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Volitional control of upper-limb exoskeleton empowered by EMG sensors and machine learning computing

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ABSTRACT

Processing multiple channels of bioelectrical signals for bionic assistive robot volitional motion control is still a challenging task due to the interference of systematic noise, artifacts, individual bio-variability, and other factors. Emerging machine learning (ML) provides an enabling technology for the development of the next generation of smart devices and assistive systems and edging computing. However, the integration of ML into a robotic control system faces major challenges. This paper presents ML computing to process twelve channels of shoulder and upper limb myoelectrical signals for shoulder motion pattern recognition and real-time upper arm exoskeleton volitional control. Shoulder motion patterns included drinking, opening a door, abducting, and resting. ML algorithms included support vector machine (SVM), artificial neural network (ANN), and Logistic regression (LR). The accuracy of the three ML algorithms was evaluated respectively and compared to determine the optimal ML algorithm. Results showed that overall SVM algorithms yielded better accuracy than the LR and ANN algorithms. The offline accuracy was 96 ± 3.8% for SVM, 96 ± 3.8% for ANN, and 93 ± 6.3% for LR, while the online accuracy was 90 ± 9.1% for SVM, 86 ± 12.0% for ANN, and 85 ± 11.3% for LR respectively. The offline pattern recognition had a higher accuracy than the accuracy of real-time exoskeleton motion control. This study demonstrated that ML computing provides a reliable approach for shoulder motion pattern recognition and real-time exoskeleton volitional motion control.

1. Introduction

Processing multiple channels of bioelectrical signals for bionic assistive robot volitional motion control is still a challenging task due to the interference of systematic noise, artifacts, individual bio-variability, a difference of sensors or devices used for signal acquisition, and human limb motion speeds [1,2]. Scientists have devoted efforts to the development of assistive robots and bionic limbs empowered by edge computing [3]. Machine learning (ML) has been a significant trend to be applied in along with other technologies for the development of the next generation of smart devices. Scientists believe that integrating ML into embedded systems can be an important approach to building the next generation of intelligent devices [4]. However, the deployment of an ML model on an embedded system faces major challenges. An embedded system used in a robotic exoskeleton system imposes constraints in terms of system performance accuracy, user experience, energy consumption, processing speed, size, and cost aiming at product commercialization [5]. An additional challenge is a feasibility of implementing the ML training process on the device for the robotic sensory and motion control systems that can be adapted online and used instantly. Online learning and adaptation are still important tasks and are required for the future generation of computing system when tackling real life challenges in unpredictable and dynamically changing environments. This paper presents an approach to adapting the ML computing to process twelve channels of shoulder myoelectrical signals for shoulder motion pattern recognition and real-time upper arm exoskeleton volitional control.

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Upper-Limb Exoskeletons have been designed for use in the industrial working environment [1,6–8] and medical rehabilitation [9,10]. Stroke survivors need long-term physical rehabilitation services [11]. The effective outcome of a traditional rehabilitation depends on the skill of therapists and the timeline of rehabilitation plans [12,13]. The traditional manual hands-on approach is labor-intensive and cannot provide long-term rehabilitation services at a low cost. The upper-limb exoskeleton systems have been studied and developed for upper-limb rehabilitation since two decades ago [14], which has shown encouraging results in the rehabilitation of upper limbs [15–17]. However, there are still many limitations and issues that exist in this area [18]. It still lacks a bionic/ergonomic mechanical design for the upper-limb exoskeleton, primarily focused on human-machine joint misalignment. Also, bioelectric signal-based volitional control for upper-limb exoskeletons is still far from satisfactory. The development of robust and reliable systems is still required targeting the recovery of lost motor control [10]. The use of active devices in rehabilitation was proved to be feasible [17], with direct benefits limited not only to patients with neuromotor injuries but also to other human movement areas of optimization of the working environment [6].

Most of the current assistive upper limb robotic rehabilitation devices use a conventional user interface (UI) such as a pushbutton or joystick, hands-free and intuitive interfaces are a desire of users. Current commercial upper arm exoskeletons used on-off mode control, this control strategy does not always align with patients' intentions. Thus, a more intuitive control strategy is needed for the upper arm exoskeleton, which could be operated by the user's intention.

The myoelectrical signals (electromyography, EMG) contain human neural information that interprets the human motion intents. Stroke patients can still generate weak EMG signals during limb motion or static muscle contraction, making it feasible for an EMG-based pattern recognition approach in post-stroke robot-aided rehabilitation [19].

EMG-control mechanisms can be divided into two groups: motion pattern recognition-based and non-motion pattern recognition-based [20]. Motion pattern recognition needs artificial intelligence (AI) for signal processing to generate classifications. Non-motion pattern recognition controllers are mainly constructed on threshold control and finite state machines, thus output limited and predefined control commands according to a sequence of input signals [21].

The implementation of computational techniques based on AI techniques embedded in a robotic upper limb exoskeleton system represents the main topic for the present study. In this paper, a novel EMG-based online shoulder motion recognition and control system is introduced. The online signal sensation system and robot motion control system are connected by LabVIEW software using a graphical computer programming approach. The essential role of this system is to connect the EMG acquisition system (the Delsys system) and stream all the sensors' data into the analysis module of the software. The system collected raw EMG data for the offline machine learning (ML) training process to generate a trained ML model, then the trained ML model was used for online EMG activation-based motion pattern recognition and robot motion control.

2. Related works

2.1. EMG for upper arm motion pattern recognition

The myoelectric signals (electromyography, EMG) have been considered a promising physiological signal for detecting motion intents and used in rehabilitation therapy [22–24], but system performance accuracy can be affected by many factors including systematic noise and artifacts [25–27] and individual bio-variabilities [28,29], leading to special procedures or electrodes required for filtering off the noise and on-site calibration for system setup [30,31]. Aiming at developing user-friendly systems, ML-based motion pattern recognition methods have been proposed to avoid the efforts devoted to noise removal or complex multiple-channel EMG signal processing [32–35]. Surface EMG (sEMG) pattern recognition has been studied for the feasibility of voluntary control of a robotic device [19,35,36], including EMG-based pattern recognition for upper-limb motion pattern recognition [37,38]. Most of the studies processed EMG signals only for one DoF motion pattern recognition [39]. We have started to develop a computer system that can sense muscle activation patterns and process the multiple channels of EMG signals for upper limb exoskeleton motion control to assist the activities of daily living (ADL) [34,35]. The performance has been evaluated and preliminary outcomes published in papers [35,40], however, the architecture of the EMG-controlled, ML-based computer system has not been introduced or published. This paper presents detail information regarding online data acquisition, signal processing, and system connection. This paper also compares the difference between offline analysis accuracy and online performance accuracy.

2.2. Shoulder exoskeleton control based on the motion pattern

Processing EMG signals for robotic upper arm control has been developed according to the neuromuscular characterization, but robot motions are still cumbersome because of the complexity of the musculoskeletal system of the upper limb [41]. The EMG-controlled prosthesis also faces challenges from electrode placement location and pattern changes of EMG activation over time, leading to a longer training process [42]. To date, most of the literatures have reported the mechanisms of hand/wrist control with fewer DoFs (degree of freedom) of motions compared with shoulder joint [41]. The bionic control of an upper-limb exoskeleton is more complex that the control of other joint exoskeletons such as the wrist, knee, or ankle joint exoskeletons. Currently, there are only a few of literature that reported the studies of EMG-controlled upper limb/shoulder exoskeletons [43–46]. Artificial intelligence-based wearable robotic exoskeletons for upper limb rehabilitation have been proposed, the main trend in the research is the development of wearable robotic exoskeletons controlled by the fusion of data collected from multiple sensors with the training of intelligent algorithms [10]. The focus of our current study is on shoulder/upper limb exoskeleton intuitive control for carrying out activities of daily living (ADL). The long-term goal of our research is to develop reliable systems through industrial or clinical validation and improvement of technical features targeting at intuitive control of the robot in order to have positive impacts on human strength augment and the rehabilitation process. The current study reports an approach of EMG-based multiple-sensors signal fusion for shoulder motion pattern recognition and integration of the sensor system and ML processing system into a customized prototype of an upper limb exoskeleton system for intuitive control. This approach will enable the systems to be used in various applications related to robotic exoskeletons, including human performance enhancement, workload reduction, medical rehabilitation, or support for daily living activities.

2.3. Machine learning in EMG sing processing

Machine learning (ML) computing can extract the specified features from the targeted data and quantify the features for model training using a supervised learning process [47], including K-Nearest Neighbor (KNN) [48], Linear Discriminant Analysis (LDA) [49], Support Vector Machine (SVM) [48,50,51], and Artificial Neural Networks (ANN) [52,53]. These supervised ML methods have been used in on EMG signal-based limb motion recognition, robot control, rehabilitation, and clinical research [54]. The accuracy of feature extraction from the EMG signals is affected by many factors, including EMG recording methods (such as different electrodes, electrode placement locations on the body surface, or recording devices), bio-variability (age and BMI (body mass index)), environmental factor (room temperature), electrical power line noise, and motion artifact. These factors reduce the efficiency of system robustness and accuracy of recognition [55], and extra efforts are subsequently required in signal processing with complex procedures.

Embedded software and firmware can be used to remove systemic noise as shown in a signal channel system [27], multiple channels systems required significant efforts and computing in system setup. ML may be the optimal approach to processing multiple-channel EMG signals for robot control without devoting effort to noise removal.

To improve the accuracy of ML in motion pattern recognition, deep learning (DL) has been proposed in signal processing, DL has made remarkable progress in image recognition, natural language, and behavior prediction [35,56–58]. Hinton et al. reduced the dimensionality of data using multiple layers of neural network algorithms [59], leading to the development of deep neural network structures, the convolutional neural network (CNN), and the recurrent neural network (RNN) [60–62]. DL has been used for EMG signal processing for motion recognition, unlike other machine learning algorithms such as KNN and LDA DL does not manually set standards to extract features. Through repeated iterations of the neural network structure to optimize the algorithm, DL implements the propagation rules from the training data. CNN algorithm yielded better outcomes in motion pattern recognition by processing EMG signals [51,63–65]. The SVM and NN algorithms have been applied in shoulder pattern recognition without controlling a robot system using EMG signals recorded from six muscles of the upper limb among 7 healthy subjects, the results showed that NN yielded an accuracy of up to 88.7% during the training process while SVM obtained an accuracy up to 85.9% in model validation [66]. Using EMG signals recorded from 12 muscles of the upper limb among 15 healthy subjects, the results showed that CNN obtained a recognition accuracy between 79.64% and 97.57%, the accuracy was affected by motion speed and the devices used for EMG signal recording [40].

Extreme learning machine (ELM) is a newer machine learning method for EMG signal processing to detect motion patterns [67]. During multiple EMG channel processing, the structural features of each EMG channel including time domain, frequency domain, and time-frequency domain information should be considered. For this reason, synergy feature extraction is required across multiple EMG channels for motion pattern recognition to simplify control strategy including the control dimensionality reduction [68]. ELM demonstrated an optimal performance for synergetic feature extraction of multiple channels of EMG signals to classify upper limb motions [69–71].

3. Materials and methods

3.1. Experiment setup and experimental protocol

Twenty-eight healthy subjects (seven males and three females, 26 ± 3.3 years) with no reported shoulder injury nor neuromuscular disorders were tested in this study. All of their right shoulders were used in this study. They were informed and signed an informed content sheet. They were instructed and practiced the specified movement before the real test. Eighteen subjects participated in the offline EMG recognition experiment, and 10 subjects participated in the real-time control experiment. This experiment has been approved by the ethics committee (Institutional Review Board) of Wayne State University and conforms to the Helsinki declaration.

Twelve muscles' surface EMG signals were acquired by a commercial EMG acquisition system (Delsys Trigno wireless system, Delsys Inc, MA, USA). The twelve muscles and their corresponding functions were listed in Table 1. These muscles activate all shoulder and partial elbow degrees of freedom. All sensors were placed at the muscle belly along the muscle fiber direction. The skin underneath the sensors was cleaned with 70% alcohol, and excessive hair was removed if needed. The EMG signal sampling rate for each sensor was 1.11 kHz. Fig. 1 shows the system setup for the experiment.

The EMG signals were processed in a real-time environment for shoulder motion pattern recognition using ML computing executed by Machine Learning Toolbox embedded in LabView software (National Instrument, Austin, TX). The motion pattern recognition outcomes were used for the control of an upper-limb exoskeleton system to perform upper-limb trajectory movements based on the user's intents.

Table 1
EMG Sensors channel and muscle function.

sEMG Sensor	Muscle	Functional Action
1	Middle Deltoid	Humerus Abduction
2	Anterior Deltoid	Humerus forward flexion
3	Posterior Deltoid	Humerus backward extension
4	Supraspinatus	Humerus abduction in initial 0-30°
5	Pectoralis	Humerus Abduction/Inner rotation
6	Trapezius	Shoulder elevation
7	Infraspinatus	Humerus external rotation
8	Teres Major	Humerus extension toward the spine
9	Bicep	Long head – abducts the arm, rotating medially Short head – abducts the arm Flexes the shoulder joint
10	Triceps	Extensor of the elbow The long head extends the arm
11	Wrist flexor	Wrist joint flexion and rotation
12	Wrist extensor	Wrist joint extension and rotation

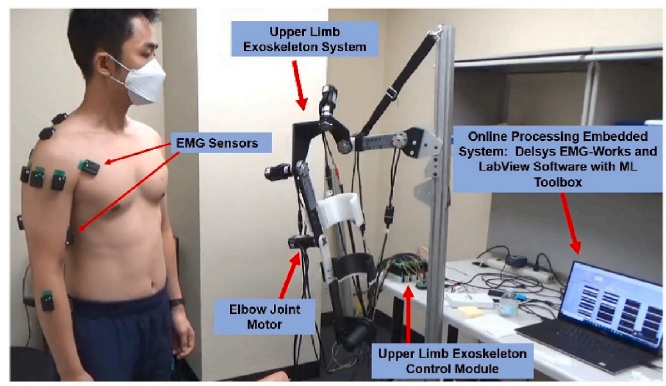

Fig. 1. The illustration of the real-time ML-based motion pattern recognition and exoskeleton motion control system. Twelve wireless Delsys EMG sensors are placed on the muscles indexed in Table 1 for EMG signal acquisition. The EMG signals are processed instantly for shoulder motion pattern recognition using ML computing executed by ML Toolbox embedded in LabView software. This system was used for the control of an upper-limb exoskeleton system to perform upper-limb motions based on the user's intents.

The experiment was divided into two sessions: 1) offline data analysis to determine the accuracy of ML algorithms in shoulder motion pattern recognition, 2) real-time shoulder motion pattern recognition, and instant upper arm exoskeleton movement control to determine the accuracy of whole system performance.

3.2. The design of an offline EMG recognition system

Eighteen healthy subjects (ten males and eight females aged 25 ± 3.1 years) participated in the experiment aiming at motion pattern recognition based on offline data analysis. Each subject was asked to follow a pre-recorded video performing a series of shoulder movements. The shoulder movements were repeated twenty times for each action, and all the movements should be controlled at a constant speed. The constant speed of movements was beneficial for the EMG data segmentation and feature extraction using a fixed time window during offline data analysis.

The EMG sensors were placed on the muscle as shown in Table 1. Delsys EMGworks (Boston, Massachusetts) was used for the EMG signals recording and segmentation into datasets. Delsys EMGworks data acquisition system is a wireless EMG recording and processing system with 16 channels available for EMG signal recording. Twelve channels of EMG sensors were used in this study.

There were four consecutive phases during a movement including arm motion initialization, arm elevation, arm isometric hold, and arm return to rest. The activities of daily living (ADL) including drinking, open-door, abduction, and resecting were selected for motion pattern recognition. The detailed movements of ADL were listed in Table 2. These shoulder movements were studied because they are frequently used in rehabilitation movement training in post-stroke therapy [72,73], as well as in the industrial workforce [74].

All the EMG data were recorded by Delsys Trigno wireless system, and the Delsys EMGworks was used to segment and label the EMG data. Fig. 2 shows the flowchart of the offline EMG recognition system. Each subject performed 7 movements, and each movement was repeated 20 times. For each subject, there were 140 segmented EMG signals sets. In the EMG model training process, 80% of the dataset was used as the training data, and 20% was used as the testing data.

3.3. The design of a real-time EMG volitional control experiment

3.3.1. The overview of the real-time control system

Ten healthy subjects (seven males and three females, 28 ± 3.5 years) without reported shoulder injury or neuromuscular disorders were recruited and tested in this real-time EMG-controlled system study. Four different movements including arm abduction adduction, drinking, arm forward and backward, and resting state was tested. Each subject was asked to stand still and relax the tested arm for a resting state. The subject performed other 3 movements respectively following a pre-recorded video paradigm to ensure the same movement speed of arm movements.

The real-time control system consisted of two subsystems: the EMG-models-ML training subsystem and the online EMG-based motion pattern recognition subsystem. The EMG-model-training subsystem collected EMG raw data and performed feature extraction, and then the features were used for data training to generate trained machine learning models.

The online-EMG-based-motion-pattern-recognition subsystem down streamed EMG raw signal data and perform feature extraction. The system then loaded the trained machine learning model from the EMG acquisition & training subsystem and performed real-time EMG-based motion pattern recognition and classification. The workflow of the two subsystems is shown in Fig. 3.

3.3.2. The EMG models training subsystem

Connected with the Delsys EGM data acquisition system, the LabVIEW acquisition program was run to read all EMG signals from the Delsys system and perform the feature extraction process simultaneously. Both raw EMG signals and EMG features were saved by the program as a CSV formatted file. Subjects were asked to perform a non-stop single pattern of motion repetitive twenty times following the pre-recorded video paradigm. For each motion, two CSV format files (one for raw EMG, one for EMG features) were saved. After the acquisition process, Python programs were developed to combine all EMG features files and label the EMG features for the later training process.

Table 2
The movement studied in the experiment.

NO	Name of movement	Abbreviation of movement
1	picking up a cup to mouth	PU
2	putting down a cup from the mouth	PD
3	pushing forward on the horizontal plane without resistance	PF
4	pulling backward on the horizontal without resistance	PB
5	shoulder abduction 90° on the coronal plane	AB
6	shoulder adduction 90° on the coronal plane	AD
7	resting of arm	RE

A customized offline machine learning training LabVIEW system was then used to generate machine learning models for the online EMG recognition process. In this study, SVM models (linear kernel-based and RBF kernel-based), one single-layer neural network model, and linear regression model were generated. The offline machine learning training LabVIEW system was developed using the Analytics and Machine Learning Toolkit. This system read the training data from the CSV file and generated JSON format trained models, which were used in the real-time system.

The first step of the model training process was to input the CSV file path into the system and define the hyperparameters of the SVM and the ANN methods. The second step was to run the LabVIEW program. Then the system saved the trained models as JASON files. For each subject, three machine learning models including LR (logistic regression), SVM (support vector machine), and ANN (artificial neural network) were trained by their training data [35].

3.3.3. The real-time EMG recognition subsystem

The real-time EMG recognition subsystem consisted of two real-time EMG processing functions and real-time recognition function. The EMG processing function was the same as the EMG acquisition and processing module used in the offline training process (section 2.2). The EMG processing function directly streamed the feature data into the online EMG recognition function. This EMG processing function used the trained model from the offline training process and made a classification decision based on the real-time input from the EMG processing and feature extraction subsystem. After the classification decision was made, a motion command was sent to the upper-limb exoskeleton system to perform the responding motion. In the system performance test, each subject was asked to perform the selected motions ten times for each motion, and the accuracy of the system performance was determined. Also, the tests were repeated for each machine learning model.

3.3.4. TCP/IP connection between LabVIEW and the Delsys system for real-time system

Trigno SDK software was used in the development of the EMG real-time control system. The Trigno SDK software was used to connect Trigno Avati EMG acquisition hardware and software to the LabVIEW software (NI, TX) for two software system interactions. Using LabVIEW, the program connected the Trigno SDK through an IP address and then communicate with a NI data board through a command port. The time window frame interval for Trigno SDK was set at 13.5 ms.

For the EMG data acquisition, there were 12 EMG channels in total, and the sampling rate was fixed at 1.11 kHz. Since the Trigno SDK frame rate was fixed at 13.5 ms, thus 15 EMG samples were streamed in every frame interval. And 960 bytes were read from the EMG port in each frame interval. This accurate number of bytes (960) was defined in the LabVIEW program set to be read for each loop to ensure the data be properly translated into readable and meaningful numbers. Fig. 4 shows the data structure of EMG signals processing output for control.

3.4. Signal processing and machine learning implementation

Multiple channels of EMG signals were processed using processing was performed to eliminate noise and extract EMG features for pattern recognition using the machine learning method in the next step.

After noise filtering, the features of EMG data were extracted. In this study, sliding root mean square (RMS) was used to extract the features from the raw EMG signals of 12 muscles with a sliding window of 540 ms and an overlapping window of 81 ms. These features were then input into the pattern recognition module. A pre-trained machine learning module was loaded into the system for shoulder motion pattern recognition.

Three algorithms were used in our study: support vector machine (SVM), artificial neural network (ANN), and linear regression (LR). All three algorithms were designed to perform multi-patterns classification.

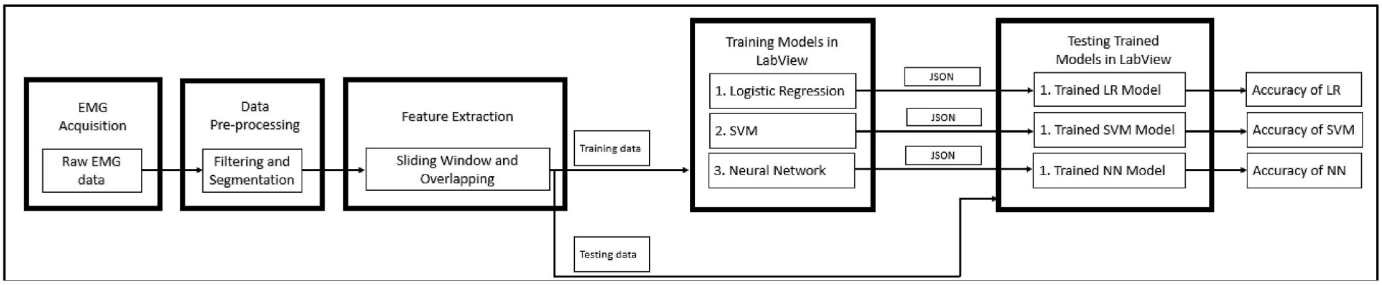

Fig. 2. Flowchart of training and testing trained machine models.

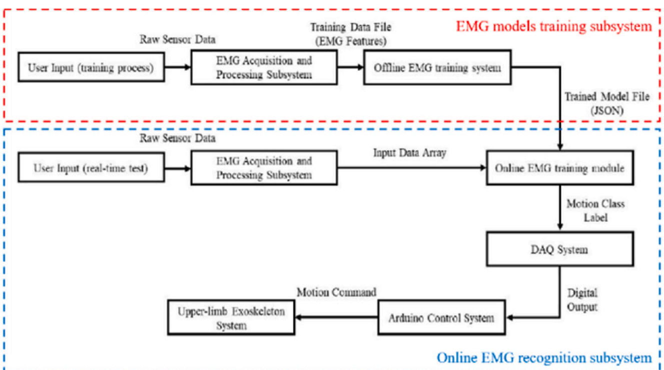

Fig. 3. The workflow of EMG models training subsystem and online EMG recognition subsystem. The motion classification outcomes were used to control the upper-limb exoskeleton to perform pre-defined motions.

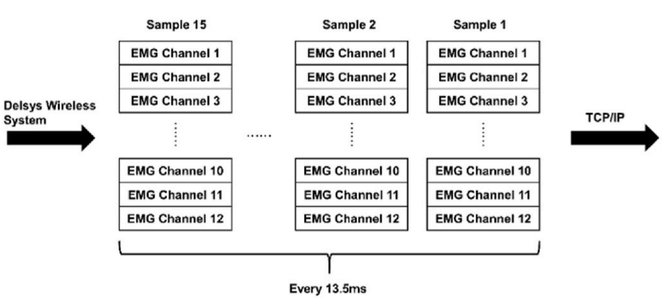

Fig. 4. The data structure and flowchart of EMG signals for processing and transporting to the communication port. Fifteen EMG datasets were streamed through TCP/IP every 13.5 ms. The LabVIEW software read 960 bytes every 13.4 ms in order to downstream the whole EMG data. Twelve EMG sensors were used for signal acquisition from 12 upper limb muscles.

ANN in LabVIEW has three types of layers: the input layer, the hidden layer, and the output layer with all hyperparameters used to implement ANN algorithms [75].

A sigmoid function was adopted in logistic regression (LR) algorithm implementation. After the input dataset training, LR generated decision boundaries to determine classification based on the highest probability. In the application of multi-class classification, LR used the one vs. rest method. For classification with more than two classes, the one vs. rest method generated and trains LR models for each class vs. the rest of the classes. The following equation defines the logistic regression model.

$$p(x) = p(y = 1|x)\Big) = \frac{1}{1 + \exp\left(-(\beta_0 x_0 + \beta_1 x_1 + \cdots + \beta_k x_k)\right)}$$

where.

x is the input vector with k+1 dimensions where x_0 is always 1.

y is the output vector with a value 0 or 1.

β is the weight vector with k+1 dimensions

$p(y = 1|x))$ is the probability of y = 1 for a known instance of x

LabVIEW 2018 (National Instruments, USA) and Analytics and Machine Learning (ML) package were used to build the training process and testing processes of the three machine learning models [76]. The same toolbox software was used to implement the SVM and ANN ML processes.

The support vector machine (SVM) finds a hyperplane in N-dimensional space (N– the number of features) that distinguishes the data points. The algorithm finds a plane with the maximum margin so that the feature dataset can be classified with maximal confidence. The SVM algorithms can implemented using a kernel. The most common kernels include the linear kernel, polynomial kernel, and radial kernel. A polynomial kernel was used in this study. SVM algorithm has been used in wrist motion classification [77] and multiple channels of EMG signals for gait pattern recognition [78]. In this study, the same SVM ML method was used for multi-DoF shoulder related motions classification and exoskeleton motion control thereafter. Fig. 5 shows the ML method and procedures of training and validating an SVM model in the LabVIEW platform, as well as the online exoskeleton motion control.

The artificial neural network (ANN) [79–81] used in this study is a feed-forward neural network, as shown in Fig. 6. Multiple hidden layer neuron numbers (5,10, 20, 40,60) were tested. Also, the influence of using multiple hidden layers was also tested. The number of output layer neurons was equivalent to the number of movement classes (4 classes). The four neurons of the output layer show the probabilities range [0,1] of the four-movement classes. The activation functions were set differently for each layer: rectified linear unit function (ReLu) for the hidden layer and Softmax for the output layer.

3.5. *Statistical analysis*

One-way ANOVA with PostHoc LSD was used to determine the statistical difference in the average accuracy of motion pattern recognition between different ML algorithms. The Chi-Square Pearson test was

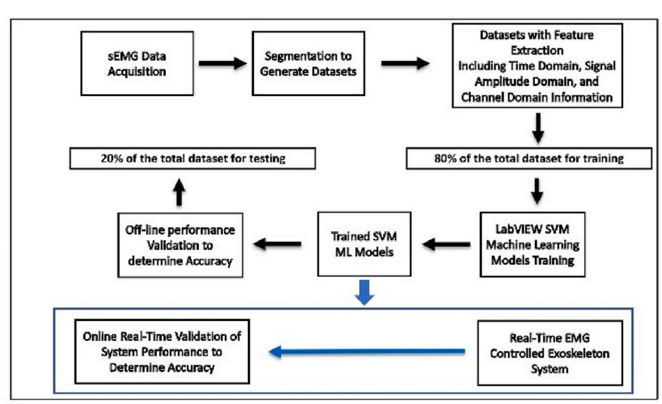

Fig. 5. The flowchart of SVM based EMG processing for exoskeleton motion control.

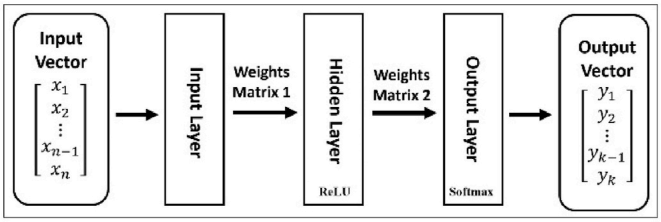

Fig. 6. Flowchart of ANN in EMG signal processing.

performed to determine the difference in accuracy of each motion pattern recognition among the three individual machine learning algorithms for different motion patterns. The accuracy of motion recognition was also compared between offline analysis and real-time performance. SPSS software (Version 28, IBM, Armonk, NY) was used for statistical analysis. A p value smaller than 0.05 was considered to be statistically significant.

4. Result

4.1. Result of offline EMG model experiment

4.1.1. Comparison of offline model training process

LR training showed that loss value decreased over the iterations (Fig. 7). The loss value of the LR model converged rapidly in the early stage of training. The loss curve plateaued after about 16 iterations, indicating that the model had converged after 16 iterations. The cost function of LR is:

$$J(\theta) = -\frac{1}{m}\left[\sum_{i=1}^{m} y^{(i)}\, log\, h_\theta\left(x^{(i)}\right) + \left(1 - y^{(i)}\right) log\, h_\theta\left(1 - x^{(i)}\right)\right]$$

where.

h_θ is the hypothesis of the LR,

$x^{(i)}$ is the feature of the ith sample,

$y^{(i)}$ is the predicted label of the ith sample.

The process of automatic optimization of the SVM model showed the observed error decreased with the increase in iterations (Fig. 8). At the 37th iteration, the SVM model had the smallest observed loss value, indicating that the SVM model achieved the most optimal parameters. The optimizer for SVM is Bayesian Optimization.

The typical loss curves were found in the ANN model training and model validation (Fig. 9). The loss curve plateaued after about 120 iterations, indicating that the model has converged after 120 iterations. The loss function of ANN is cross-entropy

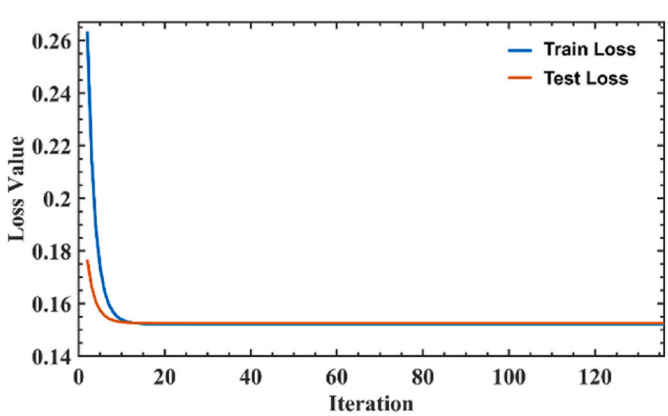

Fig. 7. LR training loss over iterations.

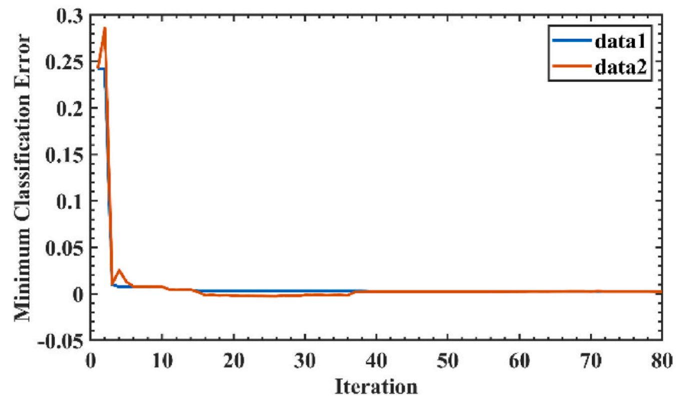

Fig. 8. SVM training loss value over iterations.

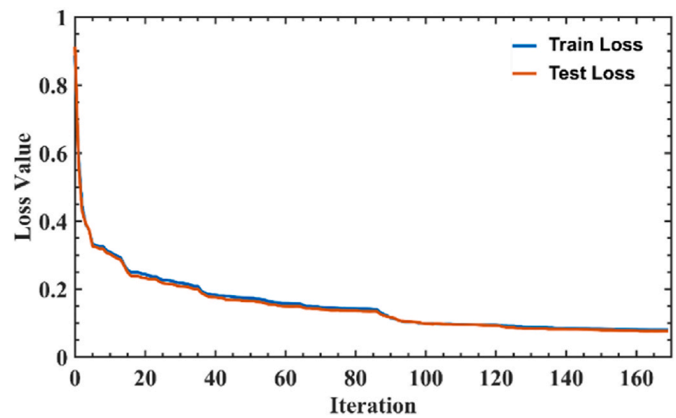

Fig. 9. ANN training loss value over iterations.

$$Loss = \sum_{i=1}^{n} y_i\, log \widehat{y_i}$$

where.

y_i is the true label of the ith sample

$\widehat{y_i}$ is the predicted label of the ith sample.

4.1.2. Comparison of classification accuracy of four ML algorithms

Fig. 10 shows the results of three confusion matrices of validation from one subject's dataset using the three machine learning algorithms as classifiers. The columns in each matrix show the number of accuracies of each motion which were predicted by the machine learning models, while the rows show the accuracy of these subjects' actual motion outcomes. The numbers on the diagonal line of these matrices show the correct prediction accuracy for the different designated motions, while other cells show the accuracy of the wrongly prediction. The accuracy was calculated from true positive, true negative, false positive, and false negative cases derived from the confusion matrix. The accuracy, together with precision, recall, and f1 score for each specific motion were thus obtained.

4.2. Result of real-time robotic motion control experiment

Fig. 11(a) shows the average accuracy of the real-time system performance following the subject's motion using SVM as a classifier with a scanning time window of 135 ms. The average accuracy was 97% for abduction motion recognition, 99% for resting recognition 99%, 84% for drinking motion recognition, and 81% for pushing forward. The results showed 16% of real drinking motions were misclassified as abduction

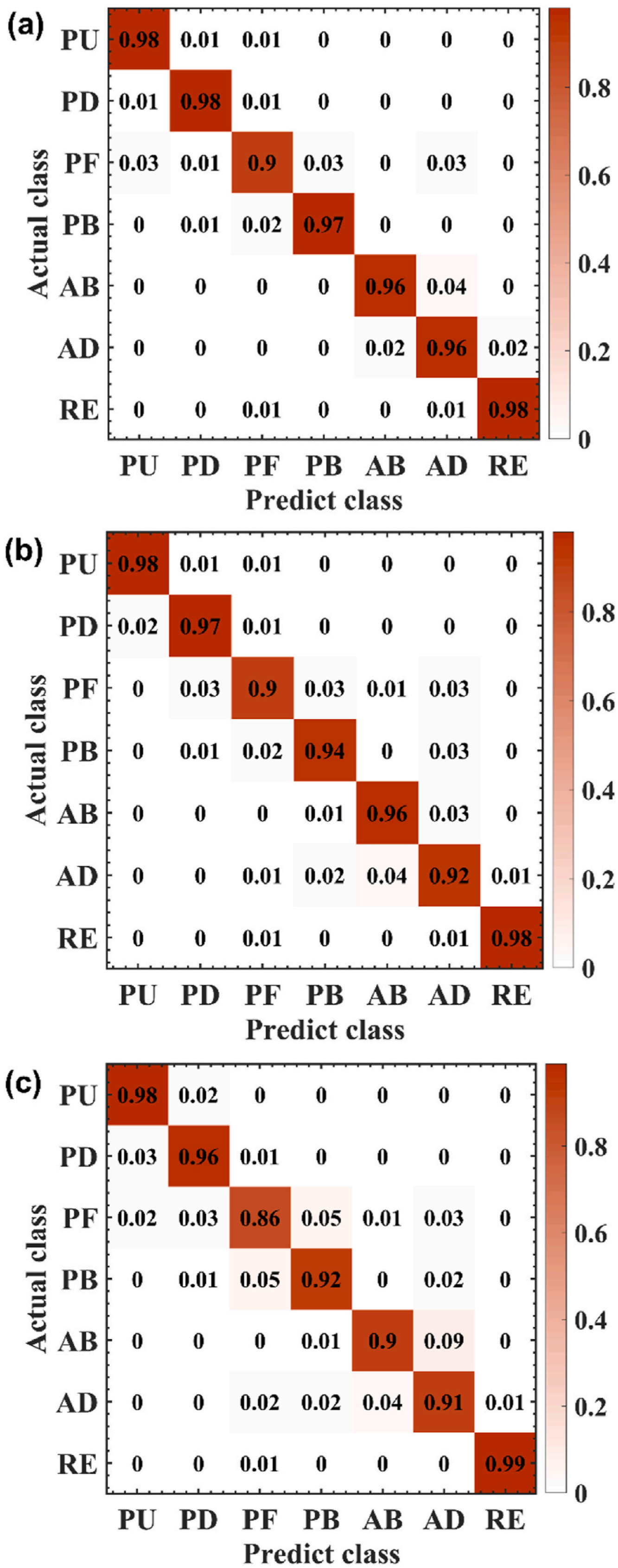

Fig. 10. Confusion matrices of offline EMG model experiment. (a) SVM; (b) ANN; (c) LR. The number in the cells represents the accuracy. The number in cells is indexed for percentage, for example, 0.98 mean 98% of accuracy.

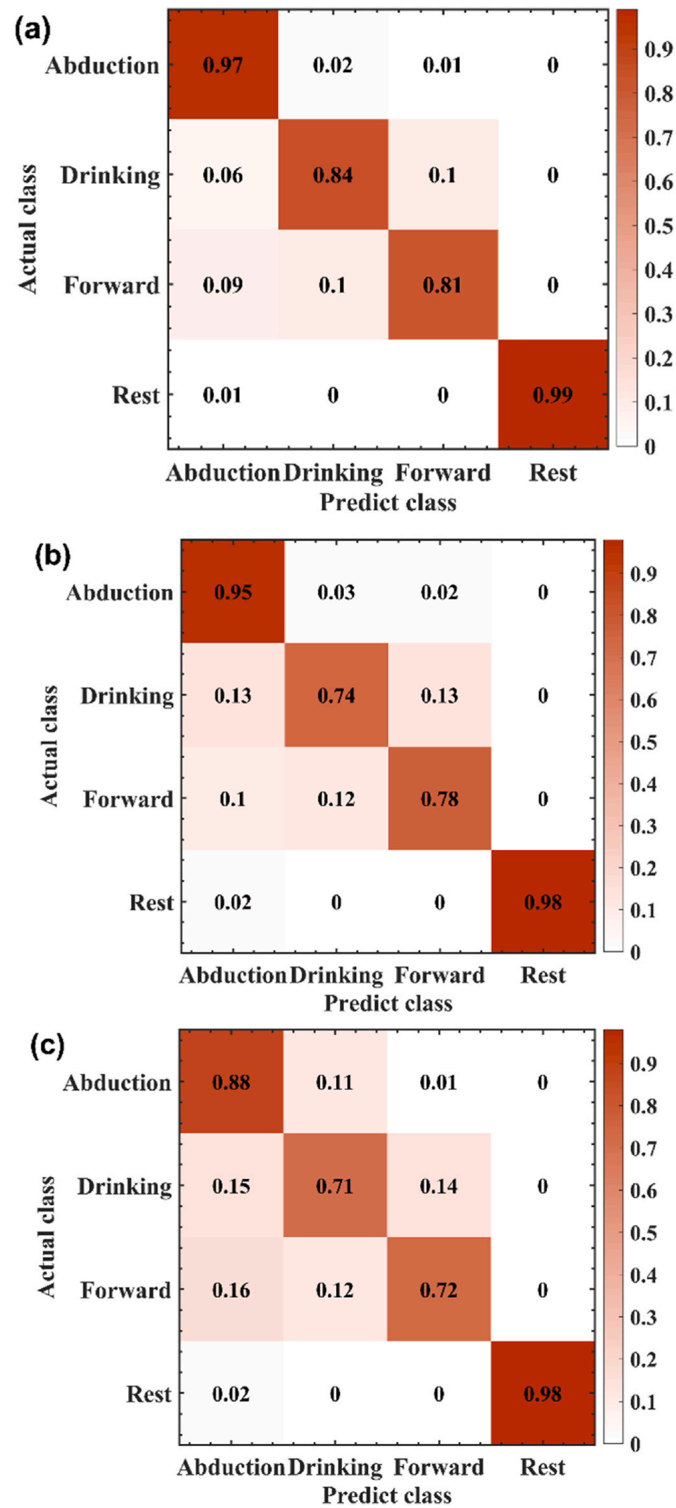

Fig. 11. Confusion matrices of real-time EMG model experiment. (a) SVM; (b) ANN; (c)LR.

and pushing forward while 19% of really pushing forward motions were misclassified as abduction and drinking.

Fig. 11(b) the average accuracy of the real-time exoskeleton system performance following the subject's motion using ANN as a classifier. The scanning time window was kept unchanged. The average accuracy of exoskeleton motion followed subject's motion was 95% for abduction, 98% for resting, 74% for drinking, and 78% for pushing forward motion. The results showed that 26% of real-time drinking motions were misclassified as abduction or pushing forward, while 22% of really pushing forward motions were misclassified as abduction and drinking.

Fig. 11(c) shows the average accuracy of the real-time exoskeleton system performance following the subject's motion using LR as a classifier and the time window is 135 ms. The average accuracy of the system performance following a subject's motion was 88% for abduction, 98% for resting 71% for drinking, and 72% for pushing forward. The results show 29% of real drinking motions were recognized as abduction and pushing forward, leading to the exoskeleton performed a wrong motion. And 28% of real-time pushing forward motions were misclassified as abduction and drinking.

4.3. Comparisons of offline analysis and real-time performance

The average accuracy of offline analysis (97.0%) was higher than real-time performance (74%) for drinking motion pattern recognition and robot control (Chi-Square, Pearson test, $p < 0.001$).

There was no a statistical difference of performance accuracy between off-analysis (88.0%) and real-time performance (95%) for abduction motion pattern recognition and robot control (Chi-Square, Pearson test, $p = 0.128$).

The average accuracy of offline analysis (89.0%) was higher than real-time performance (78%) for forward motion pattern recognition and robot control (Chi-Square, Pearson test, $p = 0.036$).

There was no a statistical difference of performance accuracy between offline analysis (99.0%) and real-time performance (98%) for resting status motion pattern recognition and robot control (Chi-Square, Pearson test, $p = 0.516$).

For offline analysis, the accuracy of LR was lower than SVM and ANN (One-Way ANOVA PostHoc LSD, $p < 0.001$). For real-time motion pattern recognition and robot control, the accuracy of SVM was higher than ANN and LR (One-Way ANOVA PostHoc LSD, $p < 0.001$) (Table 3).

5. Discussion

This research demonstrated that multiple channels of EMG signals can be processed for real-time machine-learning-based upper limb motion pattern recognition and subsequent upper-limb exoskeleton motion control. The system consisted of twelve channels of EMG signal acquisition sensors and ML-based signal processing toolkit software, a robotic motion control board and embedded algorithms, and an upper limb exoskeleton system. Three machine learning algorithms were evaluated for the efficiency in EMG signal processing for motion pattern recognition and then real-time exoskeleton motion control following the user's intents.

The novelties of this study included that an ML-based computing platform in a wearable sensor-controlled exoskeleton system was built that can be used to test various ML algorithms in the future. New AI techniques are emerging such as deep learning (DL), and extreme learning machine (ELM), etc., an effective platform is required to test new AI techniques including their applications in volitional control robot system. The outcomes of this study demonstrated the system developed in this study can perform the tasks as we desired.

The development of a volitional controlled exoskeleton system has become a hot research topic recently. In past years, research has shown that a volitional control mechanism can improve the exoskeleton performance and a user's experience [82,83]. Myoelectrical signal (EMG signal) is a promising physiological signal used for understanding a user's motion intention, and EMG signal has been widely used in robot-assistive rehabilitation therapy [23,24,83–85]. However, there are still challenges in EMG signal processing for robot control, including removing systematic noise and artifacts [25,26], increasing bio-fidelity quality such as signal-noise ratio (SNR) using special electrodes [28,29,31], precisely determining the onset and offset of muscle contraction [30,86], and reducing the complexity of algorithms [41,87]. In this study, using ML computing toolkits and the newer ML computing algorithms, we spared of manual noise filtering, on-site threshold setup and calibration, and heavy-duty complex algorithm preparation for EMG processing steps.

There are studies reported shoulder sEMG-based motion classification algorithm for controlling the exoskeleton system in real-time, most studies remain on an offline analysis level [44,88,89], however, to our best knowledge, no groups have developed a real-time ML-based EMG-based control system for the upper arm multiple joint exoskeletons, hence the performance difference has not been studied previously. The results of this study demonstrated that the accuracy of offline motion pattern recognition was higher than the accuracy of real-time motion following a subject's designated motions. This could be caused by the difference in the testing environment. A subject could pay attention to the exoskeleton's motion in real-time motion control testing, while the subject only focused on upper limb motion, indicative of a distraction from checking robot motion. There was a pause between each test in real-time motion control testing to waiting for the robot to complete its movement, while during the pure motion pattern recognition for offline analysis, a subject performed the designated motion consecutively without waiting for the completion of exoskeleton movements.

These three ML algorithms performed upper limb motion pattern recognition and exoskeleton motion control with an accuracy ranging between 71% and 98. In real-time motion pattern recognition and motion control, SVM outperformed ANN and LR. SVM is designed for small-size dataset applications. ANN fits better for medium-sized datasets. The dataset we collected in this study was smaller; thus, SVM revealed better performance [90]. LR fits better for dichotomous data [91,92] since the datasets in this study consisted of multiple-dimension information including EMG channel, EMG amplitude, and time point variables, hence the LR could yield a relatively lower accuracy in motion pattern recognition.

In real-time exoskeleton motion control testing, the system recognized resting and abduction with higher accuracy than drinking and pushing forward motions. One reason might be that these two kinds of motions are very similar, especially during the initial phase of motion. This could cause the machine-learning-based system confused in motion pattern recognition during the initial phase of drinking and pushing forward actions.

Various rehabilitation robotic devices have been developed for upper-limb training in stroke patients. Among them, MIT-Manus (1999) [93] was one of the first systems to be developed and can provide stroke survivors with plane movements. Furthermore, MIME (2005) [94], GENTLE/s (2008) [95], T-WREX (2011) [96], and NEREBOT (2014) [97] were proposed to permit three-dimensional exercise training for patients with impaired arms [98]. Most of these upper-limb rehabilitation robots were developed targeting robot-assisted therapy for the upper limb after a stroke. Our upper limb exoskeleton system was also developed aiming for medical rehabilitation; however, it can also be applied to industrial robots.

In this study, twelve upper-limb muscles were recorded by Delsys wireless sensors. The EMG signals were processed and used for training machine-learning models which can be used for motion recognition. The users didn't wear the upper-limb exoskeleton for safety concerns since

Table 3
Classification accuracy of offline analysis and real-time control.

	Offline			Real-time		
	SVM	ANN	LR	SVM	ANN	LR
Abduction	96%	96%	90%	97%	95%	88%
Drinking	98%	98%	98%	84%	74%	71%
Forward	90%	90%	86%	81%	78%	82%
Rest	98%	98%	99%	99%	98%	98%
Average	96 ± 3.8%	96 ± 3.8%	93 ± 6.3%	90 ± 9.1%	86 ± 12.0%	85 ± 11.3%

this upper-limb exoskeleton has not been validated through the FDA investigation device evaluation process.

Limitations of this study include that this real-time system can only recognize four different motion patterns, which is far from enough for the activity of daily life (ADL) training. The motion control is trajectory instead of adaptive motion control. Twelve EMG modules were used to recognize 4 kinds of discrete actions of ADL. Too many sensors may increase the complexity of actual use and commercial product development. The minimal number of sensors for optimal performance was not studied. This EMG-controlled shoulder/upper limb exoskeleton has not been tested among clinical patients or industrial workers, it is unknown how the system will work among patients with remnant weak EMG signal.

Future work will focus on the development of a better computing system for the wearable sensor-controlled upper-limb exoskeleton system to better discriminate similar motions. The investigation will be performed to determine the minimal number of EMG sensors for optimal performance. The effects of ML-based EMG signals on the adaptive control of an upper limb exoskeleton will be studied.

Since we have built a platform for EMG signal processing using ML techniques, new machine learning algorithms, and new features can be tested using this platform. More research will be performed to discover a better solution for the shorter responsiveness time and higher accuracy.

6. Conclusion

This study demonstrated the feasibility of ML computing in multiple channels of EMG signal processing for a real-time shoulder motion pattern recognition and wearable exoskeleton motion control. SVM yielded better accuracy than the LR and ANN in performance. The offline pattern recognition had a higher accuracy than the accuracy of real-time exoskeleton motion control.

Credit author statement

Biao Chen: Conceptualization, methodology, investigation, software, data curation, formal analysis, original draft preparation. Yang Zhou: Conceptualization, methodology, investigation, software, data curation, formal analysis, original draft preparation. Chaoyang Chen: Conceptualization, investigation, methodology, validation, resources, writing—review and editing, supervision, project administration, funding acquisition. Zain Sayeed: Conceptualization, methodology, investigation, writing—review and editing. Jie Hu: Conceptualization, methodology, resources, writing—review and editing, supervision. Jin Qi: Conceptualization, methodology, resources, writing—review and editing. Todd Frush: Conceptualization, methodology, resources, writing—review and editing. Henry Goitz: Conceptualization, methodology, resources, writing—review and editing. John Hovorka: Conceptualization, methodology, resources, writing—review and editing. Mark Cheng: Conceptualization, investigation, methodology, software, validation, writing—review and editing, supervision. Carlos Palacio: Conceptualization, methodology, resources, writing—review and editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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