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Training Towards Precise Control Over Muscle Activity With Real Time Biofeedback Based On Ultrasound Imaging

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Abstract. Automated algorithms for analysis of B-mode muscle ultrasound videos are computationally expensive. Thus, we propose a technique based on the comparison of pixels intensities between frames, that processes ultrasound recordings almost instantaneously, without special processing hardware. We verify the suitability of this method for feedback training of muscle activation. 15 able-bodied volunteers took part in the study practising contractions of different torque output of gastrocnemius muscle. Within 3 seconds of each trial, they received visual feedback reflecting the ultrasound video analysis, visualizing how close their attempt was to the target, allowing them to modify their strategy for the next trial. A tendency to get closer to the target contraction intensity was recorded for 60.1%, 74.4%, 67.8% of trials for *minimal*, *weak* and *medium* contractions, respectively. Considering the number of successful trials (within 10% of the target), 11 participants improved in the second session in the *weak* and 10 in the *medium* contraction task. We demonstrated that the method provides easily interpreted semi-real time feedback of muscle activation that could help with muscle training.

Keywords: Ultrasound imaging, biofeedback, muscle training

1 Introduction

Neuromuscular disorders such as stroke, spinal cord injury or peripheral nerve damage can result in partial paralysis and loss of functional activity of specific body parts. While the signals from the central nervous system are affected, the main muscles operate correctly and recovering patients can re-learn to use them [1], which can be augmented by providing feedback about the muscle behaviour.

Muscular activity is commonly measured by surface electromyography (sEMG), however it is susceptible to motion artifacts and cross-talk from various muscles [2]. Due to background noise, sEMG is not sensitive enough to register weak muscle activations and not suitable to evaluate deep muscles.

Ultrasound imaging (USI) enables to monitor muscles during movement in real-time and to record videos for offline analysis. This non-invasive, inexpensive technique can detect the activity of deeper structures, differentiate small

contractions, and precisely identify which muscle is activated. Advancements in image processing have enabled to automatically analyse videos, using feature tracking based on optical flow or cross-correlation approaches [3, 4] and feature detection in single USI image [5]. These methods proved reliable and suitable to study various muscle architecture changes. However, all of them are used offline, or require specialist processing hardware, as they are very computationally expensive, with processing times on standard hardware ranging from minutes [4] to hours [3] to analyse video recordings of only 10 s duration.

To overcome this issue a new method was developed to allow basic processing of ultrasound videos instantly after the recording. The technique is based on comparing pixel intensity between successive frames in the identified region of interest (ROI) containing the muscle. The output allows to identify precisely the instances when the muscle gets activated.

The aim of this study is to develop and test a USI system which provides feedback of the contraction intensity to the user in almost real time, to facilitate muscle training and help with practising precise movements.

2 Materials and methods

2.1 Participants and measurement procedure

Participants. Fifteen able-bodied participants (7 male, 8 female, age 30.3 ± 9.8 years) were recruited for this study, that was approved by the Ethics Committee at the College of Science and Engineering, University of Glasgow.

Experimental design. Participants were seated in an upright position with the right foot resting on the dynamometer force platform. The leg was supported at the thigh so the lower leg was parallel to the ground, with ankle in the neutral position. An ultrasound probe was positioned over the medial gastrocnemius muscle. The participant was facing a 19" computer screen positioned about 0.5 meter away, where experimental cues and feedback were displayed.

Experimental procedures. Initially, baseline USI was recorded when muscle was relaxed, and the maximum voluntary contraction (MVC) determined by pushing on the force platform as strongly as possible. The tasks involved contractions of the gastrocnemius muscle of different intensity: (i) at 25% MVC – *medium*, (ii) at 10% MVC – *weak*, and (iii) at smallest possible intensity – *minimal*. For the *minimal* tasks, participants were instructed to initiate contraction only up to the point when they became aware of activating muscle.

The tasks consisted of 15 trials, lasting 10 s each. During first 5 trials (Training), participants practised the contractions while observing feedback on the generated torque to learn how to differentiate between different intensities. During the following 10 trials (Feedback training), participants attempted the tasks and received USI based biofeedback (displayed on the screen) in form of a bar, the size of which was proportional to value of the detected muscle movement. This procedure was completed for all three intensities and repeated at two separate sessions, separated by two days.

Data collection. Ultrasound images were recorded in B-mode at a rate of 40 frames/s, using a computer-based ultrasound system (Echoblaster 128; Telemed, Lithuania) with a 96-element linear array transducer operating at a frequency of 6 MHz and a 50 mm field of view (LV7.5/60/96). A digital output signal from the ultrasound system was used to synchronize data collection. Ankle torque and joint position measurements were taken with a Biodex System 3-PRO (Biodex Medical Systems Inc., USA) dynamometer at a sample rate of 40 Hz.

2.2 Analysis methods

Ultrasound image processing. The ultrasound videos were processed using custom C++ software that extracted the pixel intensity for each of the 96 transducer elements resulting in a frame of 884x96 pixels. Using MATLAB software (The Mathworks, USA), the intensities were converted into grayscale values between 0 and 1. For an initial frame the ROI was selected by a polygon, containing the gastrocnemius muscle but excluding the aponeuroses. This was only done once for the baseline recording, and then used throughout the experiment.

In the selected ROI, the intensities of corresponding pixels were subtracted between adjacent frames, and the absolute difference values were summed over the entire region which was then scaled by the number of pixels within the ROI, giving the *normalised pixel difference*. This value would be 1 if all pixels within the ROI had changed between frames, and zero if there was no difference between pixels. Analysing the normalised pixel difference allowed detection of changes in muscle activation and differentiation between types of contractions. With this very simple technique, processing of a typical 10 s video took about 3 s on a standard laptop (Lenovo Thinkpad T440) with an Intel i5 processor.

Ultrasound based feedback. The baseline video was used to determine the value of normalised pixel difference when no movement was happening and to establish a threshold to detect muscle contraction by using the mean + 3SD to account for periodic activity of the capillaries and physiological changes in the muscles not associated with the contraction. The maximum value of normalised pixel difference was found by analysing videos of MVC. Processing of trials enabled to detect whether muscle activation occurred. During the *minimal* contractions, the trial was considered successful when the contraction threshold was exceeded and the value of the first peak corresponding to initial muscle activation stayed within 25% of the maximum. For *weak* and *medium* contractions, the target value was determined during the training session, when real-time torque feedback from the dynamometer was available. The value of the normalised pixel difference for the final successful trial was used. The maximum peak (highest muscle activation) was selected as the target value for the feedback session, and trials within $\pm 10\%$ were considered *successful*, within $\pm 30\%$ were *acceptable*, while others were *unsuccessful*. Due to the small processing times, using this algorithm it is possible to present feedback to the participant as bar graphs within 3 s after the trial concludes. A typical example for 10 completed trials is shown in Fig. 1.

Fig. 1: Example of ultrasound imaging based feedback as presented to the participant (white bars – successful, gray bars – acceptable, black bars - unsuccessful).

Outcome measures. The outcome of trials was presented in terms of normalised pixel difference (P_i for trial i , P_{max} for MVC test, P_{tgt} for target value). Then, the result of trial i relative to MVC is P_i/P_{max} , while difference from target relative to MVC is v_i (Eq1), and $|v_i|$ is its absolute value. To compare between successive trials, difference relative to MVC is used (Δv_i , Eq2).

$$v_i = \frac{P_i}{P_{max}} - \frac{P_{tgt}}{P_{max}} \quad (1)$$

$$\Delta v_i = v_{i+1} - v_i = \frac{P_{i+1}}{P_{max}} - \frac{P_i}{P_{max}} \quad (2)$$

When assessing the success rates of using the feedback, we considered:

- *number of successful and unsuccessful trials* within each session
- *distribution of trials* considering variability within each session, represented by difference from the target value relative to MVC (v_i)
- *trial-to-trial improvement* within 1 session by comparing difference from target between consecutive trials (Δv_i) and absolute difference from target ($|v_i|$)

3 Results

Considering number of successful trials, 47% of 15 participants improved in the second session in the minimal, 73% in weak and 67% in medium contraction task. Only 1 person had more unsuccessful trials in the second session for weak and medium, as opposed to 3 people in minimal contraction task. The distribution of attempts for all participants is shown in Fig. 2a representing difference v from target relative to the normalised pixel difference recorded for MVC. The biggest variability was noted for the minimal contraction. For weak and medium contraction, the variability decreased in second session with the mean approaching target.

The expected tendency from trial to trial was to get closer to the target or follow a trial below the target ($v_i < 0$) with one above ($v_{i+1} > 0$) (or opposite).

Fig. 2: (a) Distribution of attempts for the whole group, (b) Difference between trials in approaching the target for weak and medium contraction tasks.

It means that the participant was able to use feedback to increase/decrease outcome, even if difference from the target increased. It was recorded for 74.4% and 67.8% of trials for weak and medium contractions. Fig. 2b shows the difference (v_i) from the target for trial i against the difference between 2 consecutive trials (Δv_i). Results in the 1st and 3rd quadrant correspond to correct tendency. For minimal movement, improvement was considered when approaching the baseline and it happened for 60.1% of trials.

Analysing solely the tendency to approach the target, absolute difference from target ($|v_i|$) was plotted in Fig. 3 for the minimal movement task. The fitness of lines is characterised by following R^2 values and p-value significance levels: $R^2 = 0.059$, $p = 0.0121$ for session 1, and $R^2 = 0.089$, $p = 0.0015$ for session 2. This indicates that there is a very weak but statistically significant correlation between progressing in session and decreasing difference from target. For medium and weak contraction tasks, there was a decreasing trend consistent between 2 sessions (line gradient of -0.0033 and -0.0032 for session 1 and 2).

Fig. 3: Regression of feedback trials for minimal contraction task.

4 Discussion and Conclusions

We investigated ability to learn to precisely control muscle activity using ultrasound based biofeedback and analysed learning within one biofeedback session and whether it transfers to the repeated sessions. As expected the trials were more successful and variability between trials decreased for *weak* and *medium* contraction tasks in the second session indicating that prolonged use of feedback was beneficial and participants learnt to perform more consistently. For *minimal movement* there was no overall improvement in terms of variability. In majority of cases, participant was able to apply information from the feedback to modify their attempts successfully. It was hypothesised that from trial to trial participant would get closer to the target and (Fig. 3) confirmed that for minimal movement learning was slow but consistent across whole group.

To the best of our knowledge, ultrasound based biofeedback presented in near real-time, requiring no specialist computational hardware, has not previously been developed. Feedback bars shown to participants enabled them to increase their awareness of muscle behaviour and to learn to reproduce contractions of different intensities. This approach could provide the basis for a feedback system for muscle training and rehabilitation. It would be especially advantageous when practising activations of deep muscles, for example in shoulder and neck, that cannot be assessed easily with any other method.

The limitation of algorithm is that feedback corresponds to the initial change in a muscle, reflecting change in intensity of pixels, related to the change in torque, but not necessarily leading to development of a proportional torque. While it works well for detecting the onset of muscle activity, it would be beneficial to analyse whole contractions. In addition, processing time could be reduced further and the effect of more training sessions should be evaluated to assess learning outcomes of using the feedback over a longer period of time.

The authors declare that they have no conflict of interest.

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