Soft Exoskeleton Glove for Hand Assistance Based on Human-machine Interaction and Machine Learning

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***Abstract*—This paper proposes a human machine interaction system in the field of stroke rehabilitation, based on the concept of mirror therapy (MT). It aims to improve the hand motor function of stroke patients, enabling a true synchronization between the affected hand and non-affected hand (healthy hand) for the stroke patient. It consists of a soft exoskeleton glove, a surface electromyography (sEMG) signal collecting armband and machine learning (ML) algorithms. The glove is developed by integrating low-power motors to provide force strength for the hand movement. Unlike the rigid exoskeleton devices, the glove is comfortable to wear and lightweight, so it is more suitable for rehabilitation training of stroke patients in daily life. The armband collects the sEMG signals for pattern recognition by the ML algorithms. In the experiment, four subjects perform 10 hand gestures to collect data for model training. A comparison of data preprocessing is conducted to find the optimal data segmentation method and feature vector sets. A series of pattern recognition algorithms are developed and assessed in different aspects, including prediction accuracy, training time and predicting time. All 10 gestures can be recognized in offline mode with an accuracy up to 99.4%. The control of soft exoskeleton glove in real-time manner is also carried out, and the accuracy is 82.2%. The experiment result demonstrates the feasibility of the proposed system. The innovations and limitations of the work are discussed at the end of the paper.**

Keywords—soft exoskeleton glove, surface electromyography (sEMG), mirror therapy, machine learning

I. INTRODUCTION

Stroke is a life-threatening disease, caused by blockage of a blood vessel to the brain or bleeding in or around the brain [1]. About 55% to 75% of survivors have serious disabilities such as paralysis and aphasia [2-4]. Among them, the most common is the loss of part or all of the hand's motor function [5], resulting in patients unable to take care of themselves. Hand dysfunction can seriously affect the quality of patients' life, which means more demand is needed on the hand rehabilitation.

Mirror therapy (MT) is one of the traditional methods for improving hand motor function, which is simple, effective, and inexpensive [6]. The traditional mirror therapy refers to placing a mirror in front of the patient. The patient observes the image of the non-affected hand in the mirror, and imagines the affected hand making the same action, so as to achieve the therapeutic purpose through optical illusion and visual feedback. Mirror therapy is now extended to another method, bilateral movement [1, 7]. In bilateral movement, the rehabilitation equipment is used to assist the affected hand to make mirror gestures as the non-affected hand, generating direct visual feedback and promoting the rehabilitation of the patient's hands. Studies have shown that bilateral simultaneous exercise, for mirror therapy, is more effective than unilateral exercise.

Some work has been done in the field of exoskeleton gloves [8-11]. M. Cortese *et al.* [12] develop a novel mechatronics master-slave setup for hand rehabilitation. It consists of a sensor glove acting as a remote master and a powered hand exoskeleton as a slave. The master unit can control the slave unit to assist the affected hand to complete mirror gestures, including "Rest", "Pinch", and "Lateral grasp". J. H. Bae *et al.* [13] design a wearable hand rehabilitation robot, DULEX-II. The DULEX-II is with three degrees of freedom, which can assist both wrists and all fingers movements. Serpelloni *et al.* [14] design a a soft robotic glove that is driven by EMG for hand mirror therapy. The system uses a brushless motor to push and pull the cable, which drives the finger movement.

In this paper, a rehabilitation system for a power-assisted glove control employing a commercial wearable MYO armband is proposed. The system consists of a soft exoskeleton glove, a sEMG signal collecting armband and ML algorithms. The armband is worn on a non-affected hand to collect the sEMG signals to sense the hand motion of the patient. Then the ML algorithms recognize what motions the hand made and send classification results to the exoskeleton glove. The exoskeleton glove is controlled to assist the affected hand to accomplish the mirror movements. The contribution of this work includes: provide the exoskeleton glove which the patients can wear on the affected hand with higher comfort and safety than rigid exoskeletons. The patient can take rehabilitation training at home without being confined to the medical environment. Besides, the system has customized 10 kinds of fine-grained training gestures for mirror therapy, aiming to train each finger individually and train multiple fingers in coordination. Moreover, the accuracy and training time of different ML algorithms are analyzed and compared.

The rest of this paper is organized as follows. The framework of the proposed system is described in Section II. The methodology of gesture recognition and control of the soft exoskeleton glove are introduced in Section III. Then the experiment results are evaluated and discussed in Section IV. Finally, Section V concludes the whole paper.

II. FRAMEWORK OF THE PROPOSED SYSTEM

A. Overview of the System Architechture

The architecture of the system implemented in this study is shown in Fig. 1. The proposed system consists of the following parts: a human-machine interaction module collecting sEMG signals from the user, a pattern recognition module classifying different hand gestures, and an exoskeleton glove providing power assistance.

The conventional mirror therapy blocks the visual input to "cheat" the user, and the affected hand does not make any movement in fact. In this paper, we propose a rehabilitation therapy scenario that enables a true synchronization between the affected hand and non-affected hand for the stroke patient. The stroke patient wears MYO armband on the non-affected

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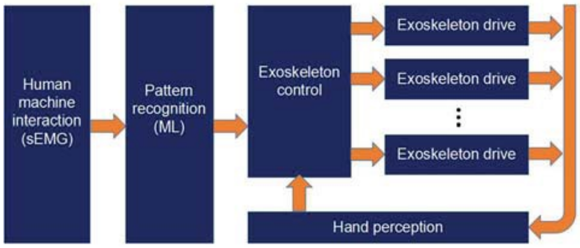

Fig. 1. Architecture of the stroke rehabilitation system.

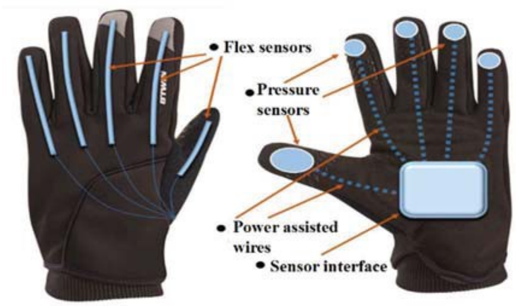

Fig. 2. The soft exoskeleton glove.

forearm and wears the exoskeleton glove on the affected hand. The user's non-affected hand performs a gesture such as bending fingers or fist. The MYO armband recognizes the gesture of the non-affected hand through the proper ML algorithms. Then the corresponding commands are sent to the exoskeleton control. With the help of exoskeleton drive modules, the affected hand can perform the same gesture. The hand perception module measures the motion state of the affected hand in real-time, providing feedback signals to the control module and correcting the fine motion of the affected hand. The advantage of the proposed rehabilitation therapy scenario is that the patient can not only get visual feedback from watching the affected hand, but also perform the same actions on the affected hand assisted by exoskeleton glove.

B. Glove Design

In this paper, we implement a soft exoskeleton glove that enables power assistance for the affected hand. The exoskeleton glove mainly consists of the following parts: a soft glove, pressure and flex sensors, an electronic control module, a power-assisted module, and a wireless module. Fig. 2 shows the placement of sensors and wires inside the glove.

Fig. 3 is the architecture of the glove control system. We select STM32F103 as the core of the control logic. A sensor interface is implemented to process the signals from pressure sensors and flex sensors, including signal filtering, amplification, and digitization. To provide enough power strength to the fingers, the micro motors are used. We implement five H-Bridge circuits to drive the motors. The details of the actuation design can be found in [15, 16]. Considering the balance between power consumption and wearable requirement, we select two 18650 Li-ion batteries that have a total capacity of 23.040 Wh. Therefore, the exoskeleton glove can fulfill the requirement of rehabilitation in daily life.

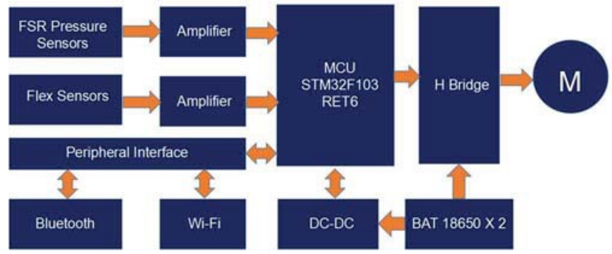

Fig. 3. System architecture of the glove.

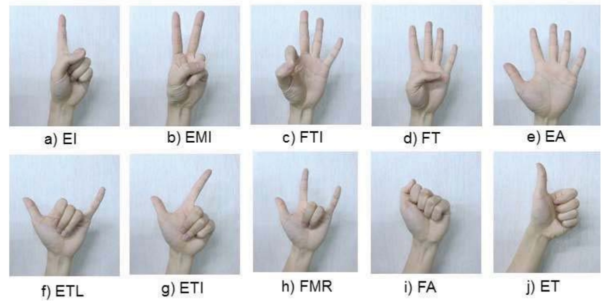

Fig. 4. The illustration of 10 hand gestures.

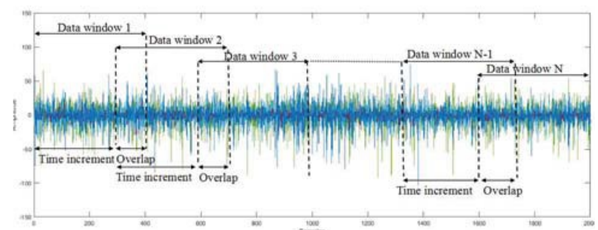

Fig. 5. The sEMG signal segmentation.

III. METHODOLOGY

A. The Human Machine Interaction

During the experiment, the subjects are asked to sit on a chair in a relaxed position, and wear the MYO armband on the non-affected forearm. The sampling rate of the MYO armband is 200 Hz. The subjects are required to make the 10 specific hand gestures, as shown in Fig 4. Each of the gestures should be held for more than 10 seconds for recording. Then the same gesture is repeated. To avoid muscle tension, enough rest is arranged for each time of recording. Each subject completes 20 sEMG data record. Therefore total 80 of sEMG data recordings are obtained. The collected data is for both model training and testing.

B. Pattern Recognition

1) Data segmentation

In order to fully utilize the sEMG signal, we chose the overlapped segmentation method [17], as shown in Fig. 5. The length of the data window and time increment are two important factors affecting the accuracy of the model training. A longer data window contains more effective information while decreases the real-time performance. A shorter time increment window results in more segmented data set, but it also increases the complexity of model training. In this sense, we conduct an experiment on how to choose the parameters

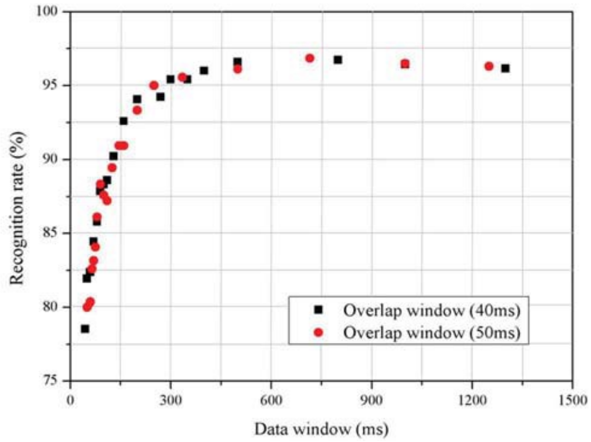

Fig. 6. Accuracy using different overlapped and data windows.

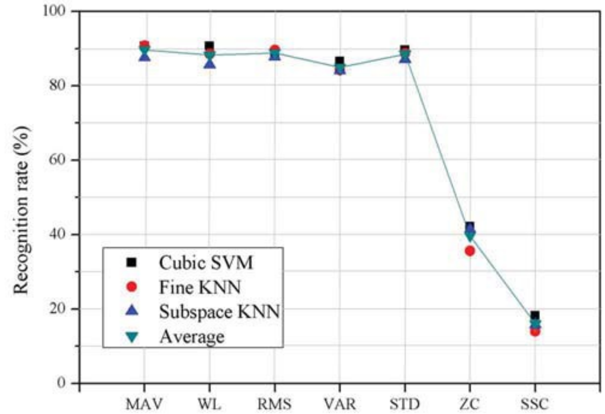

Fig. 7. Classification result of a signal feature.

for data segmentation. We compare the impact of different lengths of increment and data windows. SVM is selected as the classifier in this test. The results are shown in Fig. 6.

From the Fig. 6, we can find that with the increase length of data window, the accuracy increases synchronously. However, the growth rate of accuracy slows down significantly after the data window length reaches 200 ms. What's more, there is no big difference between the two curves. It indicates that the time increment length has little influence on the result as long as there are enough samples in training set. In addition, it is recommend that the control delay should be less than 300 ms in real-time [18], so the segmentation length is set no longer than 300 ms.

2) Feature extraction

The amplitude, energy, and frequency of the sEMG signal vary with the degree of muscle contraction. It is not practical if the raw data is fed to the classifier directly for pattern recognition. In this session, we evaluated the performance of different features. A comparison is presented to show the most effective features for pattern recognition.

There are seven time domain features involved in the comparison: mean absolute value (MAV), zero crossings (ZC), waveform length (WL), slope sign changes (SSC), root mean square (RMS), variance (VAR) and standard deviation (STD).

With the features above, we made a comparison to choose the optimal feature set in pattern recognition. The rule of the comparison is as follows. At first, the ML algorithm runs with every single feature. To avoid the impact of a specific algorithm, three ML algorithms are involved, including SVM, kNN and Subspace kNN. Once the performance of each feature is achieved, the features are sorted according to the classification accuracy. Fig. 7 shows the result of running with a single feature.

To evaluate the feature performance in different classifiers, the average value is calculated. It is shown that most of the features achieve a relative high accuracy except ZC (42.1%, 35.6%, and 41.4%) and SSC (18.20%, 14.00%, and 15.80%). From Fig. 7 we can find that there is no significant difference for MAV, WL, RMS, and STD. The accuracy is quite close to each other, around 88% respectively. Then we made a few feature sets by combing features together to find the highest classification accuracy. The optimal feature set contains MAV, WL, RMS, and STD.

3) Pattern recognition

In this session, we evaluate a variety of ML algorithms, including supervised learning and ensemble learning. The purpose of the evaluation is to find the most suitable algorithms in offline and real-time classifications, respectively.

The decision tree is a very common ML algorithm. One of the advantages of the decision tree is its interpretability. It is also fast for fitting and low on memory usage. How to set the number of leaves and branches in the tree is an issue worth considering, which is a balance between the model accuracy and robustness.

LDA is another useful ML algorithm in solving classification problems. It has shown the features of computing efficiency [19] and robust [20]. The goal of LDA is to project the data set onto the line so that the similar data is as close as possible while different types of data are as far away as possible. The maximized target of LDA is listed in the equation below:

$$J = \frac{\omega^T S_b \omega}{\omega^T S_\omega \omega} \tag{1}$$

Where S_ω is within-class scatter matrix, and S_b is between-class scatter matrix.

SVM has shown a strong capability in classifying biomedical signals in previous researches [14, 21]. The key point of SVM is to find a hyperplane that has the maximum margin for the support vectors. The equation is

$$f(x) = \omega^T \phi(x) + b \tag{2}$$

Where ω is a weight vector, $\phi(x)$ is the kernel map, and b is an offset.

kNN is another popular ML algorithm for pattern recognition. It is easy to implement with high accuracy. In this study, a variety of parameter combinations are tested, including the number of neighbors, distance weight, etc. The ensemble learning is also evaluated in this study. The serialization or parallelization method can be generated depending on whether there is a strong dependency between the base learners. The typical algorithm for each method is boosting and bagging. By combining many learners it is possible to obtain a more accurate result than a single learner.

TABLE I. RESULTS OF HAND GESTURE RECOGNITION

Machine learning algorithm		Tree	Discriminant analysis	SVM				KNN				Ensemble learning				Neural network
		Fine Tree	*Linear Discriminant*	*Linear SVM*	*Quadratic SVM*	*Cubic SVM*	*Fine Gaussian SVM*	*Fine KNN*	*Cosine KNN*	*Cubic KNN*	*Weighted KNN*	*Boosted Trees*	*Bagged Trees*	*Subspace Discriminant*	*Subspace KNN*	*hidden layer: 27, 21*
Input pattern 1	Accuracy	83.9%	68.0%	92.2%	98.6%	99.1%	99.3%	99.4%	98.4%	98.5%	99.2%	64.9%	98.6%	65.7%	99.4%	99.3%
	Training Time (s)	16.20	3.99	122.11	106.88	106.52	364.63	36.87	36.72	1090.00	35.68	302.30	87.26	32.48	578.86	31.00
	Predict Time (ms)	6.516	7.386	52.635	60.439	58.212	89.681	15.356	30.213	41.555	13.055	25.248	34.637	42.508	152.022	4.947
Input pattern 2	Accuracy	81.0%	66.4%	90.7%	98.1%	98.7%	98.8%	98.9%	97.7%	97.9%	98.6%	64.0%	98.0%	64.3%	99.0%	98.3%
	Training Time (s)	14.84	2.65	112.64	101.79	103.52	404.70	32.38	32.09	1007.60	32.35	272.23	80.92	28.43	524.30	15.00
	Predict Time (ms)	7.142	7.617	52.938	60.638	60.020	89.027	13.880	30.087	40.577	13.693	22.369	36.009	42.543	148.797	5.160
Input pattern 3	Accuracy	78.4%	64.7%	88.6%	97.0%	98.0%	97.8%	98.0%	96.5%	96.7%	97.6%	62.1%	97.0%	62.6%	98.2%	97.3%
	Training Time (s)	15.85	3.00	122.66	109.62	112.05	456.55	32.83	32.28	1037.80	33.05	275.87	86.57	29.77	536.22	22.00
	Predict Time (ms)	8.406	6.925	53.187	57.515	56.942	84.308	13.601	32.071	39.567	12.544	22.867	36.082	40.919	144.385	5.561

Input pattern 1: Data length = 300ms, time increment = 50ms; Input pattern 2: Data length = 250ms, time increment = 50ms; Input pattern 3: Data length = 200ms, time increment = 50ms

It is also worth noting that the ensemble classifiers may consume much more time compared with other classifiers. Therefore how to implement a proper ensemble classifier is an essential issue in ensemble learning.

At last, a feedforward neural network is implemented. The number of nodes for the input layer is equal to the number of feature extracted vectors. The hidden layer and output layer transfer function is tan-sigmoid function. There are two layers of hidden layer, with 27 nodes and 21 nodes, respectively. Scaled conjugate gradient backpropagation is used for network training. The weight for each node is adjusted by using a gradient descent strategy.

C. Hand Gesture Classification Result

As discussed in the previous section, a variety of ML classifiers are applied, so we can find the most suitable classifiers for gesture recognition and glove control. The result of hand gesture recognition is presented in Table I.

In this study, 3 types of input patterns are evaluated, the difference is the length of the data window. Obviously, a longer piece of data contains more sEMG signals, making it easier for gesture recognition. Considering the constraint of real-time performance, the input pattern length is set from 200 ms to 300 ms. As mentioned in the previous section the time increment is related to the total number of training sets, so it is set to 50 ms.

Accuracy is the most important factor in evaluating ML algorithms. In general, the accuracy increases with the increase of segmented data length. From Table I we can find that the decision tree's accuracy and LDA's accuracy are lower than that of other classifiers, around 80%, and 65% respectively. As to SVM, we conduct the experiment with a variety of kernel functions. Compared with the decision tree and LDA, SVM reaches a relatively high accuracy. The accuracy of SVM with Gaussian function kernel is up to 99.3% while the data length is 300ms. Linear kernel's accuracy is lower than others, from 88.6% to 92.2% among the three different input patterns. As to the kNN, different parameters result in similar results, which are fluctuating from 96.4% to 99.4% among different input patterns and distance metrics. The performance of kNN and SVM are quite similar in terms of accuracy. The ensemble learning also shows an interesting result. The subspace kNN has the highest accuracy (99.4%) among all the classifiers, which is slightly higher than kNN. Due to the combination of weak learners, the Bagged Trees can reach 98.6% when input is at 300ms, which is far more higher than the fine tree (83.9%). In contrast, the Boosted Trees' accuracy is not only lower than that of the Bagged Trees, but also much lower than that of the Fine Tree. Therefore, we believe that ensemble learning can achieve higher classification accuracy than a single classifier only through a proper combination of multiple learners. In hand gesture recognition, a parallelization method can achieve a better performance than the serialization method. Last but not least, the neural network also shows very high classification accuracy (99.3%), which is comparable with SVM, kNN and Bagged Trees.

The training time and predict time is another important aspect of evaluating classifier performance. The Fine Tree and LDA has quite short training time and predict time. Especially the LDA has the shortest training time around 3 seconds, which shows its computing efficiency. However, due to their lower accuracy, they are not the most suitable classifiers. SVM and kNN have quite high accuracies as discussed above. The training time of kNN is obviously shorter than SVM's except Cubic kNN. The real-time predict time of SVM with fine Gaussian kernel function reaches 84.308 ms while input data length is 200ms, which hardly meets the real-time performance requirement. As to ensemble learning, the training time is much longer than that of the corresponding single classifier due to the combination of multiple weak learners. The Bagged Trees get a balance between accuracy and predict time with a predicted time around 36 ms. Although the accuracy of Subspace kNN is the highest its real-time

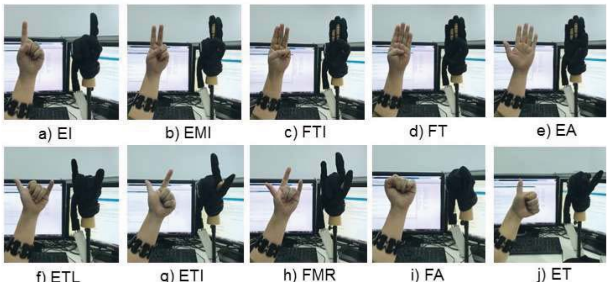

Fig. 8. The illustration of 10 hand gestures, the gestures are controlled by the hand wearing MYO armband.

predict time is also extremely long, varying from 144.385 ms to 152.002 ms. Together with the length of the input data, the total latency exceeds the constraint of 300 ms. Therefore it is not suitable for real-time controlling in this study. At last, the neural network has shown very good real-time performance. Its real-time predict time is the shortest among all classifiers, and at the same time, the high classification accuracy is guaranteed.

With the discussion and analyzation above, we can find that there is a slightly accuracy loss with the decrease of data window length. Considering the wireless transmission latency between the armband and PC, as well as PC and the exoskeleton glove, we selected the classifiers based on the data length of 200 ms, so that the real-time performance can be guaranteed. Four classifiers, fine kNN, Bagged Trees, Cubic SVM and neural network, are used for real-time control of the soft exoskeleton glove.

D. Control of Soft Exoskeleton Glove

The real-time control of soft exoskeleton glove is accomplished using the classifiers derived in the previous section. The purpose of the experiment is to assess the performance of the classifiers in real-time manner and the practical applications of mirror therapy. The soft exoskeleton glove is mounted to a wooden prosthesis which cannot provide any force by itself. Fig. 8 displays a series of snapshots of the wooden prosthesis assisted by the soft exoskeleton glove.

In the beginning, all fingers are in a relaxed state. The non-affected forearm wearing the armband is also in a relaxed state. Once the muscle onset, the classified gesture result is transmitted to the glove, thus the corresponding fingers are bent by the integrated power-assisted cable. Each gesture is repeated 10 times. The performed gestures and classified gestures are both recorded to calculate the recognition rate.

The result of real-time classification accuracy is illustrated in Fig. 9. As we can see some gestures remain the recognition accuracy as high as that of the offline classification. However, the recognition rate of some gestures is significantly lower than the results of offline classification, such as EI, EMI, and FTI. The recognition rate of these gestures is between 60% and 80% in all four classifiers. In general, the average accuracy for the four classifiers is 79.14%, 77.49%, 81.03%, and 82.19%, respectively. There are some reasons for the lower accuracy in real-time classification. First, the transient state of sEMG signals is also involved in the classification after the muscle onset, although a threshold is set to reduce its impact. The misclassification is very likely to occur at the beginning of the gesture. And it is also observed at the end of

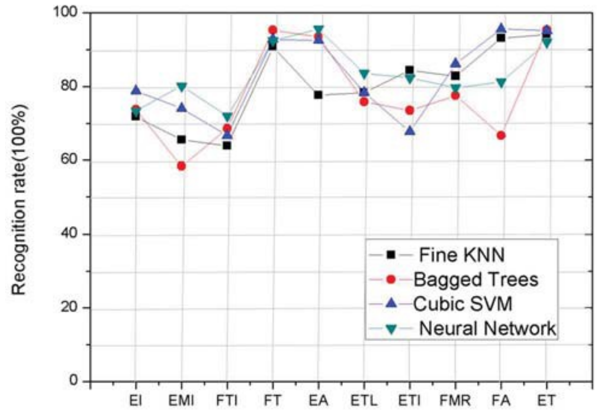

Fig. 9. Results of real-time classification accuracy.

the gesture for the same reason. Another reason is that the forearm muscle of the human body has a coupling effect, and any finger movement will generate some additional force on other fingers. These gestures are similar to each other, which leads to misclassifications. Another important issue is the calibration of the sEMG signal collecting. Although wearing the position of the armband is recorded for each subject, there is still a certain deviation of the electrode position, which is likely to introduce a few input errors during testing.

IV. Evaluation and Discussion

Compared with other work, the innovation of the work is the application of soft exoskeleton glove in the proposed rehabilitation system. In the conventional mirror therapy, the patient looks at the non-affected hand movement in the mirror and images the movement of the affected hand. While in this work, there is an authentic movement on the affected hand. Compared with the rigid exoskeletons, the soft exoskeleton glove is lightweight and comfortable for users, the affected hand can have a more intuitive experience. Thus a better rehabilitation result can be achieved in our proposed system.

There are some limitations of the system. One potential limitation of the work is that the classifier of ML is not universal for all users. The data set obtained for the ML algorithm is only from four subjects, although each gesture is repeated a few times for enlarging the data set. A possible solution is to create a larger data set by collecting sEMG signals from more subjects. Also, the classifiers can be further evaluated, considering their generalization ability.

Furthermore, sensor information fusion is also an issue worth considering. Due to the limitation of the sEMG signal, the recognition accuracy of some fine movement is not high. One approach to identifying more gestures with high accuracy is to fuse sensor information from other dimensions. It can be a future work of putting flexible sensors on the surface of the hand, detecting biomedical signals during the hand movement. Therefore a hybrid sensor signals can be used to determine the precise motion of a human hand.

Additionally, although the glove is capable of applying force to each finger of the affected hand, the direction of the force is fixed. Currently, the glove is not able to help extend fingers, it can only help bend fingers. Experiments are conducted to implement a bidirectional power assistance glove. However, this may lead to a more complex cable routing inside the glove, as well as more motors integrated to provide power strength in the opposite direction, which significantly increases the weight of the entire system. For the future work, it is worth keeping a balance between the system functionality and complexity, fulfilling the requirement of portable and wearable in our proposed system.

V. Conclusion

This study presents a hand rehabilitation system consisting of a portable soft exoskeleton glove and a human-machine interface based on ML. The glove can provide external power strength to each finger to help the rehabilitation of the affected hand. The hand gesture recognition interface is implemented with accuracy in offline mode (99.4%) and real-time mode (82.2%), respectively. The result shows the feasibility of the proposed system, and the limitations and future works are also discussed.

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