Assessing the Impact of Muscular Fatigue on Myoelectric Signals Using Myo Armband

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***Abstract*—This paper investigates the impact of muscular fatigue on myoelectric signals in order to incorporate biological feedback acquired wirelessly into a game interaction intended for rehabilitation. The study was conducted in four phases: Familiarisation, Training-1, Dumbbell exercises and Training-2 with 20 healthy participants. During the two training phases, each participant performed 5 hand gestures, each gesture was performed in 5 iterations. Each iteration lasted 5 seconds and consisted of 5 repetitions of each gesture, visually guided to last a second each. The logged data was recorded into CSV (Comma-Separated Values) files at a rate of 200Hz. In order to compare grasps before and after the fatiguing exercise, we used SVM (Support Vector Machine), using the capability to judge grasp accuracy for each phase. By comparing the grasp accuracy pre and post exercise, we found that muscular fatigue can negatively impact on gesture accuracy. The gesture accuracy detected after dumbbell exercises was significantly lower than that of the gestures performed before exercise. The data collected through subjective questionnaires also supports the results. In this study, we identified that fatigue, caused by interaction intensity and effort, can affect the accuracy of gesture detection. This has a further implication for cases where EMG (Electromyography) is used as the biofeedback involved in human-machine interactions, such as gameplay. While it is thought that more intensive interaction may benefit recovery after stroke, it is possible to optimise interactions towards reducing fatigue, for example by pacing the game difficulty based on detected level of fatigue.**

***Index Terms*—Gesture detection; fatigue; electromyography.**

I. INTRODUCTION

Humans utilise their hands to accomplish tasks, interact with their environments and also for communication via gestures. Human-computer interaction utilising hand gestures can play a significant role in this smart world. The way of interaction with devices and applications has been completely changed, smart devices use new interaction techniques such as voice commands, mimics, and gestures to communicate with humans. The hand gesture based technique is a unique approach which provides a natural way of interaction and communication [1].

In the past, researchers have used various methods such as vision-based and glove-based methods to detect hand gestures. Vision-based solutions often involve detecting the fingertips or fingers and inferring joint-articulations using inverse kinematic models of the hand and wrist skeleton [2][3]. They are susceptible to changes in illumination, rotation problem, and occlusion [4]. Glove-based methods reduce the computation time by having a direct measurement of the articulation [2] [3] of the hand and wrist joints. Glove-based techniques require the user to wear a glove, sometimes uncomfortable to wear and requiring a correct size/handedness. Also position encoders may have connection cables limiting free motion and interfere with the donning and doffing and comfort. Furthermore, gloves may impact on tactile sensations of the fingers when interacting with objects.

In our previous research, Leon et al. [5] achieved more than 90% of accuracy in gesture recognition using Support Vector Machines (SVM) while applying the technique to recordings from hand flexion and extension measured by a glove using its bending sensors. Tavakolan et al. [6] used SVM for pattern recognition of surface electromyography signals of four forearm muscles in order to classify eight hand gestures. They concluded that it was feasible to identify gestures using the four locally placed electrodes. Similarly, Wang et al. [7] used linear discriminant analysis to achieve an average accuracy of around 98% in detecting 8 hand gestures using two electrodes placed on the forearm. Using the Myo armband, researchers in our group initially achieved low accuracies using k-nearest neighbours [8] and changing the machine learning method to SVM, they achieved an overall recognition accuracy of 94.9% detecting hand and wrist gestures [9].

Similarly, in our current study, a series of dumbbell exercises were performed between two training sessions to assess the impact of muscular fatigue on myoelectric signals. This study focused on assessing gesture recognition accuracies in fatigued muscles prior to incorporating them into a rehabilitation game. While our earlier recognition results were promising, they required a training of 2.5s per gesture, repeated 25 times before a gesture could be automatically detected in 0.2s. A limitation of this approach is that incorporating such techniques in an interactive game may result in delays to gameplay due to training needed for each gesture. Hence in current study, we explore if SVM is able to perform with 1s of training data, and if such amount is suitable in detecting gestures in fatigued muscles.

The rest of the paper is organised as follows. In section II, we introduce fatigue and its potential role in machine-mediated rehabilitation. Section IV presents methodologies used for data acquisition, experiment, analysis and evaluation. Section V provides the results of the experiment with statistical analysis and section VI provides an analysis of the results. Finally,

 ISBN: 978-1-61208-686-6

section VII draws conclusion from the work presented.

II. Fatigue

Fatigue is a common problem among stroke survivors performing physical activities for rehabilitation [10]. Stroke patients often suffer from weariness, tenderness and lack of energy, initiative, and motivation. Fatigue is a condition in which a person lacks the physical and mental energy that is perceived by the individual to interfere with usual and desired activities [11]. Staub and Bogousslavsky defined fatigue in stroke patient as a feeling of early exhaustion developing during activity with lack of energy and aversion to effort [12]. It can be differentiated into two categories, subjective fatigue, and objective fatigue [13]. The subjective fatigue corresponds to the symptom that is felt by the patient, which can be estimated by self-reported questionnaires. The objective fatigue corresponds to a decrease in measured physical or mental performance over the set duration of a task [13].

In using machine learning for fatigue detection, a study was carried out by Nourhan et al. [14] using Electromyography (EMG) electrodes to measure the muscle activity during dynamics contractions. In this work, the Myo armband device was used to assess the viability of using Myo to quantify muscle fatigue. During the experiment a set of muscle fatiguing exercises was conducted where elbow flexion and extension were performed. The acquired EMG signals from muscles were analysed and features such as Root Mean Square and Median Frequency were used as indicators of fatigue using adaptive neural networks. Results show that automating the process of localised muscle fatigue detection shows higher accuracy using supervised techniques compared to thresholding or observation techniques.

III. Machine-mediated rehabilitation and games

In the context of rehabilitation for stroke, more recent machine-mediated tools often incorporate functional activities such as grasping and manipulation of objects [5], as in daily living activities. It is believed that the repetition of these training activities influence the neuromodulation needed for re-learning and performing of the activities affected by stroke [15][16].

Studies exploring the machine-mediated rehabilitation often utilise the sensory recording from robots. These include kinematic data, such as position and orientation, that can be utilised alongside other dynamic models [17], to infer on active involvement of the patient, and also to provide input for assessing the movement performance. However, rarely these methods consider fatigue that is accumulated over the interaction time, and those studies that consider fatigue, often rely on measuring fatigue using indirect methods, such as measurement of movement error [18].

Games are seen as a good medium for practicing activities of daily living. Robot-mediated activity is often limited to worn devices that are cumbersome and heavy, and cannot be utilised for a prolonged period of time. Also, robots are often tethered to their controller and therefore it is not possible to practice exercises freely. Wireless myoelectric devices such as Myo armband offer a potential solution for receiving hand gestures and incorporating them into rehabilitation games. The study conducted by Oskoei et al. [19] focused on manifestation of fatigue in myoelectric signals during dynamic contractions produced during playing PC games. The study results show that there is a significant decline in signal frequency after a period of operation, which is linked to fatigue in the muscles [20]. This led to our research question exploring suitability of machine learning in detecting fatigue from interactions sensed using the Myo armband.

IV. Material and Methods

The Myo armband [21] depicted in Figure 1 is a gesture recognition device worn on the forearm. It enables a user to control ICT technology wirelessly using various hand/wrist motions. It is designed with 8 EMG electrodes which are placed equidistantly around the arm. The armband is built with an ARMCortex M4 processor and a rechargeable lithium-ion battery allowing it to be used while communicating via Bluetooth 4. The armband is equipped with accelerometers, gyroscope and magnetometers, and also provides haptic feedback in form of vibration. It can be worn easily without any assistance.

Fig. 1. Myo Armband from Thalmic Labs

Experiment Design: The proposed study was designed to assess gesture recognition before and after a series of fatiguing dumbbell exercises. It also focused on using shorter grasp cycles of 1 second in order to train the support vector machines for gesture recognition. This was to reduce the training time needed for in-game calibration of gestures at a later time. The experiment was designed in four phases, Familiarisation, Training-1, Dumbbell Exercises and Training-2 shown in Figure 2. Subjective fatigue was assessed using a questionnaire prior to, and after the last phase of the experiment.

The experiment protocol was approved by the University of Hertfordshire's ethics committee under the approval number

COM/PGR/UH/02741. A total number of 20 participants consented to take part in the study with their demographics presented in summary table I. As an exploratory study, a sample size of 20 was seen as sufficient to search for initial evidence for impact of fatigue on recognition accuracy. Participants sat in front of a 21” monitor, wearing the Myo armband on their dominant arm.

TABLE I. DEMOGRAPHIC DATA

Gender	Participants	Age (m $\pm$ std)
Female	6	28.5 $\pm$ 3.5
Male	14	34.2 $\pm$ 7.3

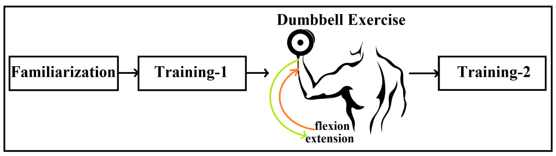

Fig. 2. Experiment Setup

Familiarisation: In this phase, participants interacted with the Myo armband and learned its operation. They performed 5 gestures shown in Figure 4, which were displayed in form of an animated image on screen (Figure 3). Each animated gesture repeated 5 times, each lasting 1 second. The familiarisation process cycled through the 5 gestures, until participants were confident in using the device.

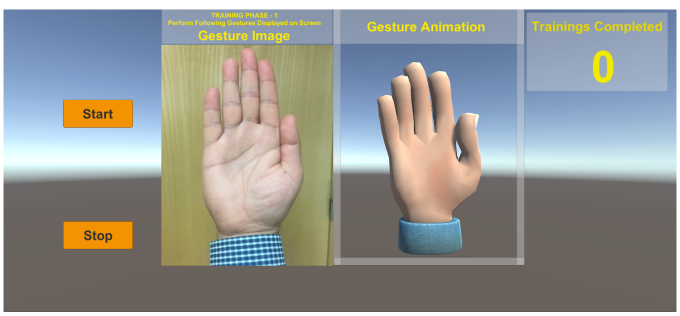

Fig. 3. Gesture image and gesture animation

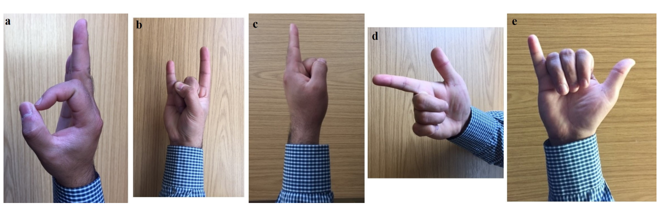

Fig. 4. Designed poses for Familiarization: (a) OK, (b) Rock, (c) Pointer, (d) Gun, (e) Phone

Training-1: During this phase, participants performed five gestures consisting of cylindrical, lateral pinch, spherical, tripod and hook grasps displayed on the screen. These gestures were randomised to appear on screen in 5 iterations. Participants were asked to perform and repeat each presented gesture 5 times as shown by the animated image on screen. The animated image timed each gesture to one second, thus 5 repetitions were expected to last 5 seconds. Based on this, each of the gestures in the list was performed 25 times, lasting approximately 25 seconds.

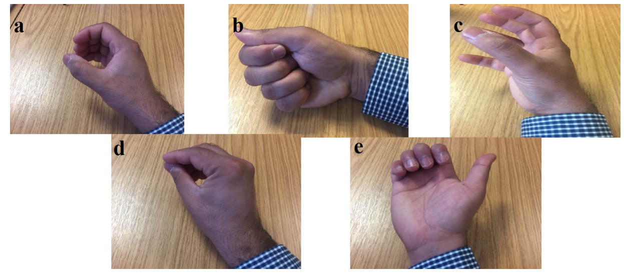

Fig. 5. Designed poses for Training-1: (a) Cylindrical, (b) Lateral Pinch, (c) Spherical, (d) Tripod, (e) Hook

Dumbbell Exercises: Next phase required performing of a series of Dumbbell exercises. During this phase, participants performed some dumbbell exercises which varied in difficulty between male and female participants, while applying a gradual increase of weight up to 10Kg for male and 7.5Kg for female participants on advise received from sport science colleagues. They performed repeated elbow flexion/extension (biceps curls) and stopped the exercise when they felt personal fatigue or tiredness.

Training-2: This phase was an exact replica of the Training-1 phase, with the only difference being that this phase occurred after the fatiguing dumbbell exercise.

Data Acquisition: Data was captured by placing the armband on the forearm making direct contact with skin. The Myo armband must be tight enough to stay in one place without losing contact with skin for better signal transmission. Data were collected at $200Hz$ sampling rate and logged into comma delimited text files. Each subject completed 2 training sessions, each training contained 5 iterations, each iteration containing 5 different gestures. Each gesture was performed 5 times making 5 repetitions. Overall, each participant performed 5 gestures under Training-1 and the same gestures under Training-2, and hence each gesture class contains 25 seconds of gesture data, corresponding with 25 repetitions of each gesture.

Feature Selection: One of the first steps to SVM analysis is the feature selection step. Oskoei and Hu showed that the waveform length (WL) feature is capable of detecting gestures with an accuracy of more than 90% [20]. Huang and Chen (1999) [22] define the waveform length as:

$$\boldsymbol{WL} = \textstyle\sum_{k=1}^{N} |\boldsymbol{x_k} - \boldsymbol{x_{k-1}}|$$

Features were selected using $N = 40$ in the above equation. This allows to reduce 200 data samples to only 5 rows, where 40 samples are reduced to one waveform length value. These values are then used for training and recognition. The choice of N is due to research by [23] that showed 200ms of data is sufficient to detect intention in muscle EMG.

SVM Classification: The classification process involves learning features in a training set, and testing the learning using what is labeled as a recognition set. We used *libsvm* and Python libraries for this assessment.

Our earlier study had identified optimal length of training and recognition sets for testing the SVM detection accuracy. In that study, gestures were held for 5 seconds; e.g. a cylindrical gesture was produced and held, and the data from the 5-second recording was used to train the SVM engine and to recognise gestures. In our results a potential drop in some recorded accuracies were linked to the delay in perceiving an action command, before it is executed. We did not try to control the task onset using audio-visual commands or screen animation [9].

In our current study, we were concerned about the speed of gesture detection in order to have a utility for seamless gameplay. A subsequent research question was raised regarding reliability of SVM if produced gestures were maintained for a shorter time. So, here we asked our participants to repeat the gesture 5 times within each iteration while providing an on-screen animation showing the gesture start and finish, accompanied by audible signals. As a post-process, we explored different lengths of training and recognition files versus their accuracies in classification.

Model: An SVM model was constructed with three iterations {1,2,3} from both training sets (Training-1 and 2) as *Train* and remaining two iterations{4,5} from both training sets as *Recognition* sets. This includes 15 repetitions of each training gesture in the training set, and 10 repetitions of each gesture in the recognition set. Data in both sets are labelled with their right classification, for example $G_{12}I_4$ is labelled as the 1^{st} gesture, 2^{nd} repetition, 4^{th} iteration. After recognition process, the SVM engine compares the label given by the SVM recognition, to the one being set for the data as its label, and comparing right and wrong recognitions lead to a recognition accuracy, at gesture and overall levels. We are also able to draw a confusion matrix that presents the reliability of our method. The resulting recognition accuracies are then gathered in a comma delimited text file and analysed using IBM SPSS version 25.

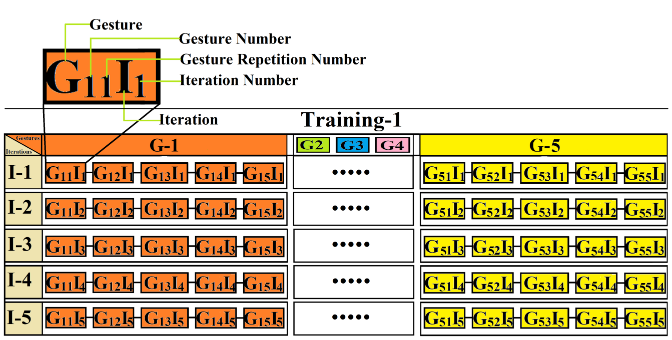

Fig. 6. The data was recorded containing 5 gestures in each iteration and 5 iterations in each Training-1 and Training-2 datasets. Each iteration consists of 5 iteration for each gesture.

V. RESULTS

This section presents the results of the experiment analysed based on gesture accuracy along with the participant's response about fatigue before and after dumbbell exercise performance. Results shows that overall gesture accuracy was higher (52.4 $\pm$ 28.54 (m $\pm$ std)) before dumbbell exercise compared to gesture accuracy after the dumbbell exercises (30.0 $\pm$ 4.144) with statistical significance ($p < 0.01$) also graphically shown in Figure 8. The data presented in Table II shows the median accuracy for each gesture pre and post-fatigue.

Questionnaire data scored the level of fatigue on a scale of 1 to 10, 10 being most fatigued. The results show that the fatigue status of participants pre-exercise (median fatigue = 0, 0.65 $\pm$ 1.137 (m $\pm$ std)) and post-exercise (median fatigue = 8, 7.5 $\pm$ 2.1) were significantly different. ($p < 0.01$) shown in Figure 7.

TABLE II. MEDIAN ACCURACY FOR EACH GESTURE

Type	Gestures	Gesture Accuracy	
		Pre-Exercise	Post-Exercise
1	Cylindrical	52	35
2	Lateral	57	27
3	Spherical	50	27
4	Tripod	49	35
5	Hook	54	25

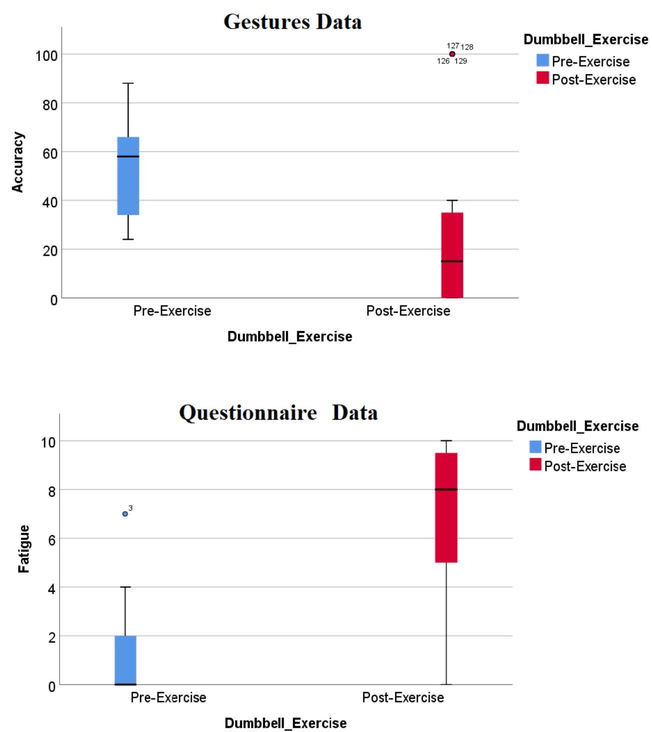

Fig. 7. Represents the impact of muscular fatigue on gesture accuracy of post-exercise compared to pre-exercise (top), and also subjective status of fatigue can be seen in post-exercise compared to pre-exercise evaluation (bottom).

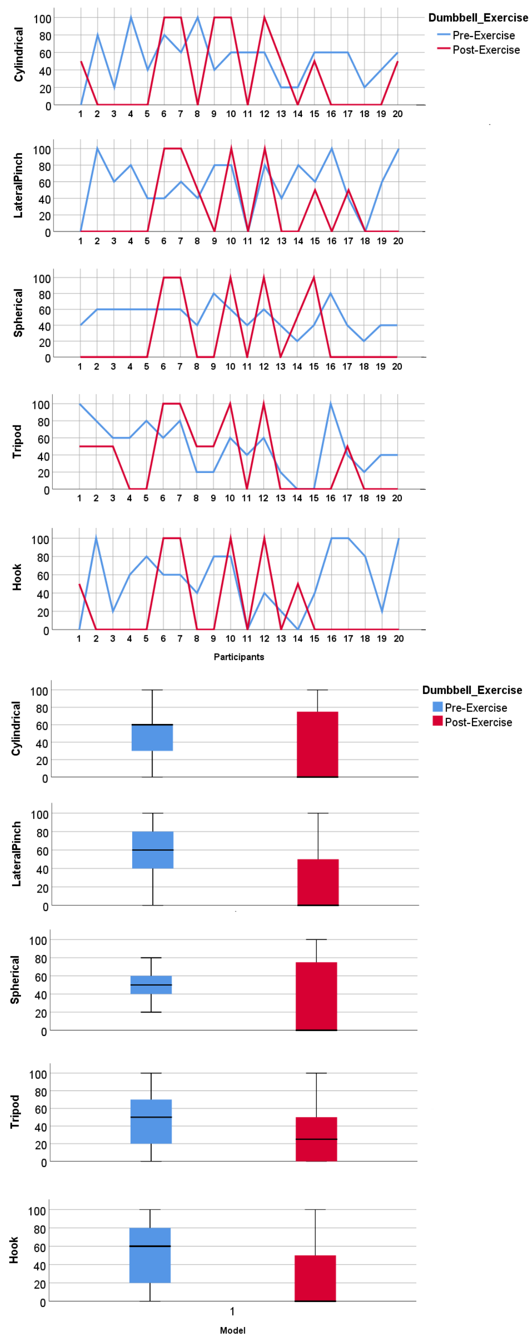

Fig. 8. Line graph on the top represents the lower gesture accuracy for post-fatigue (red line) compared to pre-fatigue (blue line), Boxplot on the bottom represents the median gesture accuracy for pre and post fatigue.

VI. Analysis & Discussion

This study was focused on the impact of muscular fatigue on hand gesture detection using myoelectric signals acquired from the Myo Armband. The result shows that muscular fatigue does affect the gesture accuracy negatively. The gesture accuracy detected after dumbbell exercises was significantly lower than that for the gestures performed before the fatiguing exercise. The data collected through the questionnaires about participants fatigue confirms the presence of fatigue in each participant. The gesture accuracy analysed separately for each of the five gestures also shows a significant reduction for each gesture performed before and after the exercise.

Observation of gesture detection accuracy pre-fatigue, compared to our earlier study shows a significant drop in gesture accuracy (reduction from 95% to 52% overall). This could be due to a number of variations between the two studies:

a) Reducing the length of training datasets for the SVM engine, from 2.5 second to only 1s in each training repetition. This was done to allow for a practical length of training data that would suit a game calibration phase. However, the drop in accuracies, pre and post-fatigue does not support using less data in training phase.

b) The current study used one gesture per second instead of a static gesture produced and maintained over 5 seconds. We intend to explore influence of these differences. We suspect that holding a gesture for a period of time greater than the amount of training data needed, allows for least variations in gesture data, while doing one gesture per second includes flexion and extension articulations that can introduce additional variability and hence, reduce recognition accuracy. We are currently assessing this using a further pilot study, thus to ensure correct choice of learning gestures and optimal parameters for best accuracies in fatigued interaction.

c) Here we used 200Hz sampling and a different reduction factor to arrive at the same waveform length, and different method to acquire the data. It could be possible that the new method to acquire the data from Myo has applied filters to the data which has negatively impacted on recognition accuracies.

The experiment was conducted with voluntary participation of 20 healthy individuals. Each participant performed 5 gestures for 5 seconds for 5 times displayed on the screen in animated form. Among all of 5 gestures, the Lateral gesture was detected with the highest accuracy 57%, Hook 54%, Cylindrical 52%, Spherical 50% and Tripod gestures was the lowest 49% shown in Table II.

In a rehabilitation scenario, it is expected that patients involved in training process will fatigue with effort and exercise intensity. Using the wireless armband may therefore offer unreliable results given the observed drop in recognition accuracy, comparing fatigue and non-fatigue conditions. In this regard, further improvements to recognition accuracy is needed, prior to incorporating our method in rehabilitation games for stroke patients.

VII. Conclusions

The objective of our analysis was to focus on hand gesture detection influenced by muscular fatigue and optimise gestures prior to incorporating them into a rehabilitation game. The conclusion drawn from this study was that muscular fatigue does significantly affect the gesture accuracy. We observed that using accuracy of recognition, it is possible to identify

 ISBN: 978-1-61208-686-6

fatigue and non-fatigued myoelectric signals. The data collected through questionnaires about participants fatigue status support our results.

We noted a significant drop in accuracy of detection, comparing non-fatigued muscles in this study and those reported in our earlier work. It is possible that our choice of recording from a steady gesture held for 5 seconds offers a more reliable and accurate data for the machine learning. This aspect would benefit from further investigations to identify best training setups.

Our approach was intended for using the SVM classifier as an online adjustment tool for exercise intensity within a serious game designed for stroke rehabilitation. While we observed that the Myo armband is reliable with data acquisition, given the low accuracies in detecting fatigued gestures, further work is needed to improve recognition accuracies. In a rehabilitation context, patients often suffer from fatigue or are easily fatigued. Given this, more work is needed to ensure recognition accuracy remains within a reliable gameplay range.

Considering motivational factors, we remain convinced that the Myo armband or similar wireless electromyographic sensors allow for free movement in space, which does not interfere with performing activities of daily living. Hence we continue our work on EMG assessment using machine learning algorithms, thus to identify best set of learning mechanisms that could enable using the armband in a rehabilitation context.

ACKNOWLEDGMENT

The authors would like to thank the volunteers who have participated in this study contributing to our understanding of fatigue and optimal gesture detection algorithms.

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 ISBN: 978-1-61208-686-6