Clinical, anatomical and external factors to improve dexterous robotic hand prostheses.

Cesare Tiengo[1], Manfredo Atzori[2], Henning Müller[2], Franco Bassetto[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)

Objective

The natural control of robotic prosthetic hands with sEMG techniques is still a challenge: current methods give some control capabilities but these are limited, often not natural and require long training times. The application of pattern recognition techniques recently started to be used in practice, however scientific literature methods can still be improved to reach the real life needs.
Clinical, anatomical and external factors (as additional data sources) can allow to improve the control of myoelectric prosthetic hands through adaptive computational methods and multimodal data acquisition systems. In this paper we describe the new opportunities in this field, that can lead to naturally controlled robotic hands through a proper integration between surgical procedures, computational analysis of multimodal data and robotics.

Methods

The data used in this paper come from the second and the third NinaPro database[1–3]. The considered exercises include a total of more than 50 hand and wrist movements plus rest. Muscular activity is measured using 12 double differential sEMG electrodes (Delsys Trigno Wireless System) including three-directional accelerometers. Myoelectric signals are sampled at a rate of 2 kHz with a baseline noise of less than 750 nV RMS. During the acquisitions, subjects were seated at a desk resting their arm comfortably on the desktop. A laptop in front of the subject provided visual stimuli for each movement while at the same time recording data from the measurement devices. The intact subjects were asked to imitate movies of movement shown on the screen of the laptop with their right hand, while amputated subjects were asked to imitate the movements shown on the screen of a laptop with the missing limb as naturally as possible. The set of movements was selected from the hand taxonomy, robotics, and rehabilitation literature [4–7]. Each movement repetition lasted 5s, and it was alternated with a rest posture lasting 3s. The sequence of movements was not randomized in order to encourage repetitive, almost unconscious movements. sEMG and multimodal data are analyzed with statistical and computational techniques from signal processing and machine learning.

Results

We show that clinical, anatomical and external parameters can strongly improve the performance of modern robotic hand prostheses. In particular, clinical and anatomical parameters that can affect sEMG signal include usage of myoelectric prosthesis (thus muscle fitness), body mass index, phantom limb sensation intensity, forearm percentage and years passed by the amputation. External factors and data sources that can easily improve the performance of robotic prostheses include computer vision and accelerometer data.

Conclusions

This paper shows that clinical, anatomical and additional data sources can strongly improve myoelectric prosthesis control and it suggests that a proper integration between medical procedures (finalized to better exploit clinical and anatomical data) and multimodal data analysis can improve current prosthesis performance, leading to better performing naturally controlled robotic hands.

Bibliography

1. Atzori M, Gijsberts A, Kuzborskij I, et al. Characterization of a benchmark database for myoelectric movement classification. *Neural Syst Rehabil Eng IEEE Trans*. 2015;23(1):73–83.

2. Atzori M, Gijsberts A, Heynen S, et al. Building the NINAPRO Database: A Resource for the Biorobotics Community. In: *Proceedings of the IEEE International Conference on Biomedical Robotics and Biomechatronics (BioRob)*.; 2012:1258–1265.

3. Atzori M, Gijsberts A, Castellini C, et al. Electromyography data for non-invasive naturally-controlled robotic hand prostheses. *Sci Data*. 2014;1:140053.

4. Feix T, Pawlik R, Schmiedmayer H-B, Romero J, Kragic D, Kragi D. A comprehensive grasp taxonomy. In: *Robotics, Science and Systems: Workshop on Understanding the Human Hand for Advancing Robotic Manipulation*.; 2009:2–3.

5. Kamakura N, Matsuo M, Ishii H, Mitsuboshi F, Miura Y. Patterns of static prehension in normal hands. *Am J Occup Ther Off Publ Am Occup Ther Assoc*. 1980;34(7):437–445.

6. Cutkosky MR. On grasp choice, grasp models, and the design of hands for manufacturing tasks. *IEEE Trans Robot Autom*. 1989;5(3):269–279.

7. Edwards SJ, Buckland DJ, McCoy-Powlen JD. *Developmental and Functional Hand Grasps*. Slack Incorporated; 2002.