, 120 features are generated after the process of DWT and feature extraction.

2) Classification: ExtraTreesClassifier is used for the personal identification. It is an ensemble learning method based on decision trees algorithm. When building multiple trees, nodes are split based on random splits among a random subset of the features selected at every node [29]. This classifier randomizes certain decisions and subsets of data to minimize overfitting and overlearning from the data [30]. In this paper, the number of trees in the forest is set to 2000. Double five fold cross-validation used in [31] is adopted for model selection and model assessment. For all 630 samples, there are 504 samples in the training set and 126 samples in the testing set.

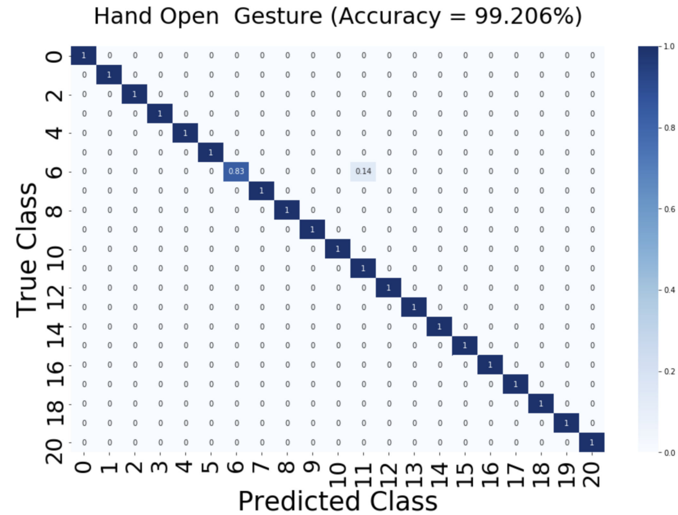

Fig. 8. Confusion matrix of identification method using DWT and ExtraTreesClassifier.

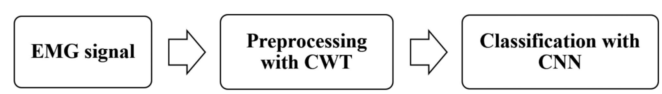

Fig. 9. Architecture of the EMG-based personal identification method using CWT and CNN.

After training, we use the generated model to identify the tested subjects. The confusion matrix is shown in Fig. 8. It shows that the identification accuracy for 21 subjects under the hand-open gesture is 99.206%, indicating the feasibility of using EMG signal for personal identication based on DWT and ExtraTreesClassifier. The limitation of this method is that it need to re-train the whole classifier when there are new data added to the system, which will consume a great deal of time and computation resources.

B. EMG-Based Personal Identification Method Using CWT and CNN

To overcome the shortcoming of the EMG-based personal identification using DWT and ExtraTreesClassifier, an alternative EMG-based personal identification approach which uses CWT and CNN is proposed. The architecture of the method is shown in Fig. 9. First, the EMG signal is captured from the arm of the experimented subjects by MYO armband. Then, the collected data is transformed into two-dimensional graphics by CWT. Finally, the CNN algorithm is adopted to classify the experimented subjects. The detailed description is presented below.

1) Data Preprocessing: The CWT method is adopted to see more feature differences between EMG signals of different subjects. CWT is a common method of time-frequency analysis. It is a convolution of the input data sequence with a set of functions generated by the mother wavelet [32]. In addition,

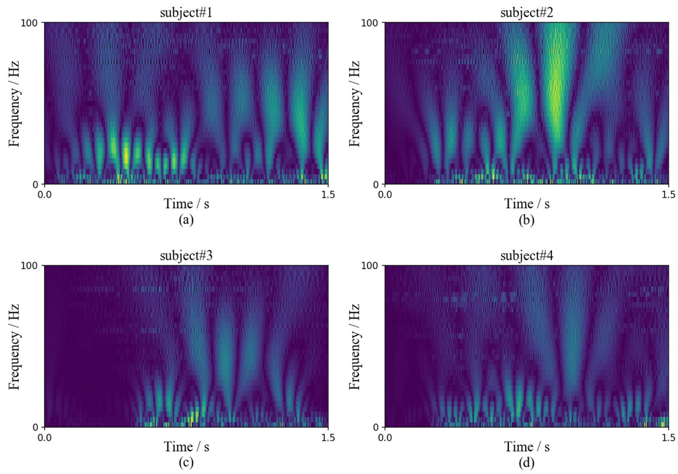

Fig. 10. Time-frequency graphs of one channel EMG signal of four subjects.

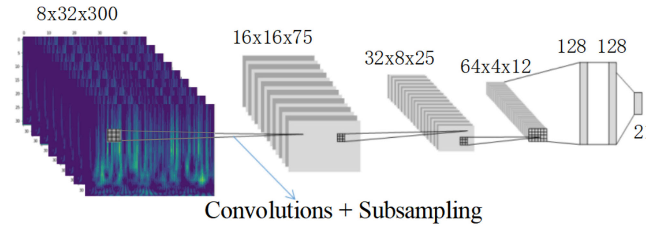

Fig. 11. Structure of the proposed CNN.

CWT can provide high-frequency resolution and low time resolution in the low frequencies, and high time resolution and low-frequency resolution in the high frequencies [33]. It makes up for the disadvantages of short-time Fourier transform (STFT) in processing non-stationary signal. The CWT of signal $x(t)$ is defined as follows [33]:

$$CWT_w(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\bar{\Psi}\left(\frac{t-b}{a}\right) dt \qquad (1)$$

where w represents the angular frequency, a is a scale parameter, b is a translation parameter. Mother wavelet $\Psi(t)$ is a continuous function in both the time domain and the frequency domain. The overline represents the operation of the complex conjugate. The selection of the mother wavelet is dependent on the properties of the mother wavelet or the similarity between signal and mother wavelet [34]. According to the accuracy on the validation set, which will shown in Section IV-B2, identification method with Mexican Hat wavelet has the highest recognition accuracy. Thus, the Mexican Hat wavelet function is selected as the mother wavelet.

The size of collected raw EMG data of each subject is 300×8. Each subject has 30 samples. For a total of 21 subjects, there are 630 samples. According to the study in [35], parameters of a and b are set to 32 and 300, respectively. After applying the CWT on EMG signal, the time-frequency distributions of EMG data can be obtained. The discrete data of one EMG channel becomes a scale image with a size of 32×300 pixels. Fig. 10 shows the transformed results of Fig. 5. It is clear that the difference is quite obvious. All the obtained time-frequency information will be fed to the classification algorithm described in the next subsection.

2) Classification: A convolutional neural network is used as the classification algorithm. It is a class of deep and feed-forward artificial neural networks that have been widely used in a classification task, especially in image recognition. Compared with the traditional machine learning algorithms, the most distinctive characteristic of CNN is that the image features can be automatically extracted through a training process [33]. Thus, CNN is adopted to extract the two-dimensional time-frequency features and recognize those images obtained by CWT.

The structure of CNN mainly consists of three layers, i.e., convolutional layer, pooling layer, and fully connected layer. The function of the convolutional layer is mainly to extract the features from the input image. The function of the pooling layer is to control overfitting of the model and reduce the amount of parameters and computation in the network by downsampling the spatial dimensions of the input. After the stacking of several convolutional layers and pooling layers, a fully connected layer will be placed at the end of the network. Then the possibility of different classes will be distributed. The structure of CNN used in this work is shown in Fig. 11. The matrix of $8 \times 32 \times 300$ yielded by CWT is taken as the input of the convolutional neural network. Following four pooling layers and four convolution layers, the sample data becomes a one-dimensional data with 128 output nodes. Finally, through two fully connected layers, the final classification output is obtained. In our experiments, double five fold cross-validation used in [31] is adopted to select hyperparameters and evaluate the performance of model. For all 630 samples, there are 504 samples in the training set and 126 samples in the testing set. Rectified Linear Units (ReLU) is applied as the activation function in the whole networks except for the last layer. The last layer is softmax-actived. The cross-entropy and ADAM are used as the loss function and optimizer of the network respectively. The learning rate is set to 0.001 and the batch size is 32. The whole model is implemented in PyTorch 1.1.0.

In order to depict the flow of the classification detailedly, the size of the kernel, and the size of each layer's shape are shown in Fig. 12. The time-frequency images are down-sampled through a maximum pooling layer firstly. Then the feature graph is extracted from a convolution layer, and so on. The reason that We apply maxpool on the input before performing a convolution is to reduce the computational load of the ConvNet during training and inference [35]. The kernel size of the convolutional layer of the first three layers and last layer is 3×3 and 2×6, respectively. Each time through the convolution layer, the number of feature's map is doubled.

Considering the option for "unknown identity," we use threshold method to identify unknown identity, as shown in Fig. 13. According to the performance of the pre-training dataset, the threshold was set to 0.7. When a person is fed to the network for inference, the output of category scores from the network is compared with the threshold. If the maximum score is greater than the threshold, the person which is fed to the network is

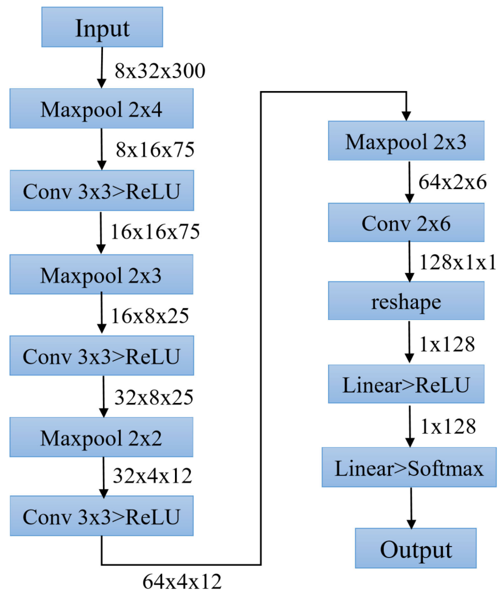

Fig. 12. Flow of the proposed CNN.

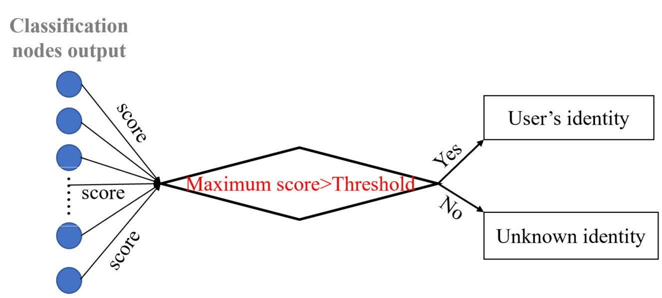

Fig. 13. Description about the option for 'unknown identity'.

identified as the category corresponding to the maximum score. If it is less than the threshold, the person is determined to be 'unknown identity'.

After training, the generated model is used to recognize the tested subjects. As mentioned in Section IV-B1, the type of mother wavelet function will affect the classification result. In this investigation, several widely used mother wavelet functions including Mexican hat wavelet, Morlet wavelet, Gaussian wavelet, Complex Morlet wavelets, Shannon wavelets, Frequency B-Spline wavelets, and Complex Gaussian wavelets, are tested on the validation set to find the appropriate one.

The identification results with different mother wavelet functions are shown in Table II. It can be seen that the highest identification accuracy on the validation set can achieve 99.20% when the Mexican Hat wavelet function is used as the mother wavelet and the identification accuracy for 21 subjects can achieve 99.203% on the testing set. The confusion matrix is shown in Fig. 14. It is clear that high identification accuracy can be observed under the hand-open gesture.

3) EMG-Based Identification Method Using Transfer Learning: The above mentioned identification result of EMG-based identification method using CWT and CNN is based on a specific number of test subjects. When there are new subjects added to the identification system, the model has to be re-trained. To save retraining time and reduce computing resources, transfer learning algorithm is adopted. Transfer learning aims to handle tasks in one domain (the target domain) much more quickly and effectively by using knowledge extracted from a related domain (the source domain) [36]. It can use pre-trained knowledge (weights, biases, etc) to train a new model, which will reduce the training time and improve the performance of the deep learning tasks with insufficient training data [37]–[40]. Thus transfer learning algorithm is well suited to situations where a model performs poorly due to outdated or scant data.

The structure of the proposed personal identification method using transfer learning is shown in Fig. 15. The whole structure is based on the previous described EMG-based personal identification method using CWT and CNN. First, we randomly

TABLE II
THE IDENTIFICATION RESULTS WITH DIFFERENT MOTHER WAVELET FUNCTIONS

Mother Wavelet	Accuracy
Mexican hat	**99.20%**
Morlet	96.03%
Eight-order Gaussian	94.44%
Complex Morlet	96.83%
Shannon	96.03%
Frequency B-Spline	96.82%
Seven-order Complex Gaussian	97.62%

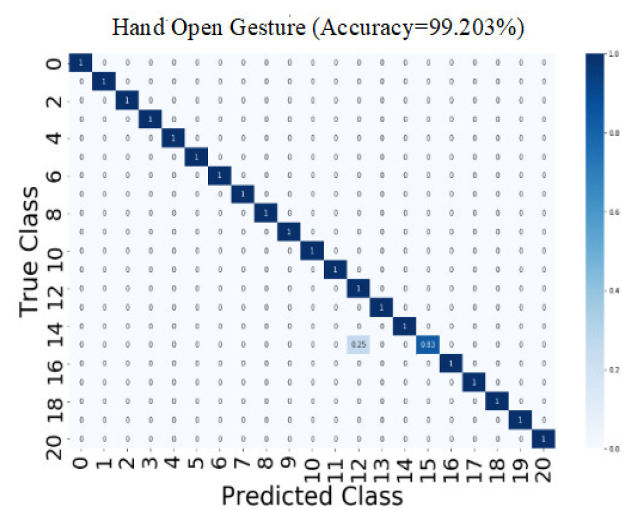

Fig. 14. Confusion matrix of identification method using CWT and CNN.

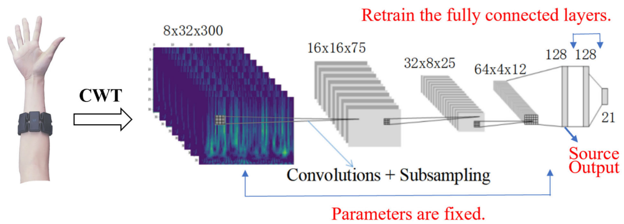

Fig. 15. Structure of the proposed personal identification method using transfer learning.

TABLE III
IDENTIFICATION RESULTS WITH TRANSFER LEARNING ALGORITHM

Number of Subject	16	17	18	19	20	21
Accuracy	92.7%	98.03%	97.22%	96.49%	96.69%	96.82%

select EMG signals of 16 subjects to train the model as the source model. Then, double five fold cross-validation [31] is adopted for select and assess the source model. Then EMG data of new subject is added to the network successively to retrain the new model. When new EMG data is added, the final output node number of the network structure changes with the total number of people to be recognized, while other part of the network structure remains unchanged. In the process of retraining and re-networking, only the fully connected layer needs to be retrained, the other parameters are all fixed.

For transfer learning task, we randomly classify 80% of the total data as training data, 20% as testing data. The identification results with transfer learning algorithm are shown in Table III. The identification accuracy of the pre-trained model with 16 experiment subjects is 92.7%. After adding new data of subject successively, the identification accuracy is still higher than 90%. The variation in the identification accuracy may be caused by the relative low number of samples.

To verify the performance of transfer learning algorithm, the training time consumed by method with and without transfer learning algorithm are compared. The time consumed by method with transfer learning algorithm is all based on a pre-trained model which is trained with data of 16 subjects. The compared results are shown in Fig. 16 . In Fig. 16, the yellow bar represents time consumed by training the entire network for different number of individuals. While, the blue bar represents time taken for transfer learning the new added sample, without accumulating the training time of the source model (entire network for 16 samples). According the results, it indicates that the training time consumed by method with transfer learning is shorter than the time consumed by method without transfer learning, showing the advantages of transfer learning algorithm. When the data set grows larger, this advantage will be more obvious.

C. Results and Analysis

Two EMG-based personal identification methods are introduced in this section. We compare the identification accuracy of the proposed methods with previous works. To get a relative fair

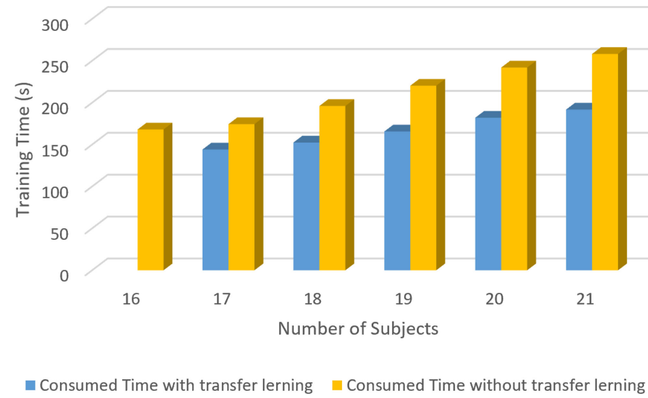

Fig. 16. Comparison of training time with or without transfer learning.

TABLE IV
COMPARISON WITH PREVIOUS WORKS

	2017 [23]	2017 [22]	**Method 1**	**Method 2**
Position	Right Forearm	Low Limbs	**Right Forearm**	**Right Forearm**
Data Preprocessing	VAR, Mean, etc	RMS, MAV, etc	**DWT**	**CWT**
Classification Algorithm	ANN	LDA	**ExtraTrees Classifier**	**CNN**
Method of Model Update	None	None	**None**	**Transfer Learning**
[a]Accuracy	None	None	**None**	**96.8%**
[b]Accuracy	96.03%	97.62%	**99.206%**	**99.203%**

[a]The identification accuracy with method of model update.
[b]The identification accuracy without method of model update.

comparison result, the identification results of previous works are obtained by applying their works on our own dataset. The compared results are shown in Table IV. Comparing with the methods proposed by the state-of-the-art works, the identification accuracy of the proposed EMG-based personal identification method using DWT and ExtraTreesClassifier algorithm is higher than that of other works. However, considering the model update problem, the method using CWT and CNN is better.

V. EMG-BASED PERSONAL VERIFICATION METHOD

In the personal verification mode, the system validates a person's identity by comparing the captured features with her or his own template(s) stored in the system database. This verification method is typically used in positive recognition, where the aim is to prevent multiple people using the same identity [41], such as secure access of buildings, computer systems, laptops, cellular phones, and ATMs. Since the two methods proposed in Section IV not only need all the categories be known in advance, but also the training examples be available for all the categories. Thus, they are not applicable for the personal verification mode.

The architecture of the proposed personal verification method based on EMG signal is introduced. First, as the previous proposed EMG-based identification method with CWT and CNN, the EMG signal is captured from the arm of the experimented subjects by MYO armband and the collected data is transformed into two-dimensional graph by CWT. Then, the siamese network algorithm is adopted to learn a similarity metric from data. Finally, a threshold is set to validate a subject's identify. The detailed description is presented below.

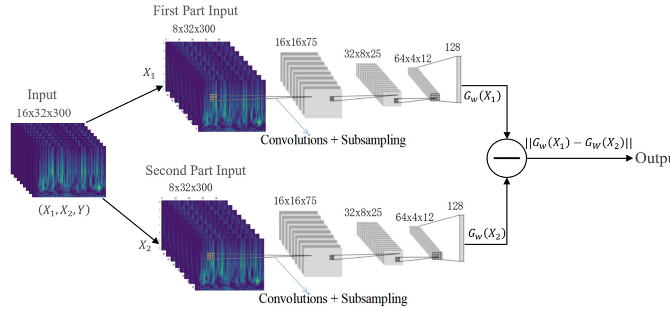

Fig. 17. Structure of the proposed siamese network.

A. Data Preprocessing

The captured EMG signals are transformed into two-dimentional graphics by CWT. The detailed processing procedure is similar to that shown in Section IV-B1).

B. Verification Algorithm

Siamese network is a general discriminative method for learning complex similarity metrics from the data. Then the learned metrics can be used to compare or match new samples from pre-unknown categories. The siamese network consists of two identical networks and one cost module that produces scalar energy. The input of the whole system is a pair of images and a label. The images are passed through the two identical networks, yielding two outputs which are passed to the cost module. The loss function combines the label with scalar energy. The gradient of the loss function with respect to the parameter vector controlling both sub-nets is computed by using back-propagation. The parameter vector is updated with a stochastic gradient method using the sum of the gradients contributed by the two sub-nets [42]. The method is best suited for classication or verication scenarios where the number of categories is very large, and/or where examples from all the categories are not available at the time of training. The traditional classification methods, such as support vector machines or neural networks, generally require all the categories be known in advance and training examples be available for all the categories. In other words, those methods are limited for applications where the number of categories is very large, where the number of samples per category is small, and where only a subset of the categories known at the time of training. Therefore, in this paper, siamese network is adopted to make up for the weakness of the traditional methods.

1) Design of the Siamese Network: The architecture of the proposed siamese network in this paper is shown in Fig. 17. The proposed siamese network comprises two identical convolutional neural networks and one cost module that produces the scalar energy. The two identical CNN consists of two layers, i.e., convolutional layer and pooling layer. Rectied Linear Units (ReLU) is used as the activation function of CNN. A pair of time-frequency images processed by CWT and a label is used as the input of siamese network. In the Fig. 17, X_1 and X_2 represents a pair of images, Y represents a binary label. When the image X_1 and X_2 belong to a same person, Y is 0, on the other hand, Y is 1. W is the parameter vector shared by the two identical convolutional neural networks using gradient backward. $G_w(X_1)$ and $G_w(X_2)$ are the two outputs of the sub-networks. Then, the two outputs are passed to the cost module E_w that measures the compatibility between X_1, X_2. It is defined as:

$$E_w = ||G_w(X_1) - G_w(X_2)|| \tag{2}$$

2) Loss Function Used for Training: The loss function is need to be carefully designed. It should minimize parameter E_w when X_1 and X_2 come from a same person and maximize parameter E_w when X_1 and X_2 come from different person. In this work, loss function used in [42] is adopted, as following:

$$L = (1 - Y)\,\frac{2}{Q}\,(E_w)^2 + 2Qe^{-\frac{2.77}{Q}E_w} \tag{3}$$

where E_w is the output of the siamese network and Q is a constant value which is set to 5 based on the accuracy on the validation set in this work. This loss function is derived from the discriminative learning framework for energy-based models (EBM). The obtained loss function is used to update the weight W.

3) Training and Testing: Based on the designed loss function, the siamese network is trained and tested. First, we use pairing method to establish sample set. 100 randomly paired samples are combined from each subject's 30 samples. For a total of 21 subjects, there are 2100 sample-pairs. This kind of sample-pair is named as genuine pair because the samples in the pair come from a same subject. Similarly, we randomly select two different subjects as a pair of combination from 21 subjects. A total of 210 different pairs of combination will be obtained. Then, 10 samples are randomly picked from each subject's 30 samples. For these 210 pairs of combination, there will be 2100 sample-pairs. Since the samples in each pair come from different subject, this kind of sample-pair is called impostor pair. Finally, we get a total of 4200 sample-pairs which include 2100 genuine sample-pairs and 2100 imposter-sample pairs. These sample-pairs are randomly separated by double ve folds cross validation method.

After training, the generated model is used to verify the tested sample-pairs. The siamese network outputs the similarity between the tested sample pairs. The Receiver Operating Characteristic (ROC) curve is given based on our model, as shown in Fig. 18. It shows the performance of the network based on

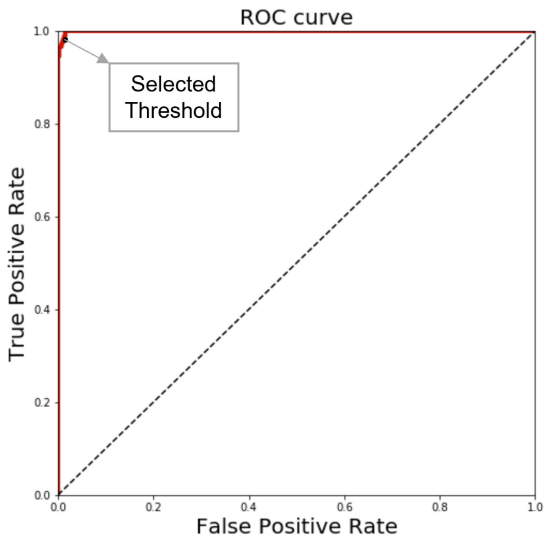

Fig. 18. ROC curve: True Positive Rate and False Positive Rate under different thresholds of the model.

the True Positive Rate (TPR) and the False Positive Rate (FPR) under different thresholds of our model. In our experiment, we choose the balance point as the threshold. It is the value that was completed by evaluating the minimum Euclidean distance from the left upper corner (0,1 coordinate) to the ROC curve. The calculated threshold in this work is 0.49. The test result shows that the verification accuracy is 99.285%, indicating the feasibility of using EMG signal for personal verification based on the continuous wavelet transform and siamese network. To verify if the model can identify unknown data, we carried out an additional test. First, we collected data from 4 new individuals. Then, the data of the four subjects were paired with the data of the subset of individuals trained for the model, generating all 672 imposter pair samples. Finally, we applied our trained model on these generated pair samples. The result shows that it can achieve a verification accuracy of 97.76%, indicating that the model was able to distinguish the unknown data.

VI. Discussion of Robustness

The robustness of the proposed EMG-based personal recognition system is discussed. First, we do additional experiment to verify if the proposed models can still perform well when the data is collected at different days or different physical conditions from the same individual. We collect some new EMG data at different days and different physical conditions from the same individual. Then we applied our trained models on these new EMG data to get the identification and verification result. The identification accuracy of the method based on CWT and CNN and method based on DWT and ExtraTreesClassifier is 91.2% and 100% respectively. The verification accuracy of the method based on CWT and Siamese networks can achieve 95.84%. These results indicate that the proposed models can still have a good recognition accuracy when the data is collected at different days for different physical conditions from the same individual. Second, the proposed models have good robustness towards minor variations in gesture. In the data acquisition stage, the collected data has already contained the minor variations of the gestures. Thus, the high accuracy on the testing set indicates that our proposed models have good robustness towards minor variations in gesture. Third, we carried out an experiments to verify if our proposed system can discern similar persons. We collect EMG data from 5 new individuals that have similar height, age, weight, and gender. Then we use the collected data to train and test the performance of our proposed model. The test result shows that the identification accuracy is 96.67% for the EMG data from this 5 similar individuals and the verification accuracy is 95.62% for 284 imposter pair from 5 individuals, indicating that the proposed method can discern between similar persons. All the above analysis indicate the robustness of the proposed EMG-based personal recognition system.

VII. Conclusion

This paper gives a study of personal recognition method based on EMG signal. The MYO armband is used to collect the EMG signal from the arm of 21 subjects under hand-open gesture. Based on the acquired EMG data, both EMG-based personal identification and EMG-based personal verification method are proposed. In the study of EMG-based personal identification method, we first use DWT combined with ExtraTreesClassifier algorithm to identify the subjects from their EMG data. Though this method can achieve a identification accuracy of 99.206%, it needs to re-train the whole network when new data is added to the system. To solve the model update problem, personal identification method using CWT and CNN is proposed. In this method, two-dimensional image which is transformed from raw one-dimensional EMG data by CWT is fed into CNN. The result shows that the identification accuracy for 21 subjects under the hand-open gesture could achieve to 99.203%. By combing with transfer learning algorithm, personal identification method with CWT and CNN can re-train the model more quickly and effectively when new data is added to the system. Finally, an EMG-based personal verification method using CWT and siamese networks is proposed. Experiment result shows that the verification accuracy of this method can achieve 99.285%.

Though, the proposed EMG-based recognition system is difficult to forge and modulate because of its characteristic of aliveness detection, it still has some limitations. For example, it is might not suitable for persons with neurodegenerative disorders. In addition, the proposed identification method based on transfer learning might be difficult to recognize a very large scale dataset. Thus, in our future work we will collect more EMG data to setup a large scale dataset for further research on the robustness and stability of the EMG-based recognition system. And will also focus on the investigation of identification method with high scalability to solve the issue of in the future, such as feature embedding method.

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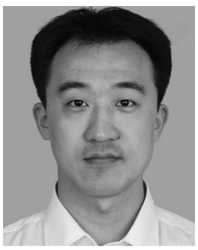

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