Feasibility Evaluation of Online Classification-based Control for Gross Movement in a 2-DoF Prosthetic Arm

Tianshi Yu, Alireza Mohammadi, Ying Tan, Peter Choong and Denny Oetomo

Abstract— **Regression and classification models have been extensively studied to exploit the myoelectric and kinematic input information from the residual limb for the control of multiple degree-of-freedom (DoF) powered prostheses. The gross movement control of above-elbow prostheses is mainly based on regression models which map the available inputs to continuous prosthetic poses. However, the regression output is sensitive to the variation in the input signal. The myoelectric signal variation is usually large due to unintentional muscle contractions, which can deteriorate the user-in-the-loop performance with respect to the offline analysis. Alternatively, the classification models offer the advantage of being more robust to the input signal variation, but they were predominantly used for fine motor functions such as grasping. For gross motor functions, the discrete output may cause issues. Therefore, this work attempts to investigate the feasibility of utilising the classification model to control a 2-DoF transhumeral prosthesis for gross movement. The performance of 6 able-bodied subjects was evaluated in performing reaching and orientation matching tasks with a prosthetic arm in a virtual reality environment. The results were compared with the case of using their intact arms and existing results using the regression model. Our findings indicate that the classification-based method provides comparable performance to the regression model, making it a potential alternative for gross arm movement in multi-DoF prosthetic arms.**

I. Introduction

In the recent development of the multiple degree-of-freedom (DoF) powered prostheses control, regression and classification models have been widely adopted as the Human-Prosthetic Interface (HPI) [1]. These models are using the electromyography (EMG) and kinematic information extracted from wearable sensors to estimate the user-intended prosthetic pose. For the regression model, a continuous mapping is constructed between the input variables and the output prosthetic joint pose estimations [2]. On the other hand, the classification model predicts discrete joint poses/gestures [3], [4], and the joints are automatically driven to the pose at a speed profile, which is also known as pattern recognition in the literature [4]–[6].

The regression models have been used predominantly in the control of transhumeral (above-elbow) prostheses for gross arm movement which involves the motion of the entire upper limb and prosthesis, such as reaching and hand orientation matching [1], [2], [7]–[9]. This is due to their ability in providing continuous prosthetic joint pose estimation which could enable natural inter-joint coordination. However, the pose estimation by regression models can be significantly affected by the noise and variance of the complex input data [10]. For example, the surface EMG (sEMG) signal variation caused by unintentional muscle contractions and its inherent noise could lead to a significant pose estimation accuracy deterioration when the user is in the loop [7], [10].

Classification-based approaches have been used in the control of prostheses, mainly in determining hand grasp types and pre-shapes for object grasping [4], [11], due to the advantage of being more robust to unintentional muscle contractions in sEMG signals [10]. However, the resulting classes capture only the discrete quasi-static poses and not the intermediate poses during the movements. The discrete output of the model may also pose challenges for gross movement tasks. The completion of the task may be impeded if there are frequent instances of misclassification during the movement of the residual limb, leading to unintended switching of the prosthetic poses and hindering the user's ability to execute the task effectively. Furthermore, the movement quality could deteriorate due to the discrete output, for instance, in terms of the movement smoothness [12] and the inter-joint coordination metrics [13].

Despite the possible shortcomings, the advantage offered by the classification-based approach prompted the need to investigate its feasibility as an alternative in prostheses control for gross arm movement. The objective of this paper is therefore to evaluate the feasibility of the classification-based method with the user-in-the-loop performing tasks involving gross arm movements. To the best of the authors' knowledge, the classification-based models have not been applied to gross arm movement. To this end, a 2-DoF active prosthesis was developed in a virtual reality (VR) environment, including an elbow flexion/extension DoF and a wrist pronation/supination DoF. The performance of 6 able-bodied subjects was evaluated in terms of task completion rate and time. Specifically, we want to investigate whether the user can complete the task in a reasonable time using a classification-based prosthesis compared to using the intact limb and the regression-based method reported in the literature. The promising results would encourage further investigation of the classification-based HPI for gross prosthetic arm movement control, such as the improvement in movement quality.

II. Method

In this section, the reaching and hand orientation matching task in this study, similar to [7], [9], is illustrated first. Then followed by the procedure of generating the targets.

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The classes to be differentiated are defined as the discrete target prosthetic joint poses [14], which the authors believe is more promising to achieve coordinated upper limb movement than the traditional classification-based HPI of taking each direction of joint movement as a class [5], [6]. Next, the experimental protocol is explained, including i) initial data acquisition for classification model training, and ii) the evaluation for the online classification-based prostheses control.

A. Experimental Setup

1) Reaching Task and Target Set: The subjects were asked to perform reaching tasks in a customised virtual reality (VR) environment using the HTC VIVE® head-mounted display (HMD), see Fig. 1. The tasks require the subjects to match the position and orientation of a target bottle (in blue) displayed in front, using the same sized bottle (in white) that follows their virtual hand movement, as illustrated in Fig. 1(b). Besides, the white and blue lines and translucent hand in Fig. 1(b) indicate the target upper limb pose for the current target. The target upper limb poses involve 3 DoFs of the upper limb: shoulder flexion/extension, elbow flexion/extension, and wrist pronation/supination, such that the targets lie in the parasagittal plane of the subject. Then, the position and orientation of the target bottle are calculated through the forward kinematics of the 3-DoF upper limb kinematic model reduced from [13], and the physical attributes of the subjects are measured by the experimenter. Furthermore, to extend the workspace beyond the parasagittal plane, the user can rotate the trunk during online control, or target upper limb poses outside the plane can be added to the set. It should be noted that transhumeral amputees often find it difficult to perform internal/external arm rotation through humerus (shoulder) rotation [15].

The detailed target upper limb poses of each DoF are given in Table. I. The full combinations of all the 3-DoF poses form the final target set which consists of 27 target positions and orientations. The HPI in this work was developed under a transhumeral amputation scenario and would predict the 3 elbow poses and 3 wrist poses based on two classification models, each for a DoF [14]. It is worth noting that all combinations of elbow and wrist poses are repeated at each shoulder pose, making tasks challenging by requiring different upper limb postural synergies.

2) Sensor Deployment and Virtual Avatar: Fig. 1(a) demonstrates the placement of the sensors. Four HTC VIVE® Trackers (with motion capture sensors and an embedded inertia measurement unit (IMU)) were placed on the subject's hand (HA), upper arm (UA), shoulder acromion (SA), and trunk (TR) in order to record upper body and arm kinematic signals and control the virtual avatar. The subject's wrist was fixed by a brace such that he/she can only do wrist pronation and supination, and the hand and forearm are considered as a single rigid body. Besides, seven Delsys® Trigno™ wireless sEMG electrodes were attached to the dominant upper arm of the subjects: two on the biceps long/short heads, two on the triceps lateral/long heads, three on the anterior, middle and posterior of the deltoid. The kinematic and sEMG sensors sample at 90 Hz and 1,111 Hz, respectively.

TABLE I

TARGET POSES

DoF	Target Pose (deg)		
Shoulder flexion/extension	30	50	70
Elbow flexion/extension	30	60	90
Wrist pronation/supination	-30	0	60

Two types of virtual avatars were designed for the two aforementioned phases of the experiment. The able-bodied avatar, as shown in Fig. 1(b), was used for the initial data acquisition, where the virtual hand and forearm follow the motion of the HA tracker. The prosthetic avatar, see Fig. 1(c), was for the online control experiments. In this phase, the elbow and wrist joints are prosthetic joints that do not follow the HA tracker movement but are controlled based on the kinematic and sEMG signals gathered from the sensors placed above the elbow. While the socket for prosthesis, see Fig. 1(c), would follow the movement of the UA tracker.

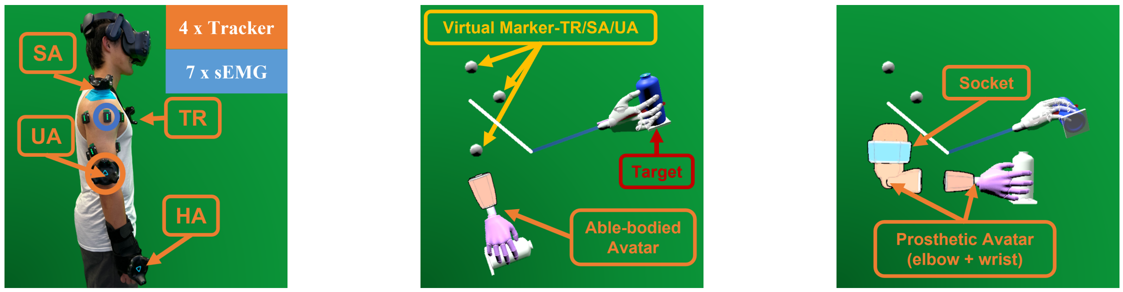
B. Experimental Protocol - Initial Data Acquisition

1) Participants: Six able-bodied subjects (5 male, 1 female; all right-handed) participated in the study. The age range was $[27, 30]$ with a median of 27. The experimental protocol is approved by the University of Melbourne Human Research Ethics Committee, project ID 11878. Informed consents were obtained from all subjects.

2) Protocol: The subjects were asked to complete 3 iterations for each target and hold their final reaching pose for 1 second upon reaching the target. In addition, instead of returning to rest (upper limb pointing downwards naturally) after each iteration, they need to reach a group of 3 targets consecutively before returning to rest to simulate a realistic scenario. The order of the targets is randomised such that the consecutive targets in a group require different target poses for each DoF. The reach position and orientation tolerance were set to 2 cm and 8 deg. The angular error is calculated by the minimum degree of rotation required from the current orientation to the target one.

3) Feature Extraction: The feature extraction was conducted under a transhumeral amputation scenario. Upon the subjects reaching the target in a coordinated way, they were instructed to hold their final pose. The quasi-static data of shoulder, trunk and scapular kinematics and sEMG during the one-second holding period were used to extract the features for the offline analysis. The time-domain sEMG and joint postural features were investigated in this study. The kinematic and sEMG features are extracted based on a moving window. The feature extraction procedure is the same as [14].

4) Sensor Selection and Classification Model: The sensors and their features are systematically refined using the method from our previous work [14] such that the information content to differentiate the target poses of each DoF is maximised. The processed features were randomly divided into training and test sets with a portion of 60% and 40%. The class separability measure in [14] was used to select, for each DoF, the best sensors for the number of 1-9 sensors out of a total of 10 sensors, including UA, TR, SA and 7 sEMG electrodes. Based on the features extracted from each selected sensor set, a Linear Discriminant Analysis (LDA) classification model was trained. The offline classification



(a) (b) (c)

Fig. 1. (a) Sensor deployment, (b) Virtual reality (VR) avatar for initial data acquisition phase and a reaching target example, (c) VR avatar for evaluation of online control of prostheses phase where the socket follows the UA tracker, and elbow and wrist are prosthetic joints without following any tracker.

accuracy of each selected sensor set is evaluated with the test data set. Finally, the sensor set for the online control phase was decided using the elbow method by checking the obtained offline classification accuracy. The corresponding classifier then serves as the HPI to predict the discrete prosthetic poses.

C. Experimental Protocol - Online Control of Prosthesis

1) Protocol: The online control evaluation starts with a familiarisation stage where the subject was given the opportunity to attempt each target using the prosthesis until they felt comfortable to start the evaluation. The target order was the same as in the initial data acquisition phase. The reaching position tolerance was relaxed to $4\ cm$ and $8\ deg$. Different from the last experiment phase, for each target, the subject was given a maximum of 10 seconds to reach the target with the prosthesis, otherwise, the target would be skipped.

2) Virtual Prosthesis: A 2-DoF virtual prosthesis as previously shown in Fig. 1(c) was designed for the subject to fulfill the reaching task, whose physical attributes are customised to the subjects. The HPI predicts the 3 discrete elbow poses and 3 discrete wrist poses every $100\ ms$ with the features extracted using the same moving window as offline analysis [14]. The joints are driven to the predicted poses using a proportional-integral (PI) controller at a maximum velocity of 90 deg/s.

D. Performance Evaluation

Two metrics are adopted to investigate the feasibility of classification-based HPI. First, to see whether the tasks can be fulfilled using the classification-based prosthesis, the **Completion Rate (CR)** (%) is adopted. It measures the rate of completing the task within a predefined threshold time. Next, **Completion Time (CT)** (s) is adopted to assess the efficiency in completing the tasks, which measures the time required to hit the targets within the threshold time of 10 s. Repeated measures one-way ANOVAs were carried out for **CT**, where the with-in subject factor was using the virtual prosthesis or the intact limb. The obtained online control results were compared to those in [7] where the same 2-DoF prosthesis was controlled in VR to carry out similar tasks involving discrete reaching targets as the ones described in this work.

TABLE II

AVERAGE COMPLETION RATE

Threshold Time (s)	Phase *Intact*	Phase *Prosthesis*
10	$99.0 \pm 2.0\%$	$69.0 \pm 11.5\%$
8	$98.6 \pm 2.0\%$	$62.8 \pm 12.4\%$
6	$97.7 \pm 1.8\%$	$54.5 \pm 11.5\%$
4	$93.6 \pm 2.8\%$	$38.3 \pm 11.5\%$

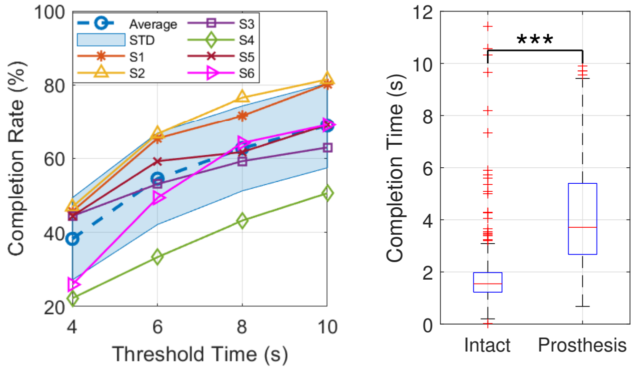
III. Results and Discussion

For ease of presentation, the performance of the subject using the intact limb and the 2-DoF classification-based virtual prosthesis are referred to as *Intact* and *Prosthesis*, respectively.

CR (%): The threshold times are chosen as 4, 6, 8, and 10 seconds. The averaged completion rate and standard deviation for both *Intact* and *Prosthesis* are summarised in Table II and the individual results in *Prosthesis* phase are depicted in Fig. 2(a). In general, the completion rate in *Prosthesis* decreases significantly when the threshold time is reduced from 6 s to 4 s. Whereas, unlike the rest of the subjects, the S4 shows a quite linear decrease in the rate versus threshold times. The S2 has the highest completion rate of 81.5% under the 10 s threshold time whereas the S4 only achieves 50.6%.

The **CR** results show two clusters of the subjects: the performance of S1 and S2 are closely aligned, as well as that of S3, S5, and S6. In addition, most subjects, especially S4, reported feeling confident in maintaining the prosthesis at certain poses and successfully hitting targets, but experienced difficulty in keeping the prosthesis at other poses, making task completion challenging. This is one of the reasons why the highest **CR** is limited to around 80% and S4 performed worse than others. Therefore, the key to further improving performance lies in developing a way to reject unintentional movements and maintain the desired prosthetic pose. Potential solutions can be utilising the post-processing technique to correct the raw class decision of the classifier [4], or regulating the joint speed appropriately instead of using a capped velocity [11]. These techniques will be investigated in future work to improve the completion rate and reduce the completion time.

CT (s): The completion time for both *Intact* and *Prosthesis* are shown in Fig. 2(b) where the pairs of iteration are filtered out for both modalities if the duration exceeds 10 seconds in *Prosthesis* phase. The median completion time for the



(a) (b)

Fig. 2. (a) the averaged and each subject's completion rate in *Prosthesis* against threshold times (**CR**). (b) the completion time **CT**. For **CT** the significance test results are shown at the top with *** denoting $p < 0.001$.

two modalities is 1.5 s (interquartile range: 1.2-2.0 s) and 3.7 s (interquartile range: 2.7-5.4 s), respectively, with p-value < 0.001, indicating statistically significant difference.

Overall, 5 out 6 subjects were able to complete more than half of the total 81 trials within $6s$. To have more insights into the classification-based approach, the obtained performance is also compared to the results reported in [7] where a similar reaching and hand orientation matching task is studied in a VR environment but using a regression-based HPI. The average completion rate obtained in our study $69.0 \pm 11.5\%$ under the 10 s threshold time is comparable to the rate achieved in [7], $71.7{\pm}16.2\%$. In terms of the **CT**, the median reaching time of 3.7 s (interquartile range: 2.7-5.4 s) was comparable to the **CT** in [7], 4.3 s (interquartile range: 3.5-5.5 s). It should be noted that the classification-based HPI in our study achieves this performance despite more restricted tolerance for a successful reach to target than the one in [7], i.e. 4 cm and 8 deg (ours) vs. 5 cm and 30 deg (in [7]). Given the comparable performance, the classification-based HPI can be considered as an alternative method for the prosthetic restoration of gross arm motor functions.

In addition to the key focus of the feasibility metrics of the classification-based HPI, we also checked the compensatory motor behavior metrics used in [16]. The subjects were observed in a relatively natural trunk and scapular pose when finishing the task. Compared to the results of using a regression model that adapts to the user's motor behavior in an online manner [17], the amount of trunk and shoulder acromion movement is at a comparable level. The adaptation process in [17] requires the user to repeat the same task tens of times with the prosthesis. Whereas the classification model investigated in this work was obtained from the offline analysis only. The finding suggests that the classification-based HPI may hold a potential advantage over the regression-based method due to its capability to precisely output the intended target pose, reducing the need for compensatory movements. The movement smoothness [12] and inter-joint coordination metrics [13] were not investigated in this feasibility study and will be considered in our future work.

IV. Conclusion

This study demonstrated the feasibility of using classification-based HPI for the gross movement of the prosthetic arm. Our findings showed comparable performance to the regression models. Therefore, the promising results encourage future investigation of the paradigm.

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