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IMU-Based Prediction of Multiple Grasping Gesture Intentions for Enhanced Functional Electrical Stimulation Control*

Guotao Gou, Kong Hoi Cheng, Jinxin Sun, Chengyu Lin,
Wei Pan, Guojing Huang, Yuquan Leng, Yixuan Guo and Chenglong Fu

Abstract— **Stroke survivors frequently face the challenge of regaining hand-grasping functions, which are crucial for performing daily activities. While Functional Electrical Stimulation (FES) has demonstrated promise for hand function recovery, the application of online control methods tailored to varied daily grasps remains underexplored. In response, our study presents a refined framework utilizing an inertial measurement unit (IMU) for the real-time recognition of grasp intentions in stroke patients. Data on arm trajectories and orientations preceding diverse grasping actions were gathered from three healthy individuals, segmented by acceleration to determine high-accuracy intervals for grasp prediction. The Support Vector Classification (SVC) model emerged as a superior method for intent recognition. By segmenting data based on acceleration, our model's general accuracy improved. Moreover, the time required to achieve a stable accuracy rate exceeding $95\,\%$ was reduced from $0.8\,\mathrm{s}$ to $0.2\,\mathrm{s}$. This research lays the groundwork for future advancements in online gesture recognition systems. The successful implementation of FES based on SVC-model predictions mark a significant step toward intuitive and adaptive rehabilitation therapies for stroke patients.**

I. Introduction

Stroke is among the most prevalent neurological disorders worldwide, leading to long-term physical disabilities, especially significant impairment in hand motor functions. This impairment severely restricts patients' ability to perform daily activities, affecting their quality of life. In recent years, the emergence of wearable robotic devices [1], [2], particularly wearable devices, has introduced new possibilities for the rehabilitation of hand motor functions in stroke survivors [3], [4]. These devices, by physically assisting or augmenting limb movements, have opened new avenues for improving the stroke rehabilitation process [5]–[7].

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Guotao Gou, KONG HOI CHENG, Chengyu Lin, Wei Pan, Guojing Huang, Yuquan Leng, Yixuan Guo, Chenglong Fu are with Shenzhen Key Laboratory of Biomimetic Robotics and Intelligent Systems and Guangdong Provincial Key Laboratory of Human-Augmentation and Rehabilitation Robotics in Universities, Department of Mechanical and Energy Engineering, Southern University of Science and Technology, Shenzhen, 518055, China.

Jinxin Sun are with Guangxi Human Physiological Information Non Invasive Detection Engineering Technology Research Center, School of Life and Environmental Sciences, Guilin University of Electronic Technology, Guilin 541004, China.

Wearable exoskeleton devices are designed to provide necessary external force support to the finger joints, assisting users in performing grasping actions [8]–[10]. Despite advancements in enhancing grip strength and improving hand coordination, these devices also face significant challenges [11]. The primary issues include the bulkiness of the devices, which restricts the user's range of hand movements, and discomfort in wearing, which can affect the device's daily usage and rehabilitation effectiveness [12].

Compared to physical assistance devices, electrical stimulation offers a different approach to rehabilitation by directly targeting muscles or nerves to facilitate limb movement [13]–[15]. Electrical stimulation can be adjusted according to the specific needs of patients, offering personalized rehabilitation therapy [16]. Significant progress has been made in recent years regarding the use of electrical stimulation in improving hand function in stroke patients [5], [13]. However, precise control of electrical stimulation to accommodate various rehabilitation needs remains a challenge.

To enhance the effectiveness and adaptability of electrical stimulation, researchers have explored various control methods, including manual adjustment, electromyography (EMG) control, visual control, electroencephalography (EEG) control, and control based on Inertial Measurement Units (IMU) [17]–[19]. Each method has its advantages; for instance, EMG and EEG control can adjust stimulation based on physiological signals, while visual and IMU controls can adjust based on the actual execution of movements [20], [21]. Yet, achieving accurate and real-time control, especially for a diverse range of daily grasping gestures, remains a technical and practical challenge [22]–[24].

Although electrical stimulation has shown great potential for hand function rehabilitation, existing studies often lack an online electrical stimulation control method for daily diverse hand gesture grasping. Addressing this research gap, this study proposes a novel method based on IMU signal for predicting multiple hand gesture intentions and online electrical stimulation control. Utilizing advanced signal processing and machine learning techniques, this method achieves high accuracy in gesture recognition and real-time adjustment of electrical stimulation, offering a more effective and adaptable daily hand function rehabilitation solution for stroke patients.

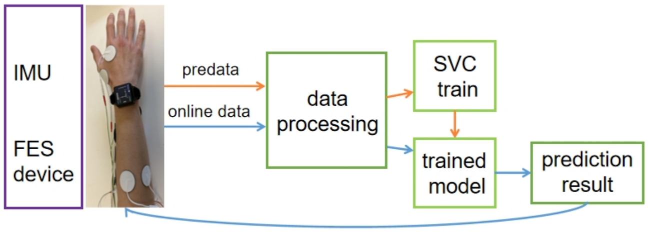

Fig. 1. General process of collecting IMU data to train Scalar Vector Classification (SVC) model and predict the intention result, therefore using the FES device for stimulation to form certain grasping gesture.

Algorithm Time-Segmented Feature Extraction and SVC Model Classification

$Acc \leftarrow \{\}$; $t \leftarrow \{\}$; $ST = 0$ ▷ Initialize accuracy, time list, start Time
Segment data by acceleration threshold
for $ST <$ maxTime; ST += windowSize **do**
  Extract features and assign labels
  Combine all features into one dataset
  Combine all labels into one label set
  Split the dataset into training and testing sets
  Optimize SVC parameters with grid search on the training set
  Fit SVC model and predict on the testing set to get *accuracy*
  $Acc \leftarrow \{accuracy\}$; $t \leftarrow \{ST\}$
end for
Plot Acc and t

Fig. 2. Pseudocode of traning the SVC model with time-segmented dataset and plot the accuracy corresponding to the start time.

II. Material and Methods

A. System Overview

In this research, we collect arm trajectory motion data from patients before performing various types of grasps using an inertial IMU. The data is then segmented based on acceleration and divided into different time periods. Machine learning techniques are applied to these segmented datasets. By comparing the accuracy of models trained on data from each time segment, we identify specific time periods that demonstrate high accuracy. These selected time periods are then used to determine which type of grasp the patient is attempting to perform. Following this determination, Functional Electrical Stimulation (FES) is employed to facilitate the identified grasp, see Fig. 1.

Data was collected using the IMU900 model. IMU900 is a small-sized nine-axis attitude sensor module compatible with Bluetooth and serial communication interfaces. This module integrates various sensors such as accelerometers, gyroscopes, and magnetometers to provide precise attitude data. The data collected includes timestamps, absolute acceleration, acceleration along the x, y, and z axes, and angular velocity along the x, y, and z axes. The IMU was placed at the foremost part of the forearm, ensuring that movements of the hand did not affect the IMU's readings.

The dataset encompasses motions with different intents, including holding a cup (labeled as 0), grabbing a larger basin (labeled as 1), pull out a drawer (labeled as 2), picking up skincare products (labeled as 3), pressing a button (labeled as 4), grasping a rod (labeled as 5), and lifting a lamp (labeled as 6). For each data set, the starting position of the arm was standardized as much as possible to maintain consistency across trials. Data recording commenced as the arm began moving from the start position to a position characteristic of grasping the specified object. The recording stopped once the arm reached the final position, with each dataset approximately spanning 2 s.

B. Intent Recognition

1) Data Processing: The absolute acceleration data obtained from the IMU served as a reference for determining the initiation of arm movement, based on an analysis of experimental data. We established a threshold where an absolute acceleration greater than 0.5 m/s^2 indicated the start of movement, marking this as the starting point. Once movement commenced, we calculated the velocity in the x, y, and z directions by integrating the acceleration data from the starting point. A subsequent integration of these velocities provided us with the distances traveled in each direction, representing the trajectory of the arm. Similarly, by integrating the angular velocities in the x, y, and z directions from the starting point, we obtained the angles in each axis, representing the orientation of the arm.

Such processing of the input data imbues it with practical physical significance, enhancing the accuracy of classification and making the data more comprehensible. Initially, we used data that was not segmented by acceleration to verify the feasibility of our approach. After confirming its viability, we proceeded with data segmented by acceleration. The IMU data for different gestures was segmented using a window size of 0.1 s, allowing for a more refined analysis of the arm's motion for intent recognition.

2) Machine Learning Process: As Fig. 2 shows, starting from the first window and moving forward, each window necessitates the retraining of the model. Each window contains data for seven different grasping intentions, with each set comprising 20 samples. Following the data processing steps described previously, we obtain the distances and angles relative to the starting point in the x, y, and z axes for each sample. These represent the trajectory and orientation of the arm, respectively. The mean, standard deviation, maximum, and minimum of the distances and angles in the xyz axes are extracted as features. Different labels are assigned to the data sets corresponding to different grasping intentions. Thirty percent of the total data is used for testing, while seventy percent is used for training the model. After considering a variety of machine learning models, including Support Vector Classification (SVC), Decision Trees and Gradient Boosting, we found that SVC demonstrated higher and more consistent accuracy in later time windows.

SVC is a powerful method for classification that seeks the best hyperplane in the feature space of the dataset to differentiate between data points of different categories. SVC is particularly suitable for complex, small to medium-sized classification problems. It enhances the model's applicability and flexibility by using different kernel functions to handle non-linearly separable data. To identify the optimal

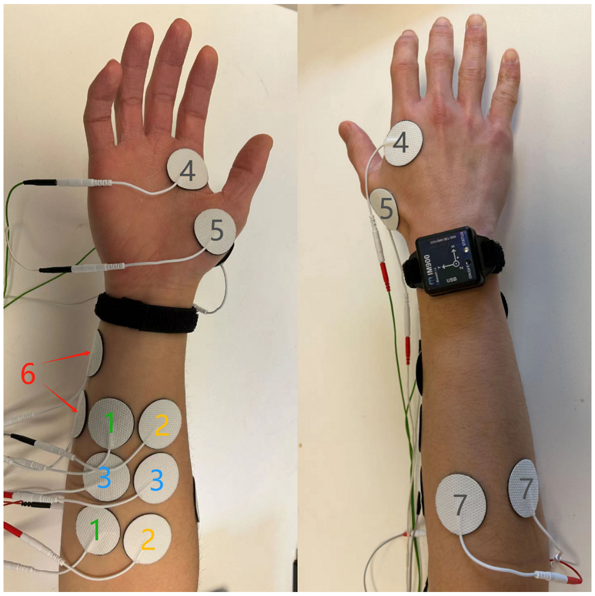

Fig. 3. Seven pairs of electrodes are strategically positioned on the right forearm and palm to precisely stimulate targeted muscles for enhanced muscle activation and rehabilitation. Electrodes of the same number correspond to the same group, regardless of positive and negative poles.

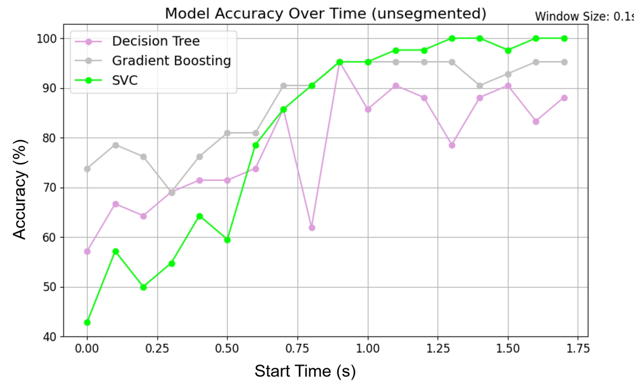

Fig. 4. First participant's accuracy of different models when data was not segmented according to acceleration threshold.

parameter configuration for the SVC model, we employed GridSearchCV, a method that tests different parameter combinations through cross-validation to select the best set of parameters. GridSearchCV systematically explores various parameter combinations, determining the optimal model settings by assessing the performance of each combination. For SVC, key parameters include the regularization parameter C (which controls the penalty strength of the error term), the kernel type (such as linear, polynomial, radial basis function, etc.), and gamma (relevant only for the radial basis function kernel, controlling the influence range of a single training sample). Through GridSearchCV, we were able to determine an optimal set of parameters that enabled the SVC to achieve the best performance on our dataset.

C. *Functional Electrical Stimulation*

Electrical stimulation is a therapeutic technique used in upper limb rehabilitation for post-stroke patients, involving the application of electrical currents via electrodes placed on the affected limb. In this method, seven pairs of electrodes are strategically placed on the affected upper limb. These electrodes deliver electrical impulses at a frequency of $90\,\mathrm{Hz}$, with the amplitude typically ranging between $8\,\mathrm{mA}$ to $20\,\mathrm{mA}$. These impulses stimulate the nerves and muscles, promoting muscle contraction and facilitating motor recovery. By targeting specific muscle groups, electrical stimulation helps improve muscle strength, coordination, and function in the affected limb. Additionally, it can enhance sensory perception and reduce spasticity, contributing to overall rehabilitation outcomes. Electrical stimulation is often used in conjunction with traditional therapy methods, offering a non-invasive and customizable approach to upper limb rehabilitation post-stroke, see Fig. 3.

III. Results and Discussion

A. *Data Collection*

In this experiment, a total of three participants were involved. Written informed consent was acquired from all participants before the commencement of any experimental activities. The study's protocol received approval and was overseen by the Sustech Medical Ethics Committee, with an approval number of 20230226 on the date of 2023/12/25. We designed seven distinct grasping intentions for different objects. For each grasping intention, each participant collected 20 sets of data, with each set lasting approximately $2\,\mathrm{s}$. Participants continuously collected 20 sets of data for the same grasping intention, taking a $2\,\mathrm{s}$ break between each set. After completing the data collection for one grasping intention, participants rested for 1 minute before proceeding to the next. The total duration of data collection for a single participant was approximately $50\,\mathrm{min}$.

B. *Classification Results*

Fig. 4 shows that when the data was not segmented by acceleration thresholds, and start time increment $0.1\,\mathrm{s}$ window size, the accuracy of the SVC model was below $90\,\%$ before $0.7\,\mathrm{s}$. However, as time increased, the classification performance of the SVC improved significantly. After 1 second, the accuracy stabilized above $95\,\%$, indicating a good classification performance and a noticeably higher accuracy compared to other models.

Fig. 5 shows that upon training with data segmented by acceleration thresholds, and start time increment $0.1\,\mathrm{s}$ window size, an improvement in accuracy was observed across all models. Despite this, other models remained unstable. The SVC model, while exhibiting high accuracy in the early stages, maintained a stable accuracy greater than $95\,\%$ after the time window moved past $0.6\,\mathrm{s}$. And Fig. 6 shows the average confusion matrix of three participants using SVC model when start time is $0.6\,\mathrm{s}$, and the general accuracy is $95.5\,\%$. The actions of grabbing a larger basin, picking up skincare products, and pressing a button have been assigned the labels 1, 3, and 4, respectively. The analysis of the

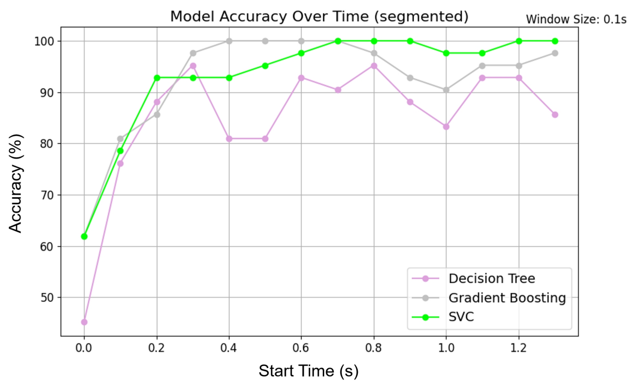

Fig. 5. First participant's accuracy of different models when data was segmented according to acceleration threshold.

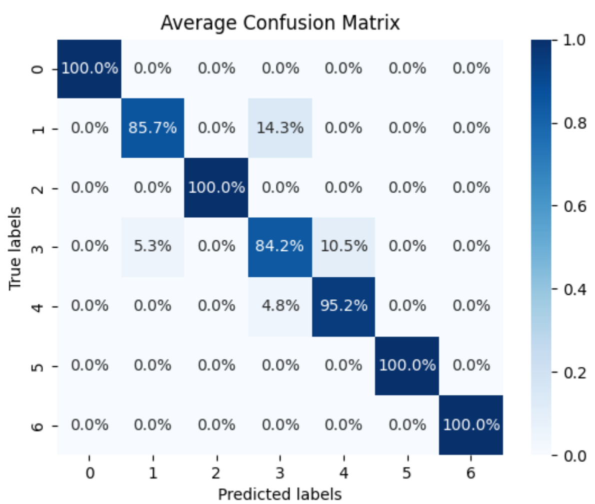

Fig. 6. Average confusion matrix of three participants using SVC model with segmented dataset when start time is 0.6 s.

average confusion matrix, as presented in Fig. 6, reveals pronounced instances of misclassification among these activities. This misclassification can be attributed to the similarities in the arm's trajectory and orientation during the execution of these motions, leading to challenges in achieving distinct classification for these specific actions.

IV. Conclusion

Stroke patients frequently face the challenge of being unable to perform hand grasps, a critical function for daily activities. Our research has delved into the potential of utilizing an IMU in conjunction with SVC machine learning algorithms and FES to facilitate the real-time identification of grasping intents in stroke patients, yielding high and consistent accuracy rates.

A threshold based on absolute acceleration was employed to exclude data representing a lack of motion. Through integration, we were able to derive meaningful representations of the arm's trajectory and orientation.

Our initial models trained on unsegmented data were instrumental in demonstrating the viability of our approach. The SVC model, in particular, showcased a consistent increase in accuracy over time, affirming its superiority. Upon refining the training data through acceleration threshold segmentation, the SVC model not only upheld its exceptional performance but also exhibited a marked improvement in overall efficacy. Notably, it quickly reached a high level of accuracy above $90\,\%$ in $0.2\,\mathrm{s}$, maintaining this with remarkable stability. In contrast, alternative models displayed significant fluctuations in accuracy, underscoring the SVC model's robustness and reliability in our study's context.

Hence, the SVC emerged as the most fitting model for our methodology, attaining a remarkable accuracy rate exceeding $97.5\,\%$ post the $0.6\,\mathrm{s}$ mark. This investigation has not only affirmed the viability of our real-time intent recognition system for grasping but has also solidified the foundation for forthcoming endeavors in this arena.

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