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Shoulder muscle activation pattern recognition based on sEMG and machine learning algorithms

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ABSTRACT

Background and Objective: Surface electromyography (sEMG) has been used for robotic rehabilitation engineering for volitional control of hand prostheses or elbow exoskeleton, however, using sEMG for volitional control of an upper limb exoskeleton has not been perfectly developed. The long-term goal of our study is to process shoulder muscle bio-electrical signals for rehabilitative robotic assistive device motion control. The purposes of this study included: 1) to test the feasibility of machine learning algorithms in shoulder motion pattern recognition using sEMG signals from shoulder and upper limb muscles, 2) to investigate the influence of motion speed, individual variability, EMG recording device, and the amount of EMG datasets on the shoulder motion pattern recognition accuracy.

Methods: A novel convolutional neural network (CNN) structure was constructed to process EMG signals from 12 muscles for the pattern recognition of upper arm motions including resting, drinking, backward-forward motion, and abduction motion. The accuracy of the CNN models for pattern recognition under different motion speeds, among individuals, and by EMG recording devices was statistically analyzed using ANOVA, GLM Univariate analysis, and Chi-square tests. The influence of EMG dataset number used for CNN model training on recognition accuracy was studied by gradually increasing dataset number until the highest accuracy was obtained.

Results: Results showed that the accuracy of the normal speed CNN model in motion pattern recognition was 97.57% for normal speed motions and 97.07% for fast speed motions. The accuracy of the cross-subjects CNN model in motion pattern recognition was 79.64%. The accuracy of the cross-device CNN model in motion pattern recognition was 88.93% for normal speed motion and 80.87% for mixed speed. There was a statistical difference in pattern recognition accuracy between different CNN models.

Conclusion: The EMG signals of shoulder and upper arm muscles from the upper limb motions can be processed using CNN algorithms to recognize the identical motions of the upper limb including drinking, forward/backward, abduction, and resting. A simple CNN model trained by EMG datasets of a designated motion speed accurately detected the motion patterns of the same motion speed, yielding the highest accuracy compared with other mixed CNN models for various speeds of motion pattern recognition. Increase of the number of EMG datasets for CNN model training improved the pattern recognition accuracy.

1. Introduction

When a muscle contracts in response to the intention of the brain, efferent nerve signals are generated and sent to motor units to control muscle contraction. The nerve activity signals and bio-electrical signal in the muscle fibers can be recorded using

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electromyography. The electrical signal magnitude over time can be showed in the electromyogram (EMG). EMG contains the temporal and spatial information of the nerve action potential of terminal axons and endplate potentials of neuromuscular junction, and the action potentials propagated through sarcolemma and T tube membrane during muscle contraction. EMG has been used in clinic to check the nerve muscle excitation and nerve conduction functions [1]. Surface electromyography (sEMG) can be performed by placing non-invasive electrodes on the skin's surface to record underneath muscle activities. sEMG has been extensively utilized in clinical medicine, ergonomics, rehabilitation medicine, sports science, and now into the field of intuitive robot control engineering [2,3].

Using sEMG for the motion control of robotic assistive device is an emerging technique in rehabilitation engineering; EMG-controlled hand prostheses or EMG-controlled elbow exoskeleton for amputee or stoke patients have been reported in literature [4,5], in which residual weak EMG signals are extracted as command signals to operate these assistive robotic devices for rehabilitation or improvement of daily life activity. To improve system performance in signal recognition, machine learning algorithms and techniques have been considered a better approach than traditional methods for multiple channels of EMG signals processing and proposed for developing new bio-electrical signal processing and motion pattern recognition methods [6]. Currently these machine learning methods are mainly used in the hand gesture and elbow motion pattern recognitions using multiple channel EMG signal processing and pattern recognition algorithms [7]. For example, K-Nearest Neighbor (KNN)[8], Linear Discriminant Analysis (LDA)[9], and Support Vector Machine (SVM) [8] have been studied and applied in hand and elbow and lower limb motion recognition, robot control, post-injury rehabilitation, and clinical research [10].

The shoulder joint has complex motion patterns with five degrees of freedom (DOF) of movements [11]. The shoulder girdle includes the sternoclavicular joint, scapulothoracic joint, acromioclavicular joint and glenohumeral joint. Multiple muscles surrounding the shoulder joint are activated during movement, in which muscle activation patterns determine the direction of shoulder motion. The basic shoulder joint motions include abduction, adduction, flexion, extension, internal rotation, and external rotation; these motions are required for activities of daily life (ADL), including drinking, backward and forward movement of the upper arm, abduction, and lifting of the arm. The EMG-controlled shoulder joint exoskeleton has not been fully studied or developed. The reasons include that there are challenges in extracting multiple shoulder muscle activity signals for motion pattern recognition and for shoulder exoskeleton motion control at user's intent. Processing all these individual muscles for shoulder exoskeleton motion control in activity of daily life (ADL) needs complex algorithms [12]. Appropriate control strategies are still lacking for the wearable devices assistive in shoulder movements at user intent [13]. Machine learning batch-processing approach may reduce the efforts devoted to process multiple individual EMG signal channels for motion intent recognition. For these reasons, some machine learning algorithms have been developed and used in the analysis and pattern recognition of bioelectrical signals associated with limb motions [7].

To date, some machine learning algorithms can extract the specified features from the targeted data and quantified the features for model training using supervised learning process [14]. Examples include using K-Nearest Neighbor (KNN) [8], Linear Discriminant Analysis (LDA) [9], Support Vector Machine (SVM) [8], and Artificial Neural Networks (ANN) [15] in model trainings. These supervised machine learning methods on EMG signals have been used in limb motion recognition, robot control, rehabilitation, and clinical research [16]. However, the accuracy of feature extraction from the EMG signals are affected by many factors, including the methods of EMG recording (using different electrodes or recording devices), subject physiologic variability (age and BMI (body mass index)), environmental factor (room temperature), EMG electrode location on the body's surface, electrical power line noise, and motion artifact. These factors reduce the efficiency of system robustness and accuracy of recognition [17], extra efforts are subsequently required in signal processing with complex procedures.

Deep learning (DL), as a branch of machine learning, has made remarkable progress in image recognition, natural language, and behavior prediction [18–20]. Hinton and Salakhutdinov proposed to reduce the dimensionality of data with neural networks algorithms [21], leading to the development of deep neural network structures, the convolutional neural network (CNN), and the recurrent neural network (RNN) which are now used in many research fields [22–27]. In terms of EMG signal processing for motion recognition, the deep learning method does not manually set standards to extract needed features, unlike other machine learning algorithms such as KNN and LDA. Instead, DL implements the relevant propagation rules from the training data through repeated iterations of the neural network structure to optimize the algorithm. It has been reported that CNN algorithm yields better outcomes in motion pattern recognition by processing EMG signals [10,28–30]. Using the CNN for shoulder motion recognition based on EMG signals has not been reported in the literature.

Extreme learning machine (ELM) is a newer machine learning method for EMG signal processing to detect motion patterns. During multiple EMG channel processing, the structural features of each individual EMG channel including time domain, frequency domain, time-frequency domain information should be considered. For this reason, the synergy feature extraction is required across multiple EMG channels for motion pattern recognition so as to simplify control strategy including the control dimensionality reduction [31]. ELM demonstrated an optimal performance for synergetic feature extraction of multiple channels of EMG signals to classify upper limb motions [32–34].

In this paper, we proposed a novel machine learning strategy considering both temporal and spatial convolution of CNN structure for upper arm and shoulder motion pattern recognition using sEMG signals from 12 muscles of the shoulder and arm. The long-term goal of our research is to develop the motion pattern recognition algorithms to processes the shoulder muscle EMG signals for a bionic shoulder exoskeleton volitional control. Additionally, our goals also include the development of a machine learning system to aid in clinical diagnosis of sport injury, evaluation of surgical treatment outcomes, determination of time points for athlete to return to the sports, as well as the assessment of stroke rehabilitation and improvement of activity of daily life. The specific aims of this study were to construct an inference model using CNN algorithms that can detect a user's upper limb motion intents. EMG data recorded under different motion speeds using different EMG recording devices were used for data training. The efficiency of the trained model was validated to determine its accuracy. The CNN model performance under the influence of motion speed, individual variability, EMG recording device changeability, and dataset amount used for training was investigated. Overall, this study describes EMG processing using machine learning methods for upper arm motion pattern recognition, potentially the algorithms obtained from this study can be used in rehabilitation practice, as well as orthopaedic surgery and sports medicine projects.

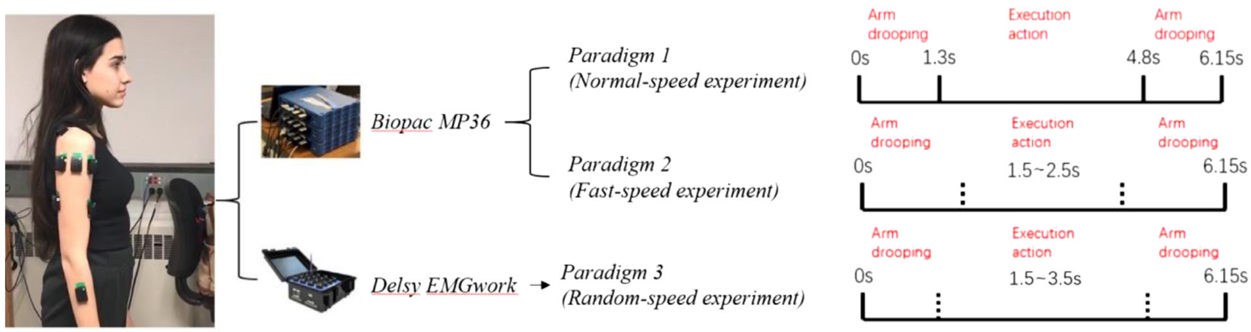


Fig. 1. The sequence diagram of the three experimental paradigms. In paradigm1, 2, Biopac system was used to collect the EMG signals of 7 subjects' shoulder movements. In paradigm 3, Delsy system was used to collect the EMG signals of 8 other subjects' shoulder movements. The execution speed of paradigm 2 and 3 was determined by the subjects, and the execution time was limited within 1.5-2.5s and 1.5-3.5s respectively.

Table 1
The series number of the sEMG electrodes and the name of the muscle in which they are located.

Electrode Number	Muscle	Electrode Number	Muscle
1	Middle Deltoid	7	Infraspinatus
2	Anterior Deltoid	8	Teres Major
3	Posterior Deltoid	9	Bicep
4	Supraspinatus	10	Triceps
5	Pectoralis Major	11	Wrist flexor
6	Trapezius	12	Wrist extensor

2. Materials and methods

2.1. Subjects

This experiment has been approved by the university ethics committee (Institutional Review Board) and conforms to the Helsinki declaration. Fifteen healthy subjects (nine men and all right-handed) participated in the study after signing an informed consent form. None of the subjects had a previous or a current neurological or physical illness or injury. Before the experiment, each subject was informed of the experiment content, the purpose of the experiment and the detailed experimental process.

2.2. Shoulder movements and muscle selection

The subjects performed upper limb movements including drinking, abduction, and forward and backward (BF) because they are the main basic shoulder movements. These movements are also the basic training processes in the rehabilitation of the disabled patients and frequent motions in activity of daily life (ADL) [35]. The natural dropping state of the arm (resting state of the shoulder) was added for a baseline recording of EMG signals.

EMG signals from 12 muscles that control the movements of the upper arm were recorded. Muscle names and the corresponding electrode numbers are shown in Table 1.

2.3. Experimental equipment and paradigm

The Biopac data acquisition system (Model MP-36, Biopac Inc, Goleta, CA) and Delsys EMGwork (Delsys Inc, Boston, MA) were used to collect EMG signals from these 12 muscles. The sampling frequency was set to 1000 Hz. The Ag-Cl gel surface electrodes (Biopac Inc, EL503) were used with 20 mm between probe and reference electrodes. The ground electrode was placed on the T1 spinal process. The skin was wiped with 70% alcohol before the electrodes were placed to the skin.

Fifteen healthy subjects participated in this study. Shoulder EMG data were collected in different groups using the following three paradigms. An experimental schematic diagram is shown in Fig. 1.

Paradigm 1 (Normal-speed experiment): 7 subjects followed the normal-speed paradigm video and were asked to perform four kinds of shoulder movements: drink, abduction, forward and backward, and static resting while connected to the Biopac MP36 data acquisition system. A total of 180 EMG datasets were collected for each subject, including 45 datasets for each movement. Resting state datasets were collected from the baseline EMG signals for about 1.3s before and after each movement. During EMG baseline signal recording, the subjects were asked to keep their bodies relaxed and arms down naturally at their sides. During each movement, the subject watched the normal speed video and followed the motion speed as showed in the video to ensure the movement was completed at a designated moving speed. Each action was completed at the speed of one movement in 3.5 seconds.

Paradigm 2 (Fast-speed experiment): The same subjects participated in the following motion test. The experimental platform (Biopac MP36) and the actions required to be performed are the same as in *paradigm 1.* A total of 180 EMG datasets were collected from each subject, including 45 for each movement. The subjects followed the fast-speed paradigm video and the data was collected. As per *paradigm 1*, the action execution and collection interval are located between the two ends of the basic state interval. The time for each action is random between 1.5s and 2.5s, and the total time for data collection remains unchanged.

Paradigm 3 (random-speed experiment using another EMG recording system): In this group, the Delsys EMGwork system was used for the EMG signal recording. The remaining 8 subjects moved their arm to perform drinking, abduction, forward & backward actions at their will at random speeds. Static motion was recorded while the arm was at rest at the participants side between test. A total of 180 EMG datasets were collected in each subject, including 45 datasets of each movement.

An experimental schematic flowchart is shown in Fig. 1. The purpose of the experimental paradigms is as follows: 1. In the experimental paradigm without distinguishing velocity, we can verify the basic performance of the model (shoulder muscle activation pattern recognition at constant velocity). 2. In real situations, the execution of actions is affected by many factors and is definitely not uniform. By predicting and recognizing the movement of random speed, we can explore the adaptability of this method in actual situations. 3. Test the robustness and adaptability of the model through predictive analysis on other data acquisition platforms.

2.4. Data preprocessing

The original EMG signals collected by the EMG signal acquisition platform were 12 channel EMG signals with a sampling

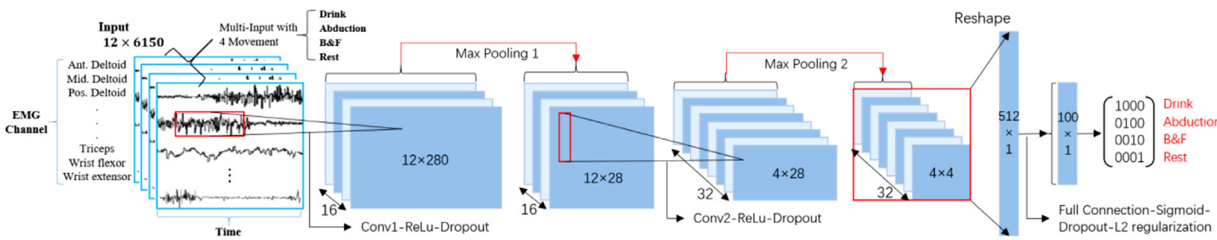


Fig. 2. The main structure of CNN model. The two convolution layers extract the one-dimensional receptive field in time domain and space domain respectively, and the two max pooling layers reduce the dimension in time domain. The intermediate matrix passes through the full connection layer after plastic operation. Final output is the action prediction results. The activation function is ReLU and Sigmoid. Dropout and L2 regularization are used to reduce overfitting. “Conv” is the abbrevation for Convolution.

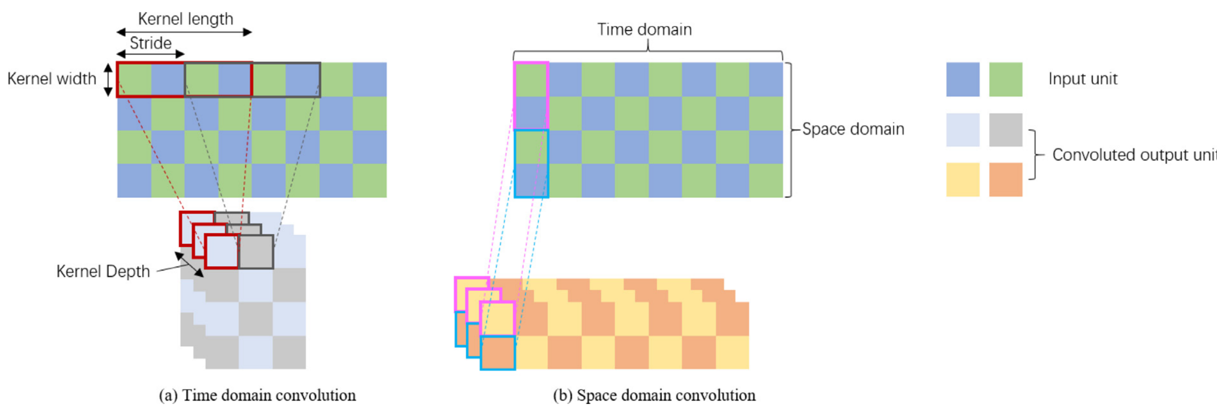


Fig. 3. Fig. (a) and Fig. (b) demonstrate the convolution processes in time domain and space (12 EMG recording channels) domain. The length and width of the convolution kernel of 1 × 40 in time domain and the kernel of 3 × 1 in space domain represent the size of the receptive field respectively, the depth of the convolution kernel represents the number of layers of the feature graph, and the step length of the convolution kernel (3 × 1) represents the overlapping size of two adjacent convolution kernels. The matrix element of local receptive field can be reduced, and local features are extracted by convolution operation.

frequency of 1000Hz. In order to obtain effective information in the EMG signals, and to filter out noise and artifacts, a band pass filter of 5-250hz was selected. A finite impulse response (FIR) filter was selected as the band pass filter. In order to reduce the computation of neural networks, many studies performed down-sampling operations on the data [36,37]. Since there are pooling layers in the neural network for data down-sampling, the original sampling frequency was kept to retain the information in the original data as much as possible. Due to the small value of the original EMG singal voltage collected, in which the order of magnitude of most points was 10^{-3}, therefore, in order to match the initial weight of the neural network and reduce the loss value at the beginning of the iteration, we enlarged the original data by 1000 times.

Four shoulder movements were evenly and randomly distributed among all datasets. The data were preprocessed and imported into CNN network for training.

2.5. Convolutional neural network

Compared with traditional machine learning algorithms, CNN uses a multi-layer structure to improve the generalization performance and abstract performance of the recognition model [38]. The main structure of the CNN built in this study consisted of five layers, including two convolution layers, two pooling layers, and one full connection layer as shown in Fig. 2.

The convolutional layer applied the strategy of a local connection and weight-sharing to simulate the local receptive field [39]. The size of the receptive field was determined by the convolution kernel. The convolution kernel was convolved with the input matrix to generate featured graphs by the ReLU activation function. The pooling layer reduced the sampling of the convoluted intermediate matrix in the time domain and the space domain; this reduced the parameters and computational need of the neural network and effectively minimized the over-fitting problem [40]. The full connection layer weighted the output matrix of the previous layer and integrated the local features into the global features. The final output was a one-dimensional eigenmatrix representing the shoulder muscle activation pattern associated with different movements.

Two training datasets were processed in our CNN algorithm: forward propagation and back propagation. First, the raw, forward-propagated EMG signal datasets, were analyzed through all the CNN layers to obtain an output value. The errors between the output values and the expected values were then calculated to determine the accuracy of outputs. Next, the error back-propagation process was used to modify the weight value. These two processes were performed repeatedly by the iterative operation system until the loss value of the network was minimized. The gradient descent algorithm was then used to modify the weighted value.

The EMG recording channels and the duration of EMG responses associated with a motion were processed in the CNN to represent spatiotemporal characteristics in this study. This characteristic information processed method was similar to the methods reported in the literature [12]. A CNN structure of time-space convolution was also used to process shoulder EMG signals for motion pattern recognition as shown in Fig. 3. The time-domain convolution was used to generate dimensionality reduction and feature induction of raw EMG sequencing. The spatial convolution was used to establish the connection between 12 EMG channels. The purpose of this process was to enhance the relevance of feature integration of the full connection layers including the EMG voltage amplitude values from 12 muscles over the time during shoulder movements.

In our CNN model, the weights of the convolution kernel were initialized using Xavier initialization [41] to make the output and input obey the same probability distribution as much as possible. The dropout [42] layer was used to eliminate random points

Table 2
The forward propagation method and its parameters of each layer in CNN, as well as the model optimization algorithm and its parameters.

Layer	Method	Parameter	Value
Convolution 1	Time Domain	Size Stride depth	1 × 40 1 × 20 16
Pooling 1	Max Pooling	Size Stride	1 × 10 1 × 10
Activation Function	ReLu	–	–
Convolution 2	Space domain	Size Stride Depth	3 × 1 3 × 1 32
Pooling 2	Max pooling	Size Stride	1 × 7 1 × 7
Activation Function	ReLu	–	–
Reshape	Dimensionality Reduction	Input Matrix Output Matrix	4 × 4 × 32 512 × 1
Fully Connected	–	Hidden Modes	100
Regression	Softmax	–	–
Output	One Hot Code	Nodes	4
Regularization	L2	Coefficient	0.004
Dropout	Dropout	Percentage	0.7
Loss Function	Cross Entropy	–	–
Loss Reduction	Gradient Descent	Learning Rate	0.001
Training Acceleration	Batch Normalization	Batch Size	15

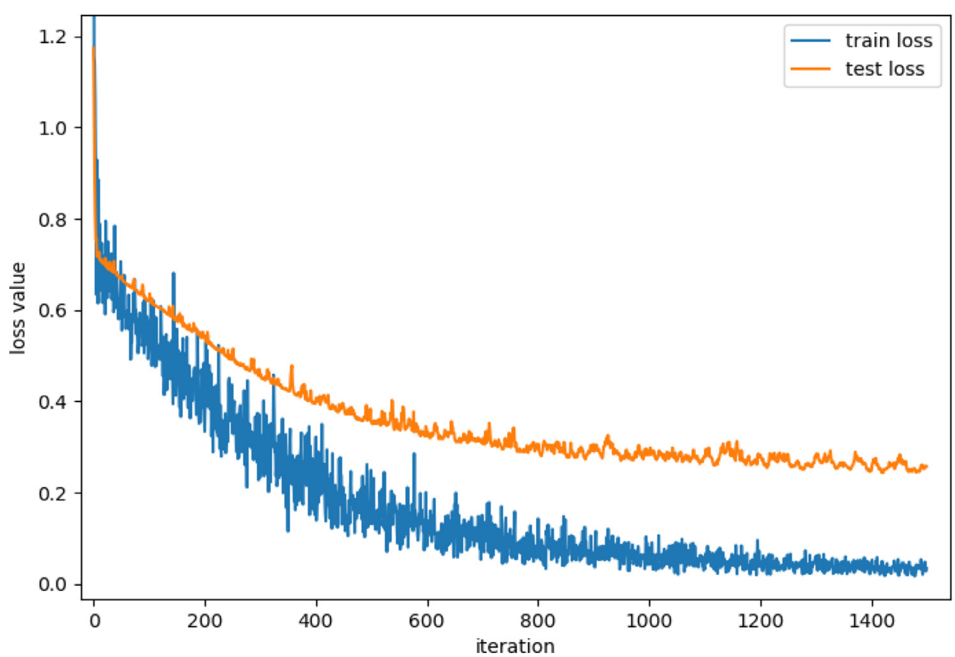


Fig. 4. The curve of loss value. The curve showed the validation accuracy over the epochs demonstrating an attenuation curve of loss value in the training process. The X-axis represents the number of training iterations, and the Y-axis represents the loss value. Loss is the cross entropy of the predicted output and the target output.

of the intermediate matrix. L2 regularization [43] was applied to the full connection layer. The complexity index model was added into the loss function to improve the model's ability to recognize random noise. Both the dropout layer and L2 regularization were used to reduce overfitting [44]. Cross entropy was adopted in the model to calculate the loss value, the gradient descent algorithm was used for the loss reduction rule. Batch normalization [45] was used to accelerate model training. In this study, the construction and training of the CNN model were implemented using TensorFlow (Google Inc, version: 1.12.0, PyCharm IDE and Python 3.5 language). Data transmission was processed through serial communication. The forward propagation method, variable information, parameter and values for each layer of the above optimization algorithm in the CNN model are shown in Table 2.

In this study 60% of a subject's EMG dataset were utilized to train an inference model, and the rest of 40% of EMG datasets were used to test the accuracy of the trained model in motion pattern recognition. Four shoulder movements were evenly and randomly distributed among them. A designated CNN trained model was validated and finalized through iterations after the loss value reached to the lowest level (Fig. 4). The accuracy of a saved trained model was then tested to determine its accuracy in motion pattern recognition. The effects of subject's variability, motion speed, and EMG recording devices on performance accuracy were investigated.

Table 3
Accuracy of seven subjects with normal speed motion predicted by normal speed model.

Motion	Drink	F&B	Abduction	Static	Total
Subjects					
Subject1	99.44%	99.44%	100%	100%	99.72%
Subject2	95.03%	96.30%	96.30%	98.53%	96.54%
Subject3	100%	100%	100%	100%	100%
Subject4	96.75%	97.25%	92.75%	99.25%	96.50%
Subject5	93.33%	93.33%	94.81%	98.89%	95.09%
Subject6	99.44%	100%	100%	98.34%	99.45%
Subject7	92.22%	91.66%	98.89%	100%	95.69%
Average	**96.60%(±3.16%)**	**96.85%(±3.33%)**	**97.54%(±2.94%)**	**99.29%(±0.72%)**	**97.57%(±0.21%)**

Table 4
Accuracy of seven subjects with fast speed motion predicted by normal speed model.

Motion	Drink	F&B	Abduction	Static	Total
Subjects					
Subject1	68.75%	66.67%	70.83%	98.67%	76.23%
Subject2	44.22%	49.83%	61.33%	99.17%	63.64%
Subject3	78.37%	81.72%	83.47%	95.65%	84.80%
Subject4	67.67%	70.47%	87.54%	99.33%	81.25%
Subject5	87.83%	88.25%	94.89%	98.03%	92.25%
Subject6	70.37%	66.75%	75.25%	97.30%	77.42%
Subject7	72.59%	82.37%	79.78%	92.87%	81.90%
Average	**69.97%(±12.34%)**	**72.29%(±12.04%)**	**79.01%(±10.28%)**	**97.29%(±2.15%)**	**79.64%(±8.16%)**

2.6. Determination of performance accuracy of trained CNN models

Normal-Speed Model: An inference CNN model was obtained using EMG datasets recorded under a constant normal motion speed as described in Paradigm 1. 60% of EMG datasets were utilized for training and 40% of data for accuracy testing.

Random-Speed Model: The subjects' EMG data of normal and fast speeds were mixed and input in CNN for training; the speed label was not marked during data training. 60% of EMG datasets were utilized to train the Random-Speed model and 40% of data for accuracy testing.

Cross-Subjects Models: Cross-Subjects models were constructed to achieve cross-subjects adaptability. EMG datasets from seven subjects were utilized for cross-individual random subject testing. EMG datasets from i subjects were mixed for training, and EMG datasets from $(7 - i)$ the rest of subjects were utilized for accuracy testing. i was incremented one by one $(i < 7)$. The number subjects i used for model training increased successively from 1 to 6.

The first model was trained using the EMG data from 1 subject; the model's accuracy was tested using the EMG data from the rest of 6 subjects to obtain the average rate of accuracy .

The second model was trained using the EMG data from 2 subject, the model's accuracy was tested using the EMG data from the rest of 5 subjects to obtain the average accuracy rate.

Using this manner, a total of 6 CNN models were constructed and tested. In the sixth model, 6 subject datasets were used for training the model, and one subject dataset was used for recognition accuracy testing.

Effect of Cross-Devices on Motion Pattern Recognition Accuracy: EMG data of normal-speed and fast-speed motions recorded by Biopac system from 7 subjects was used to construct an inference model. The accuracy of the model performance was tested by EMG datasets recorded by the Delsys system under normal-speed and fast-speed movements respectively.

2.7. Statistical analysis

The accuracy of created inference models in motion pattern recognition was tested 3 times using saved EMG datasets labeled with corresponding motions. The average accuracy of each model in motion pattern recognition was measured and compared between the different inference models using ANOVA, and GLM Univariate analysis. Statistical analysis was also performed to determine if accuracy difference between different models had a statistical significance using Chi-Square method by SPSS software (Version 25, IBM, Chicago). A *p*- value smaller than 0.05 was considered to be significant.

3. Result

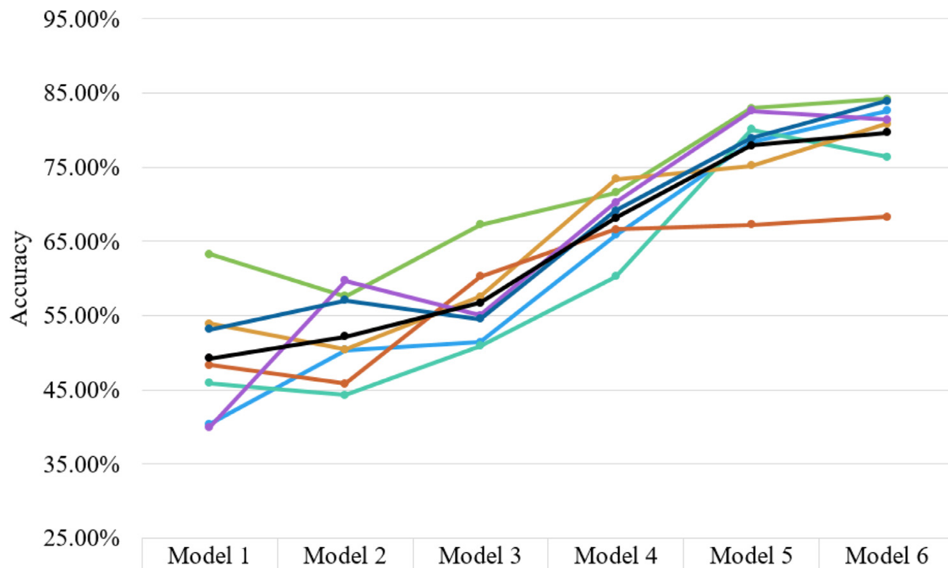
The convolutional neural network converged after repeated weight iterations in model training as showed in Fig. 4. All 3 trained models including mixed-speed, cross-subject, and cross-device models achieved a convergence outcome. Average accuracy for motion pattern recognition ranged from 69.96 to 97.5% (Tables 3 and 4, Fig. 5).

3.1. Accuracy of normal-speed model for normal speed motion recognition

The accuracy of the normal speed inference model in the recognition of normal speed motion using EMG signals was 96.60 ± 3.16% for drinking movement, 96.85% ± 3.33% for forward and backward movement, 97.54% ± 2.94% for abduction, and 99.29 ± 0.72% for resting state. There was not a statistical difference (Chi Square, Pearson test, $p=0.736$). The overall average recognition accuracy was 97.57% ± 0.21% (Table 3).

3.2. Accuracy of normal-speed model for fast speed motion recognition

The accuracy of the normal speed CNN model in recognition of fast speed motion using EMG signals was 69.97 ± 12.34% for drinking movement, 72.29 ± 12.04% for forward and backward movement, 79.01 ± 10.28% for abduction, and 97.29 ± 2.15% for resting state. The accuracy of resting state recognition was higher here than in the other 3 motion groups (Chi Square, Pearson test, $p=0.001$). There was not a statistical difference among drinking, F&B, and abduction groups (Chi Square, Pearson test, $p=0.316$). The



	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Sub 1	40.36%	50.31%	51.37%	65.80%	78.40%	82.59%
Sub 2	45.89%	44.25%	50.89%	60.28%	80.03%	76.40%
Sub 3	63.27%	57.63%	67.24%	71.54%	82.91%	84.17%
Sub 4	53.88%	50.42%	57.54%	73.40%	75.20%	80.82%
Sub 5	48.32%	45.84%	60.28%	66.61%	67.25%	68.25%
Sub 6	39.95%	59.67%	55.01%	70.23%	82.61%	81.38%
Sub 7	53.12%	57.05%	54.52%	69.09%	78.91%	83.90%
Average	49.26%	52.17%	56.69%	68.14%	77.90%	79.64%

Number of subjects in the training combination

Fig. 5. The accuracy of models' in motion pattern recognition. The horizontal axis is the number of subjects used for model training. The vertical axis is the accuracy of each model in motion pattern recognition. With the increase of the subject number used in model training, the accuracy of motion pattern recognition increased.

overall average recognition accuracy for the CNN model was 79.64 ± 8.16% (Table 4).

3.3. Accuracy of random-speed model for mixed speed motion recognition

The accuracy of the Random-Speed model in recognition of mixed speeds of motions using EMG signals was 96.79 ±1.80% for normal speed motions, 97.77 ±1.83% for fast speed motions, and 97.07 ±1.62% for mixed speed motions. (Fig. 5). There was not a statistical difference in the recognition of the 3 kinds of speeds of motions. (Chi Square, Pearson test, p=0.902).

3.4. Accuracy of cross-subjects model in motion recognition

With the increase of the subject number and training samples, the accuracy of motion pattern recognition increased from an average of 49.26% to 79.64% (Fig. 5). The accuracy of Model 6 motion pattern recognition was higher than in Model 1 (GLM Univariate, PostHoc LSD, p=0.042).

3.5. Accuracy of cross-device model in motion pattern recognition

The average recognition accuracy of the cross-devices CNN model in predicting motion patterns based on EMG datasets recorded by Delsys system was 88.93% for normal speed motions and 80.87% for mixed speed motions. The accuracy of the model in normal speed motion pattern recognition was higher than the accuracy in mixed speed motion pattern recognition (Chi-Square, Pearson test, p=0.001).

4. Discussions

This study investigated the feasibility of using CNN machine learning algorithms for upper arm motion pattern recognition based on surface EMG signals recorded from 12 muscles that control motions of drinking, forward and backward movements, abduction, and resting. Our CNN models obtained from CNN training discriminated upper limb motion pattern under different motion speed among different subjects using different EMG recording systems with an average accuracy ranging from 69.96 to 97.5%. The long-term goals of our research are to use these EMG signals to control an upper arm exoskeleton and to evaluate functional recovery outcomes after shoulder surgery and postoperative rehabilitation. The accuracy of signal processing for user's motion intents is critical to be successful. Our results demonstrate that sEMG signals from these 12 muscles of shoulder and upper arm can be processed for motion pattern recognition among different individuals using different EMG recording devices.

4.1. The state-of-the-arts of shoulder motion pattern recognition using ML algorithms

In recent years, sEMG signals have been increasingly used in pattern recognition using machine learning algorithms (Table 5). The machine learning methods include K-Nearest Neighbor (KNN)[8], Linear Discriminant Analysis (LDA)[9], and Support Vector Machine (SVM) [8], Extreme Learning Machine (ELM)[32, 33], Gaussian Mixture Model (GMM)[46], Artificial neural networks (ANN)[47], CNN[48-50]. Most of these studies recruited 5-11 volunteers yielding acceptable outcomes with accuracy of pattern recognition ranged from 60.5% to 96.2%, suggesting that machine

Table 5
Summary of machine learning methods using in motion pattern recognition.

Author	Years	Subjects	Parts	Motion	Method	Accuracy	Attributes	Reference
Siqi Cai	2019	5 healthy subjects (age 25 ± 4 years, 70 ± 5 kg, 174 ± 6 cm, all male and all right-handed)	shoulder and elbow	5 upper-limb motions (shoulder flexion, abduction, internal rotation, external rotation, and elbow joint flexion)	SVM	Average recognition rate: 93.34 ± 0.59%	Journal	[51]
Chris Wilson Antuvan	2016	7 healthy subjects (6 males and 1 female, age 26.85 ± 1.57 years)	shoulder and elbow	5 upper-limb motions (elbow flexion, shoulder flexion, shoulder protraction, shoulder retraction, elbow extension)	Synergy Feature + ELM; EMG features + ELM	Synergy Feature + ELM: 65.73 ± 2.60% (Offline) 91.79 ± 9.86% (Online); EMG Feature + ELM: 99.37±0.81% (Offline) 84.09±14.35% (Online);	Journal	[33]
Emilio Trigili	2019	10 able-bodied subjects (8 male, 2 female, age 26 ± 5 years)	shoulder and elbow	2 motion start of upper limb (Go-forward, Go-backward)	GMM (Gaussian Mixture Model)	Sensitivity: 89.3% for Go-forward and 60.9% for Go-backward; Specificity: 96.2% for Go-forward and 94.3% for Go-backward	Journal	[46]
Qin Zhang	2017	6 able-bodied subjects (all male, 23 ± 1 years old, 62 ± 4.5 kg)	shoulder and elbow	4 joint angles across shoulder and elbow	PCA/ICA-ANN	Best method(ICA-ANN): 91.12% in 70-s intra-cross validation; 87.00% in 2-min inter-cross validation	Journal	[47]
Maurício C. Tosin	2017	10 healthy subjects	hands and wrists	8 fingers motion and 9 wrist motion	SVM-RFE+ELM	Average recognition rate: 88.53%	Conference	[52]
Lason Batzianoulis	2018	8 able-bodied subjects (6 males and 2 females 25– 32 years old); 4 subjects with transradial amputation	upper limb and hands	reach-to-grasp motions for 5 grasp types	LDA; SVM-RBF kernel; SVM-linear kernel; ESN (Echo State Network)	Best method(SVM-RBF kernel): 60.45 ± 8.2%, 65.82 ± 8% and 77.4 ± 5.88% for 5,4 and 3 classes, respectively	Journal	[53]
Khairul Anam	2016	11 able-bodied subjects (2 females and 9 males, 20 -37 years old)	upper limb and hands	8 hand gestures in 5 arm positions	AOS-ELM (Advanced Online Sequential Extreme Learning Machine); OS-ELM	AOS-ELM: 86.13 % OS-ELM: 86.07%	Conference	[34]
Ali Ameri	2019	10 able-bodied subjects (ages: 31.4±4.1 years, 1 left-handed, 9 right-handed)	upper limb and wrist	4 wrist motions (extension, flexion, supination, pronation) and 4 combinations of them	CNN; SVM	CNN: DoF (Fle/Ext): 94.2± 0.6% DoF (Pro/Sup): 91.4± 1.1% SVM: DoF (Fle/Ext): 88.7± 1.5% DoF (Pro/Sup): 91.4± 1.1%	Journal	[48]
Muhammad Zia ur Rehman	2018	7 able-bodied subjects (4 males and 3 females, age: 24–30 years, mean age: 27.5 years)	upper limb and wrist	7 hand motions (close hand, open hand, wrist flexion, wrist extension, pronation, supination, and rest)	SSAE-f (Stacked Sparse Autoencoders With Features); CNN	Cross-day comprehensive accuracy rate: SSAE-f: 89.02 ± 5.47%; CNN: 90.21 ± 4.57%	Journal	[49]
Ali Raza Asif	2020	18 healthy male subjects (right-handed, aged 20–35 years, mean age 26.2 years)	upper limb and wrist	10 hand motions (hand open, hand close, wrist flexion, wrist extension, forearm pronation, forearm supination, side grip, fine grip, agree and pointer)	CNN	Action with excellent accuracy(close hand, flex hand, extend the hand and fine grip): 83.7% ± 13.5%, 71.2% ± 20.2%, 82.6% ± 13.9% and 74.6% ± 15%, respectively	Journal	[50]

learning methods can contribute to the development of more accurate surface EMG-based motion pattern recognition algorithms, potentially to be used for the motion control of upper limb wearable exoskeleton.

4.2. Challenges of EMG processing for robot control

Upper arm motion pattern recognition is important in EMG-controlled robotic rehabilitation engineering; there are challenges due to the complex activation of multiple muscles and multiple DoFs of upper arm movements [54,55]. Although only four arm motions were involved in this study, they are important basic functional movements in the activity of daily life. The combination of these four motions in healthy subjects is an important start in rehabilitation robotics systems [56]. The availability of upper limb assistive devices in a clinical settings is still limited due to the tradeoff between the complexity of mechanical configuration and the complexity of control systems [57].

4.3. Justification of CNN in EMG signal processing

Although motion pattern recognition of one or two DoFs at one joint [58] has been reported, there is little research on motion pattern recognition of multiple DoFs across the shoulder and elbow joint [59]. EMG-controlled whole upper limb exoskeletons have not been reported in literature. This could be due to the challenges in signal processing from the complex activation of multiple muscles for multiple DoFs of upper arm movements [54,55]. We hypothesized that CNN machine learning algorithms can make multi-channel EMG signal processing simple for downstream robotic system control based on motion pattern recognition. Our results demonstrated that using Tensorflow, PyCharm IDE with Python language, and algorithms, upper arm motion patterns were accurately identified based on surface EMG signals recorded from 12 muscles that control motions of drinking, forward and backward movements, abduction, and resting. This potentially makes downstream trajectory control of an exoskeleton system much simpler.

The reason for lower accuracy in discriminating motion patterns included in drinking and F&B motions are the similar movements with similar activations of primary shoulder muscles for these two movements [60]. Traditional pattern recognition methods can detect the difference between motion patterns through matrix dimensionality reduction, but cannot extract the synergic information between channels from the time domain datasets [17]. EMG signals of shoulder muscle activation has multi-domain, spatiotemporal characteristics including: information associated with EMG recording locations, amplitude difference of electrical signals, activation duration, sequence of activation degree, frequency distribution of electrical signals, and dynamic changes with time [61]. The strategy of convolution in the time domain and the space domain applied in the CNN model takes the above characteristics into full consideration. After extracting the local features of the convolution layer, feature integration is implemented with the full connection layers. It not only extracts the characteristics of the time domain and the space domain, but also analyzes the correlation between them.

The convolutional and the dropout layer of CNN can provide regularization and the use of the ReLU activation function. This model speeds up training and avoids the need for pre-training, which essentially improves the speed of the training process and eases the complication of implementation. All 3 trained models, including: random-speed, random-subject, and random-device, achieved a convergence outcome within approximately 300 iterations (Fig. 4).

4.4. Effects of movement speed on model performance accuracy

Shoulder muscle activation pattern varies with individual habits, body structure, environment, and movement intention [62]. The amplitude, frequency, and activation distribution of EMG signals vary with different speed of motions, and between different recording devices. To determine the feasibility of using a universal model for recognition of a motion pattern under different speeds, we compared the accuracy of different trained models' recognition under the influence of these factors. Using the normal-speed trained model to test the random-speed data, the result showed a decrease of about 20% in accuracy. Using a model trained by both normal and fast speed EMG data, the results showed an 97% accuracy in pattern recognition. This is suggestive of the feasibility of using mixed EMG datasets to train a universal model for motion pattern recognition with a high degree of accuracy. Except for static motion, there was a statistical difference in recognition accuracy among the 3 trained models (Chi Square, Pearson test, $p<0.05$); the standard deviation was greater than $\pm10\%$.

4.5. Effects of individual variability on model performance accuracy

However, a recognition model that only applies to single subject is far from enough. Each person's body structure, movement habits, and environment have great individual variability. Some studies have shown that when there is no retraining, the performance of the model will decrease due to the non-stationary characteristics of the sEMG signal [63]. Therefore, in order to have excellent recognition performance when applied to new subjects, single-subject models need to be retrained. This undoubtedly increases the complexity of the recognition process. We assumed that the mixed training of experimental data from multiple subjects (Training sample enhancement strategy) can weaken the confounding factors of EMG signals. This is caused by the environment and individual differences; these differences must be addressed as to strengthen the weight of movement difference characteristics. After actual verification, the motion recognition effect of the model with an increasing enhancement degree of samples on the 7 subjects showed an upward trend, as shown in Fig. 5. From the results, there is a big gap in recognition performance between each subject, among which the global optimal accuracy rate of no. 3 is 84.17%, while the accuracy rate of no. 5 is only 68.25%. This may be due to the influence of many factors, the activation pattern of shoulder muscles of the tested subjects has different components than that of other subjects, and the model cannot extract effective features well. The Fig. also shows a partial decrease in performance as the sample increases. This situation mainly occurs when there are few training samples from 5-subjects to 6-subjects. We hypothesized that the former was due to the limited training sample, which limited the model's ability to filter confusing information unrelated to shoulder movements. Therefore, the model does not have good universality, and the model is unstable. The latter may be due to the fact that with the increase of training samples, when n approaches 7, the combination forms of the subjects in the verification model decreases. In the test of the 6-subject model, there is only one combination form for each subject's test model, which reduces the cardinality, the effectiveness, and the persuasion of the results.

4.6. Effects of cross-devices of CNN model performance accuracy

Different EMG acquisition devices have different hardware, man-machine interactions, signal acquisition systems, and software. These differences may include surface electrodes with different impedances for different systems, wired or wireless data communication, sampling rates and system delay. Our results demonstrated the cross-device CNN model may not predict the motion pattern as accurate as the CNN model constructed on an identical individual EMG dataset. The CNN model built on the Biopac device recorded EMG data predicted a motion pattern with an accuracy of 97% on the down-streaming EMG data from the same and individual device. While the accuracy of this model dropped from 80.87% to 88.93% on the EMG data when change from a different device for different individuals. This suggested that there was effects of individual variability and device difference on the CNN model motion prediction accuracy.

4.7. Advantages of CNN model in EMG signal processing

Traditional EMG decoding steps mainly include: (1) data preprocessing, (2) feature extraction and (3) classification. The neural network can combine step (2) and step (3) and automatically identify relevant data features. Its main advantage is not that it simplifies steps, but that it can automatically and dynamically adjust the selection and weight of features to suit different experiments, different subjects, and perhaps even different tasks [64].

In order to achieve an excellent recognition effect, the CNN model can use the repeated parameter adjustment process, including convolution kernel, pooling layer, activation function, and relevant parameters of the optimization algorithm. Overfitting means that the Neural Network model overmatches the noise in the signal, which is unfavorable to the extraction of important information [44]. Therefore, in the construction process of the Neural Network model, we consider to adopt regularization [43] and dropout [42] rules to avoid overfitting problems. In addition, during the training of the Neural Network, the learning rate of the loss reduction algorithm, and the initial weight variable of the model affect the fitting efficiency and iteration of the network [65]. For example, a small learning rate causes gradient descent to be limited to a local minimum, while a large learning rate causes a loss descent oscillation. Improper selection of an initial weight variable can lead to an excessive loss value at the beginning of the iteration and affect the training efficiency. All 3 trained models including random-speed, cross-subject, and cross-device models achieved a convergence outcome, suggesting of that our models were properly trained.

4.8. Influence of the number of datasets on outcome accuracy

Theoretically, the more datasets can yield a better ML model for pattern recognition. As showed in Fig. 5, increase of dataset number produced a higher accuracy in pattern recognition. The number of datasets increased from Model 1 to Model 6 with the consideration of all motion speeds, device difference, and individual variability, the pattern recognition accuracy increased. Fig. 5 also shows the accuracy of Model 5 was not higher than Model 6, suggesting that the dataset number in Model 5 and Model 6 may be enough to yield the highest accuracy of shoulder motion pattern recognition based on EMG signals.

4.9. Limitations of this study

There are still some limitations worthy of further study.

Because this paper is mainly an innovative attempt on deep learning algorithms in the EMG signal processing of shoulder movement, and mainly describes the universality of the model to various influencing factors (random speed, cross subjects, cross devices), an experiment for people with movement disorders is not considered.

Fifteen subjects may not be sufficient for the construction of the training enhanced universal model. It is not clear if increasing the sample size will yield a better accuracy. It has been proposed that the performance of a CNN model lies in the size of data set; more subjects will strengthen the feature selection characteristics of the model and enhance the robustness of the model [66].

4.10. Future studies

Because of the lack of experiments on people with movement disorders, in further studies we will focus on research regarding muscle activation characteristics of the disabled or patients with weak remnant EMG signals. In this paper, the deep learning model is mainly used to identify the shoulder EMG signals, and the universality of the model is analyzed for the cross-speed, subjects, and device. The other state-of-the arts machine learning algorithms will be investigated and compared to determine the best ML method. Next, we will transform the model to real-time online control. This CNN model for EMG signal processing will be integrated into a software system to control an upper arm wearable exoskeleton system.

5. Conclusion

To predict upper limb motion patterns including drinking, B&F, abduction and resting using shoulder and upper arm EMG signals, CNN models built on the identical speed yielded a up to 97.57% accuracy using EMG signals from the same individual and device. The Cross-Subjects CNN model and the Cross-Devices CNN model yielded motion pattern recognition accuracy of 79.64% and 88.93% respectively. This study demonstrated that the EMG signals of shoulder and upper arm muscles from the upper limb motions can be processed using CNN algorithms to decode the identical motions of the upper limb including drinking, forward/backward, abduction, and resting. Increase of the number of EMG datasets for CNN model training improved the pattern recognition accuracy. This study describes the general adaptability analysis of EMG recognition in rehabilitation exercise and provides support for further rehabilitation projects for movement disorders.

Ethical approval

The study was approved by the IRB Administration Committee of the Wayne State University (Protocol number: 1905002258).

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Declaration of Competing Interest

The authors have no conflicts of interest.

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Supplementary materials

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