Variability of sEMG classification accuracy in different hand movements for intact and hand amputated subjects.

M. Atzori[1], C. Tiengo[2], M. Coppola[2], M. Cognolato[1,3], D. Faccio[2], F. Bassetto[2], H. Müller[1]

[1] Clinica di Chirurgia Plastica, Azienda Ospedaliera Universitaria di Padova, Padova (Italia)
[2] Department of Business Information Systems, University of Applied Sciences Western Switzerland (HES-SO Valais)
[3] Rehabilitation Engineering Laboratory, Department of Health Sciences and Technology, ETH Zürich, Zurich, Switzerland

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Introduction: Hand amputations can dramatically affect the capabilities of a person. Machine learning applied to Surface Electromyography (sEMG) is currently among the best solutions to control dexterous prosthetic hands. However, it still affected by low robustness[1,2] and by the fact that sEMG control performance in amputees is highly subject-dependent (also due to clinical parameters, including remaining forearm percentage and phantom limb sensation)[3]. This paper analyzes the variability of classification accuracy in different hand movements (both in intact and hand amputated subjects) with the aim of identifying solutions that can improve prosthesis control robustness.

Materials and methods: The considered subjects include 5 hand amputees and 5 matched intact subjects respectively from the 2nd and 3rd Ninapro dataset[4]. The acquisition setup includes 12 Delsys Trigno electrodes, a Cyberglove II and a portable laptop. The acquisition protocol includes 6 repetitions of 40 different hand movements. Both the acquisition setup and protocol are described in detail in Atzori et al.[4]. Movement classification includes windowing at 200 ms, signal feature extraction and classification[5,6]. The features consist of the normalized concatenation of: Root-Mean-Square (RMS), time domain statistics (TD)[7], Histogram (HIST)[8], marginal Discrete Wavelet Transform (mDWT)[9]. As classifier we used Random Forests[10]. Classification accuracy was normalized subtracting the sample average and dividing by the standard deviation. The Kruskal-Wallis test was used to perform statistical comparisons.

Results: Different movements are classified with different average accuracy and there is an overall correspondence in how well the movements are classified in intact subjects and hand amputees (Fig. 1). The normalized classification accuracy of different movements is significantly different on average both in intact and hand amputated subjects ($p<0.01$). In almost all cases, there are not significant differences between intact and hand amputated subjects in the normalized classification accuracy of each movement, thus there is a correspondence in how well each movement is classified in the two samples. In general, basic hand movements are classified better than the average, basic wrist movements have average performance, hand grasps have lower than the average, functional movements strongly depend on the movement.

Conclusions: The results correspond well to the organization of the muscle into the forearm. Prostheses control robustness may be augmented by developing control systems that are based on the movements that obtain higher average normalized classification accuracy. The correspondence of the normalized classification accuracy of each movement in intact subjects and hand amputees may allow to develop successful transfer learning strategies to train the algorithms faster and to make them more robust. A deeper analysis of the results may allow to differentiate them according to the clinical parameters of the amputation and the surgery procedures.

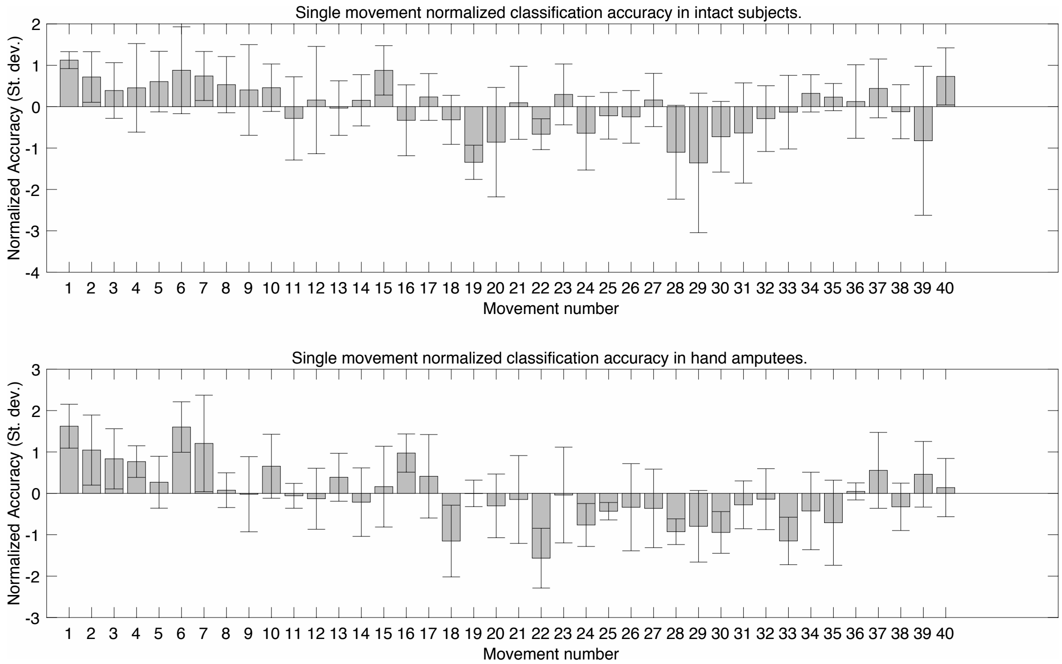

Figure 1 Normalized classification accuracy of each movement in intact subjects and hand amputees. The bars represent the normalized average in terms of standard deviations (St. dev.) and the value zero corresponds to the average classification accuracy of all movements. The errorbars represent the standard deviation of each movement.

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