Gaze and EMG coordination during targeted pick-and-place tasks for upper-limb prosthesis control

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***Abstract*— We recorded 16 channels of EMG, motion capture, and gaze data from a wearable gaze tracker, during targeted pick-and-place tasks. A single subject performed an experiment, in which a target was presented on a horizontal monitor, and an object was repositioned over the target. EMG data was evaluated using two SVRs and shown to have large errors in the x-direction, especially if only more proximal muscles were included. The gaze tracking was shown to be very fast and accurate in its directional estimation. We combined these modalities using a Kalman filter and preliminary results showed that gaze can improve prediction of the motion of the hand.**

I. Introduction

Electromyography (or EMG) has extensively been used for controlling upper-limb prostheses. Different approaches have allowed for control of a single joint or terminal device [1,2], or even the simultaneous control of a terminal device and a wrist [3]. However, the control of an entire arm has not yet been considered, due to limitations in EMG control sites. We believe that adding gaze information could help reduce the control burden on the user and provide useful information. We aim to develop a system for semi-autonomous control of a full arm, which ideally could be controlled by an individual with a more proximal amputation (such as a shoulder disarticulation). In this work we investigated the possibility of using EMG for control of a full arm, as well as the potential for gaze to improve performance for high-level amputees.

II. Methods And Results

A horizontal virtual interface was developed. A target was presented on a screen and subjects would reposition a bottle above the next fixed target location. Data was recorded from a single subject, and the task was performed with the right-hand. EMG was recorded from sixteen muscle groups, and a Vicon motion capture system recorded the position of a marker on the hand. A wearable gaze tracker was used to record the subject's field of view and gaze position during the task.

The data was analyzed offline. The EMG data was processed and two support vector regressions (SVR) were trained to estimate the hand position in x and y based on EMG from all 16 muscles. The decrease in performance when using a subset of muscles was also considered, as shown in Fig. 1.

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The target was tracked in each frame of the user's view, and the drift between frames was used to eliminate head motion during the reaching task. The drift-less x and y position of the gaze was then estimated from each frame, as well as the fixation and initiation timing (in this case gaze initiates at 230 ms and fixates at 600 ms). This allowed for fusion with EMG.

Next we combined the prediction from the SVR with data acquired from gaze. In this preliminary work we modified the SVR prediction of the x-position using a Kalman filter in which the prediction (state) is updated by the speed of the gaze data. Results shown in Fig. 2.

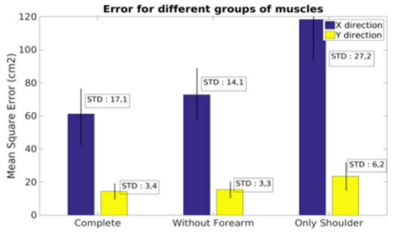

Figure 1. Error in the prediction of x and y position for a complete muscle set, for the upper arm and shoulder muscles, and only shoulder muscles

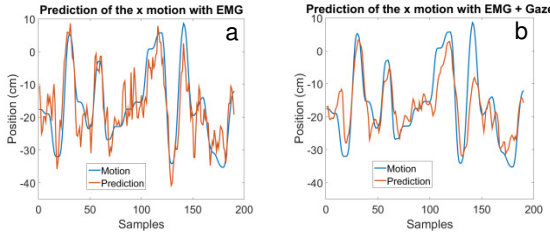

Figure 2. Prediction of x-motion using a) EMG, b) EMG and gaze.

III. Discussion and Conclusion

The EMG results from Fig. 1 show that the error increases with a reduction in included distal muscle groups (especially in x-direction). Also, the EMG results show that even with all muscle groups the estimated x-position of the target had high errors. Thus, we combined data from the gaze tracking (in this case speed) with results from the EMG predictions using a Kalman filter, and found that the motion prediction improved. Next, we will evaluate this data for more subjects, and continue investigating how best to combine EMG and gaze for ideal target position estimation, and we will test this approach online with a robotic platform.

References

[1] C. Cipriani, et. al., "On the shared control of an EMG-controlled prosthetic hand: analysis of user-prosthesis interaction," IEEE *TRO*, Vol. 24, No. 1, pp. 170-184, 2008

[2] L.J. Hargrove, et al., "A comparison of surface and intramuscular myoelectric signal classification", *IEEE TBME*, Vol 54, No. 5, pp. 847-853, 2007

[3] L.H. Smith, et al., "Evaluation of linear regression simultaneous myoelectric control using intramuscular EMG", IEEE *TBME*, Vol 63, No. 4, pp. 737-746, 2016