A Wearable Hand Rehabilitation System With Soft Gloves

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***Abstract*—Hand paralysis is one of the most common complications in stroke patients, which severely impacts their daily lives. This article presents a wearable hand rehabilitation system that supports both mirror therapy and task-oriented therapy. A pair of gloves, i.e., a sensory glove and a motor glove, was designed and fabricated with a soft, flexible material, providing greater comfort and safety than conventional rigid rehabilitation devices. The sensory glove worn on the nonaffected hand, which contains the force and flex sensors, is used to measure the gripping force and bending angle of each finger joint for motion detection. The motor glove, driven by micromotors, provides the affected hand with assisted driving force to perform training tasks. Machine learning is employed to recognize the gestures from the sensory glove and to facilitate the rehabilitation tasks for the affected hand. The proposed system offers 16 kinds of finger gestures with an accuracy of 93.32%, allowing patients to conduct mirror therapy using fine-grained gestures for training a single finger and multiple fingers in coordination. A more sophisticated task-oriented rehabilitation with mirror therapy is also presented, which offers six types of training tasks with an average accuracy of 89.4% in real time.**

***Index Terms*—Hand rehabilitation, machine learning (ML), mirror therapy, soft glove, task-oriented therapy, wearable system.**

I. Introduction

STROKE is a life-threatening disease caused by the death of brain cells [1], leading to about 55% to 75% of survivors suffering from disabilities, such as paralysis and aphasia. Hemiparesis, the loss of ipsilateral motor function, is one of the most common after effects of a stroke [2], [3]. This condition often results in a severe degradation of the quality of life and a significant burden to family and society. Though recent advances in medicine dramatically increase the survival rate of stroke cases, there is still a high demand for rehabilitative treatments to enhance motor recovery for poststroke patients.

Rehabilitative treatments with assistive devices have been effectively used for paralysis with limb disorders, particularly for large motions and extremity function [4], [5]. However, the rehabilitation of fine motor skills, such as finger movement and coordination, which usually requires a relatively long time, remains challenging. The ideal assistive rehabilitation device for hand function should be inexpensive and portable so that it can be used in home-based rehabilitation; it should also be user friendly and comfortable to facilitate ease of use for extended training periods. Furthermore, it is expected that application software for assessments and interactions with therapists and doctors will facilitate Internet of Things (IoT)-based healthcare.

In 1999, Altschuler *et al.* [2] conducted a rehabilitation experiment on poststroke patients with hemiparesis by placing a vertical, parasagittal mirror between the nonaffected (healthy hand) and the affected hand. The reflection of the healthy hand's movement mirrors the intended motion of the affected hand. This visual input enables the patient to imagine the affected hand moving, which helps to restore damaged neurons in the brain. Task-oriented therapy is another common rehabilitation method in which patients perform activities, such as grabbing bottles or picking up blocks. Recently, benefiting from the rapid development of robot technology, there have been several robot-assisted therapy systems for hand rehabilitation proposed, mainly to support mirror therapy through bilateral movements [6], [7] and task-oriented therapy [1], [8]. Related innovations on the exoskeleton [9], flexible gloves [10], pneumatic exoskeletons [11], etc., have also emerged.

This article presents a novel hand rehabilitation system with a pair of soft gloves that supports both mirror and task-oriented therapies. The sensory glove, integrated with force and flexion sensors, captures the nonaffected hand motion of the hemiplegic patient. Then, a machine learning (ML) engine classifies the gestures and sends the driving signals to the motor glove that provides assistive power to the affected hand to perform the corresponding movements. The contribution of this work over existing systems includes the soft, flexible gloves that provide superior comfort and safety compared to that of rigid

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exoskeletons. Patients can perform home-based rehabilitation training without being limited to a clinical environment. The flexible sensors, and ML algorithms, enable the system to offer 16 kinds of fine motor training gestures for mirror therapy, and six types of motions for task-oriented therapy, which can train each finger movement individually as well as multiple fingers in coordination. An evaluation platform is developed to supply application software and interface to health IoT systems.

The rest of this article is organized as follows. Section II introduces the related work. Section III describes the architecture and design of the proposed system. Section IV provides details of the implementation and experiments in the mirror therapy scenario. Section V presents the design of the task-oriented therapy combined with mirror therapy. Finally, Section VI concludes this article.

II. Related Work

A. Robot-Assisted Therapy

Robot-assisted therapy has been widely used for high-frequency, repetitive, and interactive rehabilitation treatments, such as walking assistance [12] and upper limb rehabilitation [13]. More recently, researchers have started to focus on hand rehabilitation for hemiparesis patients. In 2014, Loureiro *et al.* [14] evaluated a robot-assisted therapy for neurorehabilitation. The stroke subjects interact with a robotic system called Gentle/G and perform reach-grasp-transfer-release movement sequences. Yeh *et al.* [15] developed a virtual reality system integrated with robot-assisted haptics simulation to emphasize the thumb–index finger pinch skill and enhance finger strengthening. Ben-Tzvi and Ma [16] developed a robotic glove for patients with varying degrees of functionality loss. It can record the finger motions and forces while grasping different objects. The glove can then replay the recording to assisting the patient in repeating the hand gestures.

Flexible and wearable electronic devices are also employed in robot-assisted therapy. Popov *et al.* [10], In *et al.* [17], and Yi *et al.* [18] implemented multiple types of soft robotic gloves to facilitate hand gestures in activities of daily living. In 2016, Serpelloni *et al.* [19] implemented a soft robotic rehabilitation system driven by electromyography (EMG) for hand mirror therapy. Such a system allows a hand impaired person to perform the gesture of "hand closing" and "hand opening," with a success rate of 98%.

B. Sensing

Biomedical signals are commonly used for motion detection from patients. Chowdhury *et al.* [20] presented a rehabilitation system with a positive rehabilitative outcome based on a brain–computer interface by means of electroencephalogram (EEG). Surface-electromyogram (sEMG) has also been widely used in recent works [21]–[25]. One example is the commercially available Myo armband that provides convenient development flow with software development kit while relaxing the requirement of precise electrode placement. However, it is relatively expensive and supports only five simple hand gestures with an accuracy of 83% [26]. The main limitation for sEMG is its low spatial resolution caused by muscle crosstalk [27] and fatigue [28]. Georgi *et al.* [29] presented a multimodal approach combining sEMG and inertial measurement units (IMUs). In total, 32 electrodes are placed on the subject's forearm to collect EMG signals, and the IMU is placed on the wrist. Hidden Markov models are used to classify 12 different gestures, with 97.8% accuracy in session-independent experiments and 74.3% accuracy in person-independent experiments.

Another approach is to integrate multiple sensors into a data glove. For instance, knitted piezoresistive fabric sensors [30], position sensors [16], customized tactile pressure sensors [31], IMUs [32], and air pressure sensors [33] are reported in several literatures. Park *et al.* [34] developed a sensing glove using linear potentiometers and flexible wires wherein the joint angle of each finger is calculated by measuring the change in the length of the wires. Sundaram *et al.* [35] implemented a scalable tactile glove that can learn signature grasping gestures, which can be incorporated into prosthetics and human–robot interactions. A sensor array (548 sensors) is integrated in the glove to interact with 26 different objects.

C. Actuation

There are various kinds of actuation mechanism developed for exoskeleton robotic glove, such as pneumatic actuators [18], elastomeric actuators [36], rigid linkage [8], and tendons [10]. Based on these approaches, multiple rigid and soft solutions have been demonstrated. For the rigid glove, Ben-Tzvi and Ma [16] and Lee *et al.* [37] developed a rigid exoskeleton robotic glove for rehabilitation and assistive applications. The main structure is manufactured from aluminum and thrust ball bearings are used to act as the joints. Miniature dc motors actuate the articulated linkages, each of which drives a finger through a cable routing system. As to the soft gloves, Polygerinos *et al.* [36] presented a soft robotic glove to augment hand rehabilitation. The actuator of the glove is made of molded elastomeric chambers with fiber reinforcements.

Tendon-driven soft robotic gloves have been extensively studied in recent years, successfully demonstrating the feasibility in rehabilitation and force augmentation applications [10], [38], [39]. The artificial tendon is embedded in fabrics, and the power is transferred through the wire. The actuator can be remotely placed in a compact factor. The tendon-driven glove presented in [38] uses a motor to move eight DOF of the hand. The actuator is located on a belt and transmits the power through the Bowden cable. Gerez *et al.* [39] demonstrated two types of robotic gloves with tendons for grasping capabilities enhancement. One of the gloves is body-powered, whereas another is motorized. Despite simple, lightweight, and flexible properties of tendon facilitating fully soft, affordable, and portable solutions, most of the works are well-functional for flexion yet a few support both flexion and extension of the hand [10], [18]. There are still several challenges, such as friction, derailment, and deformation, that may become more severe in extension.

D. Gesture Recognition

A variety of ML algorithms have been considered for gesture classification and recognition. The classifier can be k-nearest

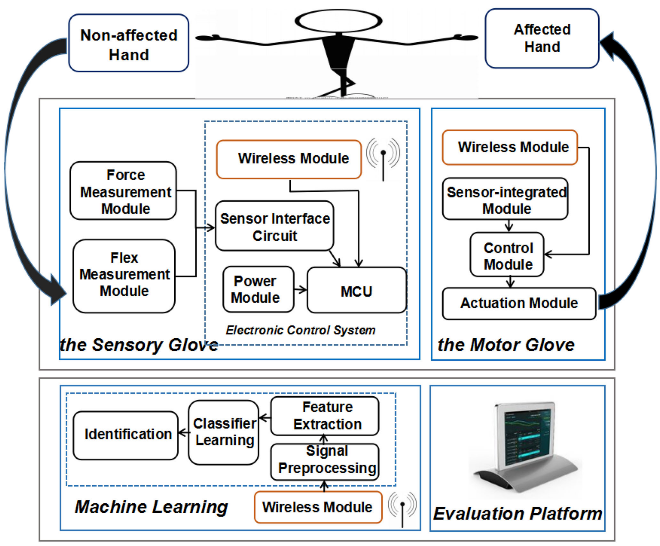

Fig. 1. Architecture of the proposed hand rehabilitation system.

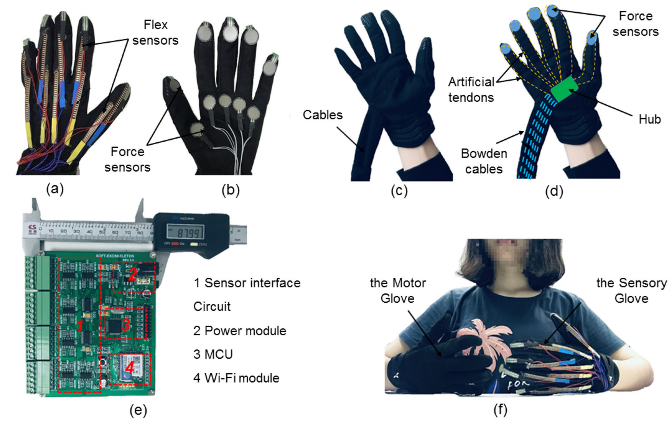

Fig. 2. Design of the glove hardware. (a) Dorsal side of the sensory glove. (b) Palm side of the sensory glove. (c) Motor glove. (d) Motor glove with animation of tendon design. (e) Electronic system. (f) Subject is wearing the motor glove and sensory glove.

neighbor (kNN) [40], dynamic time wrapping (DTW) [26], linear discriminant analysis (LDA) [41], supported vector machine (SVM) [42], and neural network (NN) [43], with different tradeoffs between classification accuracy (CA) and complexity among the different methods.

Mummadi *et al.* [44] implement a real-time, embedded recognition of sign language. The data glove is integrated with multiple IMUs and an embedded classifier for French sign language recognition. The random forest (RF) is selected as the classifier to optimize the accuracy in real time. RF functions with a recognition rate of 92% within 63 ms. Plawiak *et al.* [40] conduct an experiment on gesture recognition with a specialized data glove. In the experiment, 10 people perform 22 hand body language gestures. Three ML algorithms, probabilistic NN, SVM, and kNN, are evaluated. SVM has an accuracy of 98.24% and shows the lowest computational complexity.

In summary, the existing robot-assisted rehabilitation systems mostly support coarse-grained tasks, such as hand extension, flexion, and wrist movement. Few works are dedicated to the fine motor skills required for complex, fine-grained coordinated finger motion. Treatments for the latter stages of poststroke rehabilitation demand abundant and accurate fine-grained gestures [45], for instance, thumb-to-finger tapping, finger flexion, and gripping. The rich combinations of gestures can motivate the patients' enthusiasm and improve long-term rehabilitation compliance. Therefore, a hand rehabilitation system for fine motor functions that supports both mirror therapy and task-oriented therapy is proposed.

III. System Design

The architecture of the hand rehabilitation system proposed in this article is shown in Fig. 1. It consists of a sensory glove, a motor glove, an ML engine, and an evaluation platform. The sensory glove is worn on the nonaffected hand to collect the force and flexion information for hand motion detection. The ML engine classifies the gestures and sends the control signals to the motor glove, aiding the patient to perform the training tasks.

A. Hardware Design

1) Sensory Glove: The sensory glove, worn on the nonaffected hand, integrates multiple sensors to capture the hand's motion for gesture recognition and visualization. The flexible and bendable sensors are employed. Ten flexion sensors are placed at the joint of each finger to measure their bending angles [see Fig. 2(a)]. Another ten force-sensing resistors are mounted on the fingertips and the palm [see Fig. 2(b)]. In mirror therapy, the raw data captured from the flexion sensors are used as the input data of classifiers, whereas data from both flexion sensors and force sensors are collected for gestures of touching and grasping in task-oriented therapy.

A battery-powered embedded electronic system is developed for data processing and control, as shown in Fig. 2(e). It consists of a sensor interface, a power supply module, a Wi-Fi module, and an embedded processor. An ARM Cotex M3 processor is used. It has up to 72-MHz frequency at a maximum power consumption of 227 mW. A sensor interface, including signal filter, amplifiers, and analog-to-digital convertors (ADCs), is carefully designed to sample and process the signals from the ten force sensors and the ten flexion sensors. The sampling frequency is set to 200 Hz. Two AD7490 ADCs are used and each ADC provides up to 16 channels, which is sufficient for all the sensors mounted on the glove. A Wi-Fi module is integrated to connect the gloves with the ML engine.

2) Motor Glove: The tendon-driven motor glove, worn on the affected hand, is illustrated in Fig. 2(c). Based on these state of the arts [10], [38], [39], we implemented the motor glove mainly focused on a simple, affordable, lightweight, and portable solution with improved comforts for patients. As shown in Fig. 2(d), the artificial tendon made of the nylon wire is embedded in the inner layer of the glove; thus, it is fully soft. The nylon wire routed around the finger is wrapped by fabric as the textile sheath

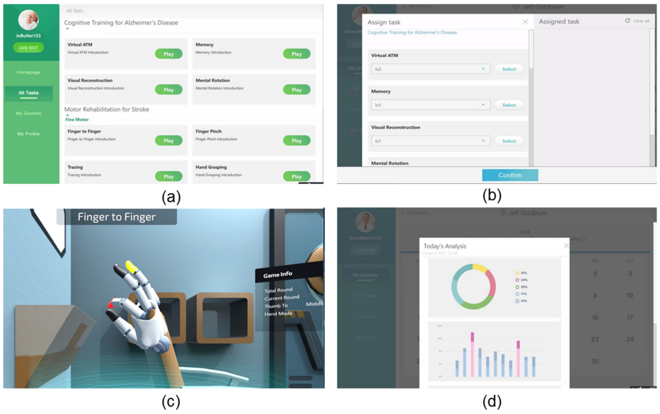

Fig. 3. Evaluation platform for rehabilitative training. (a) User interface. (b) Task assignments. (c) Virtual reality environment. (d) Data analysis.

fixed on the glove (such as drawstring structure). Compared to a signal-wire-driven tendon, such a dual-wire structure provides an improved balance of force distribution along with the finger during flexion. A 3-D printed structure is mounted on the palm served as the anchor and hub. The Bowden cable connected to the tendon is driven by a linear actuator powered by a dc micromotor. The actuator provides a maximum force of 15 N to the tendon, which is adjustable according to the therapeutic need. Five dc motors are integrated into the system, i.e., each finger can be controlled independently. It is noted that the presented motor glove supports flexion only, and the extension function can be integrated in future work. Similar to the sensory glove, sensors are also employed. At the dorsal side, flexion sensors are mounted on each finger's proximal interphalangeal joint. At the palm side, force sensors are attached to the fingertips of each finger. Data collected from the affected hand can be utilized for further assessment of training progresses. It can also measure the hand movements while the force is applied, providing feedback for actuation when it necessary. A Wi-Fi interface is also implemented to receive control signals from the ML engine. The power applied to each finger is modulated by the pulsewidth modulation waves generated by a controller through an H-bridge. The prototype of the motor glove is lightweight, i.e., approximately 100 g of the soft glove, and 850 g of the actuation module, including the two 18650 Li-ion batteries that is remotely placed.

B. Software Development

An ML engine is developed for gesture recognition. Classifiers of SVM, kNN, and decision tree (DT) are implemented. There are four steps for gesture recognition, including signal preprocessing, feature extraction, classifier learning, and identification. The implementation details will be discussed in Section IV.

An evaluation platform is also proposed to provide application software and an interface to health IoT systems, as displayed in Fig. 3. Rehabilitation therapists can set the content and intensity of rehabilitation training according to the patient's progress. This can help the doctor analyze each patient's condition more effectively and objectively and prescribe a more personalized training program for each patient. The evaluation platform also accommodates a virtual reality environment to interact with the glove for hand rehabilitative training.

IV. Experiments for Mirror Therapy

Two types of experiments for mirror therapy are performed in this work. One is an offline experiment to investigate approaches of feature extraction and selection for gesture recognition. The other is an online experiment assessing the real-time performance for sensing-actuation combination of the gloves.

Based on previous works and our laboratory condition, as well as the limitation of real clinic trail at the current stage, eight subjects (five male and three female), with normal hand motor function and ranging in age from 22 to 32 years, were engaged. The target uses of the proposed system are hemiparesis patients with hand paralysis, i.e., one of his/her hand is relatively healthy (i.e., nonaffected/less affected), whereas the other hand is affected. Though the subjects are not the real hemiparesis, the experiment is still applicable for proof of concept. The subject's one hand is to perform gestures as normal while the other hand contributes no force to the motion to imitate the affected hand in hemiparesis.

The ML engine is implemented on MATLAB 2016a, running on the PC with 64-b Windows 10, 3.6-GHz Intel i7-7700 processor, and 16 GB of RAM.

A. Gesture Design for Mirror Therapy

To facilitate finger motor training with fine-grained gestures, we designed 16 kinds of finger gestures, as illustrated in Table I. They are divided into four groups. The first group contains CH, RH, and FA, which refer to the movement of all the fingers together. The second group is finger flexion (FT, FI, FM, and FR), focusing on single finger's movement. The third group is thumb-to-finger tapping (FTM, FTR, FTL, and FTI), which is a strong indicator of coordinated hand motor function. The fourth group includes several common gestures, such as "GOOD" and "VICTOR."

B. Offline Data Processing and Pattern Classification

1) Data Preprocessing: To quickly obtain a large amount of training data for further offline analysis, we chose the overlapped segmentation method on the steady-state sensor signals. The data are collected by maintaining each fine-grained gesture for 10 s. To ensure the quality and integrity of gesture signals, the data of the first and the last 5% are removed. As illustrated in Fig. 4, the length of a window is set to be 200 ms, and the overlap of the adjacent window is 100 ms. The data collected by a single sensor for each gesture can be divided into 90 windows. The 200-ms data window contains enough information to recognize the hand gesture. The 100-ms overlap of the adjacent window fully utilizes the data segment to produce a refined, dense classification scheme to meet the real-time demands.

2) Feature Extraction and Classification: Different features of the time and frequency domains can be used for gesture

TABLE I
SIXTEEN FINE-GRAINED GESTURES

Gestures		Brief Description	Gestures		Brief Description
	CH	close hand		FT	flex thumb
	RH	relaxed hand		FI	flex index finger
	FTM	flex thumb and middle finger		FM	flex middle finger
	FTR	flex thumb and ring finger		FR	flex ring finger
	FTL	flex thumb and little finger		GOOD	GOOD
	FTI	flex thumb and index finger		POINT	flex thumb, middle, ring and little finger
	FA	flex all fingers		VICTOR	flex thumb, ring and little finger
	FMRL	flex middle, ring and little finger		FRL	flex ring and little finger

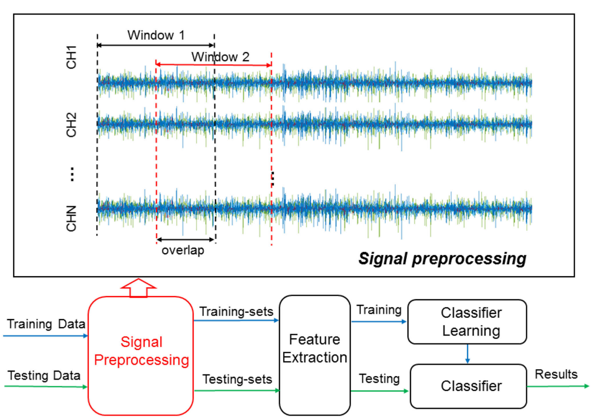

Fig. 4. Time windows for signal preprocessing.

recognition. Typical time domain features are mean absolute value (MAV), root mean square (RMS), waveform length (WL), etc. Power spectral density and continuous wavelet transform are two useful methods for frequency domain feature analysis. The sensors used in this work provide a relatively high signal-to-noise ratio, which helps sufficiently accurate pattern recognition when low-complexity features and classifiers are used. Five time-domain features are evaluated in this work, including RMS, MAV, WL, variance (VAR), and standard deviation (SD). RMS and MAV contain information of the signal strength and amplitude. WL indicates the waveform complexity, including

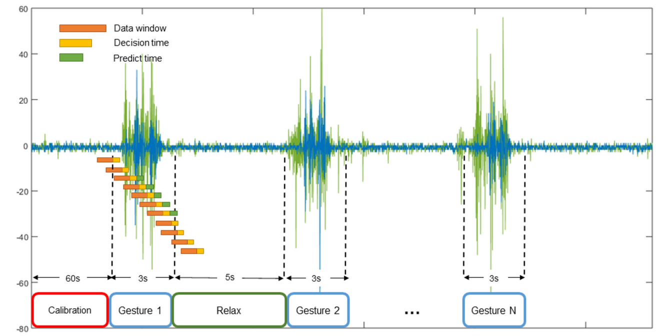

Fig. 5. Real-time test protocol.

amplitude and frequency. VAR and SD show the signal strength distribution.

Feature selection is used to improve the accuracy [46]. It selects the optimal feature subset from the original features. Each feature is tested independently. Then, combinations of different features are evaluated. To evaluate the performance of different feature sets, 10×10 fold cross-validation is adopted. It works as follows: the dataset is randomly and equally divided into ten parts. Nine of the ten parts are used for training the classifier, and the remaining part is used for testing. The tenfold cross-validation is repeated ten times, yielding an average CA. CA is a significant indicator of the classification results. It is defined as follows:

$$\mathrm{CA} = \frac{\text{Number of correct testing samples}}{\text{Total number of testing samples}}. \quad (1)$$

Table II reports the classification results. The RMS, MAV, and WL have the highest CA in all the classifiers. A combination of the three aforementioned features (denoted as "Top-3") yields a higher degree of accuracy than either algorithm alone. We further extended the combination of all five features (denoted as "All"), yielding a marginal increase compared to "Top-3," yet at the expense of increased training time and data size.

With respect to the different classifiers, SVM has the highest average accuracy of 99.2% for "Top-3." kNN is about 3% lower in accuracy than SVM but it has a much shorter execution time. The accuracy of DT is only around 80% among all the feature sets. In this experiment, it is found that the most common features in the time domain, such as MAV, RMS, and WL, ensure >95% accuracy when SVM is used. It is mainly because the flexible sensors used in this work offers high-quality signals for classification compared to sEMG and noninvasive EEG. Meanwhile, embedding sensors in the glove eliminates the variation issue of the electrode placement. As a result, the requirement and complexity of features and classifiers can be relaxed.

C. Real-Time Test

The real-time test is conducted using SVM with "Top-3" to assess the performance of the classifiers in a real-time manner, as well as its functionality in mirror therapy. Subjects taking part in this study performed the hand gestures according to the experimental protocol designed in Fig. 5. In the beginning, a

TABLE II
COMPARISON OF THREE ALGORITHMS OF SVM, kNN, AND DT

Algorithms		Parameters	RMS	MAV	WL	VAR	SD	Top-3	All
SVM	Accuracy (%)	Kernel: Gaussian Radial Basis (RBF) Function	98.83	98.72	97.63	92.6	94.2	99.2	99.65
	Training Time (ms)		833.64	829.55	843.49	830.07	820.79	892.76	1216.95
	Predict Time (ms)		67.92	67.89	67.83	67.07	66.36	67.89	68.13
	Data Size		28800	28800	28800	28800	28800	86400	144000
kNN	Accuracy (%)	Number of Neighbors: 10	95.21	94.63	94.95	92.4	92.5	96.19	96.27
	Training Time (ms)		7.93	7.86	7.98	7.76	7.92	10.38	27.61
	Predict Time (ms)		4.93	4.95	4.89	4.84	4.87	5.06	5.12
	Data Size		28800	28800	28800	28800	28800	86400	144000
DT	Accuracy (%)	Maximum Number of Splits: 100	80.78	79.64	80.14	75.2	76.4	80.5	81.73
	Training Time (ms)		11.09	11.86	10.31	10.11	10.39	20.04	37.49
	Predict Time (ms)		3.90	3.96	3.83	4.01	4.04	4.10	4.15
	Data Size		28800	28800	28800	28800	28800	86400	144000

Fig. 6. Training results of 16 kinds of fine-grained gestures for mirror therapy. (a) CH. (b) RH. (c) FTM. (d) FTR. (e) FTL. (f) FTI. (g) FA. (h) FMRL. (i) FT. (j) FI. (k) FM. (l) FR. (m) GOOD. (n) POINT. (o) VICTOR. (p) FRL.

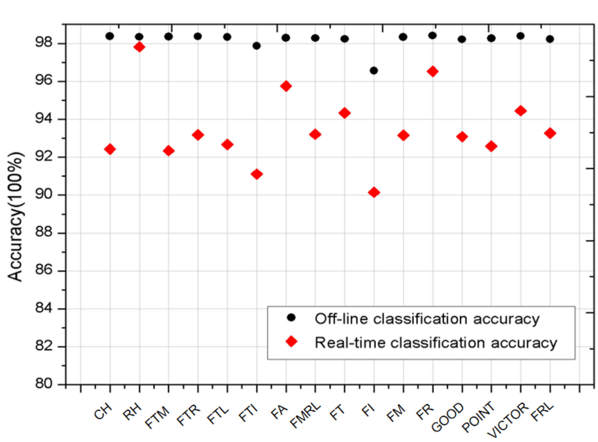

Fig. 7. Offline and real-time CA of the 16 kinds of training gestures for mirror therapy.

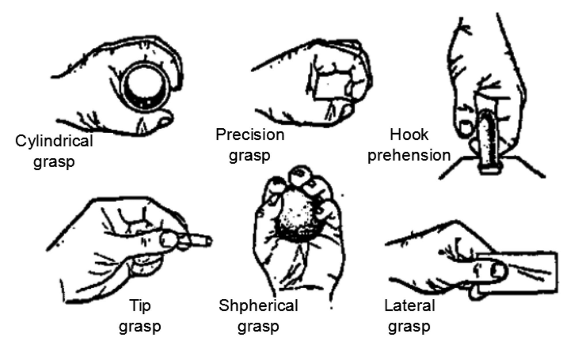

Fig. 8. Basic grasp primitives according to Schlesinger: cylindrical grasp, precision grasp, hook prehension, tip grasp, spherical grasp, and lateral grasp. Figure adapted from Kyberd and Pons [47].

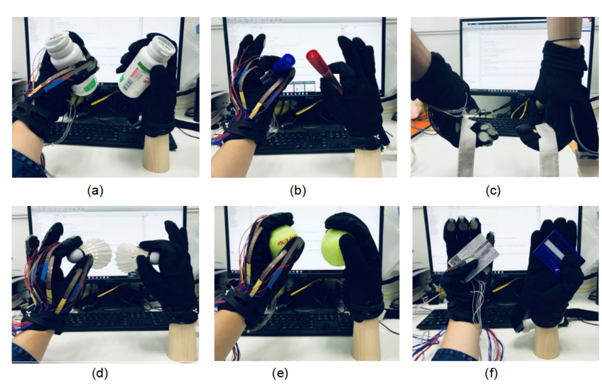

Fig. 9. Experiments of grasping different objects based on the six basic gestures. (a) Cylindrical grasp. (b) Precision grasp. (c) Hook prehension. (d) Tip grasp. (e) Spherical grasp. (f) Flex thumb.

calibration phase of 60 s is reserved to reduce sensor variation as well as variations due to different hand sizes. After that, the subject is guided to perform the first gesture, holding it for 3 s according to the instruction on the screen. Then, the subject is instructed to relax for 5 s and prepare for the next gesture. The segmentation algorithm is used to detect the hand gestures from

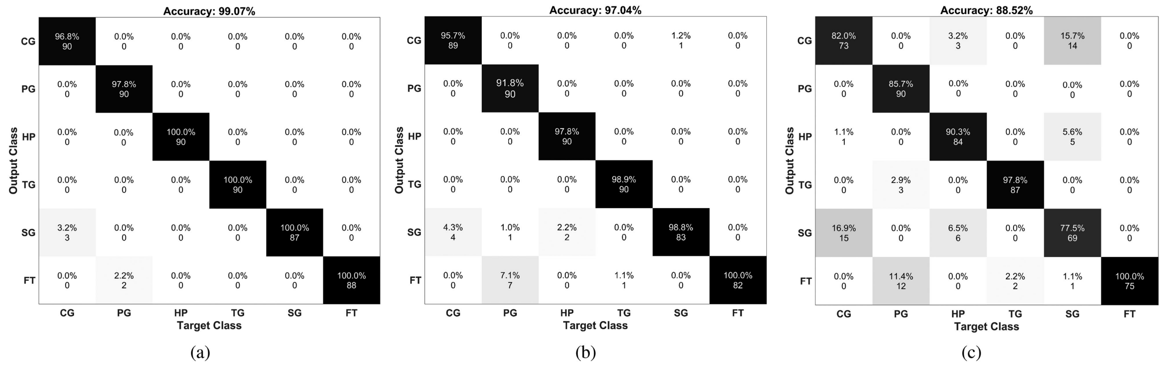

Fig. 10. Confusion matrices of three classifiers. (a) SVM. (b) kNN. (c) DT.

TABLE III
PROPOSED SYSTEM COMPARISON WITH THE STATE OF THE ART

References	Sensing signals	Gestures	Algorithm	Offline / Real-time Accuracy (100%)	Target application
S. Benatti *et al.* [23]	sEMG	7	SVM	- / 90.00%	Wearable real-time gesture recognition
N. Duan *et al.* [25]	sEMG	10	CNN	94.06% / -	Gesture recognition
G. Yang *et al.* [21]	sEMG	9	LDA	99.82% / 96.20%	Robot-assisted rehabilitation
A. Chowdhury *et al.* [20]	EEG	8	SVM	- / 70.21%-81.05%	Mental practice (MP) and physical practice (PP)
S. Jiang *et al.* [41]	EMG + IMU	8 (air gestures) 8 (surface gestures)	LDA	- / 92.60% - / 88.80%	Gesture recognition
M. Cortese *et al.* [48]	Accelerometer	3	DT	- / 100%	Robot-Mediated Hand Telerehabilitation
Z. Ma *et al.* [8]	Force sensor + position tracking	4	DTW	- / -	Robotic hand rehabilitation system
Shull *et al.* [45]	Barometric pressure sensor	6 (wrist gesture) 6 (finger gesture) 10 (Chinese number)	SVM/ KNN/ LDA	94%	Gesture recognition
This work	**Force sensor + flexion sensor**	**16 (finger gestures) 6 (task-oriented gestures)**	**SVM**	**99.2% / 93.32% 99.07% / 89.4%**	Mirror therapy & task-oriented therapy

the continuous data streams. It compares the input sensor signals with a threshold to activate the classifier. Finally, the control signal is generated and broadcast to the motor glove according to the recognition result. Such a process is repeated until all gestures are performed. Fig. 6 displays a series of snapshots of the hand assisted by the motor glove.

System latency is an important factor that affects the training experience. As discussed in previous sections, the length of data window is 200 ms, and the prediction time of SVM approximates to 70 ms. The transmission delay is less than 10 ms in the local wireless network, thus the total system latency is less than 300 ms, which can meet the real-time requirement.

Fig. 7 presents the offline and real-time CA with respect to the 16 fine-grained training gestures. The average offline accuracy (99.2%) is higher than the real-time accuracy (93.32%). This is mainly because of the additional noise introduced from the transition between gestures. It is also worth mentioning that the accuracy of FI and FTI is slightly lower than other gestures in both offline and real-time experiments. It can be explained by the fact that the thumb and the index finger are close to each other, so there is little thumb movement in FTI, which tends to be misclassified as FI.

The proposed wearable system is portable, and the battery life is considered. The power consumption of the gloves with the electronic board is measured under different operation modes. Based on the measurements and the duty-cycle factor of the training protocol shown in Fig. 5, the system's average power is approximately 5 W, i.e., 0.625 W for the sensory glove and 4.35 W for the motor glove. As a result, up to 4.5 h of battery life for continuous training tasks can be expected using the two 18 650 Li-ion batteries with a capacity of 23.040 Wh.

V. TASK-ORIENTED THERAPY WITH MIRROR THERAPY

In this section, we present the combination of task-oriented and mirror therapy for rehabilitative hand motor training using the proposed system.

Six tasks are designed in this work, which cover 90% of the most common dexterous movements for basic grasp: Cylindrical grasp (CG), precision grasp, hook prehension, tip grasp, spherical grasp (SG), and lateral grasp (see Fig. 8). It is worth mentioning that the gesture of flex thumb [see Fig. 9(f)] is employed instead of lateral grasp. The assisted force applies to the finger through the tendon driven by the actuator. Such a structure can only support the finger to bend toward the palm, whereas the lateral grasp requires a pinch movement of the thumb to the index finger side. Therefore, we redesign this gesture to perform the same task of object fetching. Based on the six basic grasping gestures, six commonly used objects are selected as training tools in this work, including a medicine bottle, a roller pen, a handbag, a badminton, a tennis ball, and a bank card.

To better demonstrate the proposed system, a wooden prosthesis is used to model the affected hand. The motor glove is worn on the prosthesis, which does not contribute any force to the motion. The subject wearing sensory glove grasps objects based on the predefined six gestures, then the motor glove drives the wooden hand to perform the mirror gestures, as shown in Fig. 9. Classifiers of SVM, kNN, and DT are also applied for gesture recognition. The offline confusion matrices of these three algorithms are presented in Fig. 10. Similar to the results of mirror therapy, SVM holds the highest accuracy (99.07%), followed by kNN (97.04%) and DT (88.52%). It is also found that SG is the most misclassified gesture because it is very close to CG. SG is often misclassified as CG since the two gestures are quite similar. The real-time test was also conducted with the same setup as the mirror therapy, demonstrating an average accuracy of 89.4%.

VI. Conclusion

In this article, we presented a hand rehabilitation system that supports both mirror therapy and task-oriented therapy for fine motor recovery of poststroke patients. The gloves with sensing-actuation combination exploited flexible and wearable techniques, which provided a safe, comfort, portable, and affordable solution over the rigid exoskeleton devices. Compared to those using biomedical signals, a dedicated data glove with sensors integrated offers improved signal quality while eliminates the need for precise placement of electrode, thus ensures fine-grained classification of training gestures. The user-friendly application software allows patients or nonprofessions to carry out daily training tasks and interact with therapists. Table III compares the proposed work with other state-of-the-art research. Our work demonstrated a promising IoT healthcare application for home-based hand rehabilitation.

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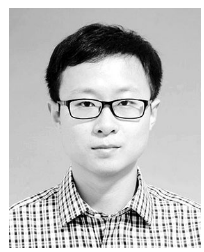

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