# Combining object recognition, gaze tracking and electromyography to guide prosthetic hands – experiences from two research projects\*

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*Abstract*—Hand amputation can completely change the life of the concerned persons in terms of every day activities and personal independence, even much stronger so if both hands are lost. Most hand prostheses are little accepted by amputees and only give basic functionalities back to the amputees, such as simple opening and closing. Some modern prostheses allow for much more complex movements but the control mechanisms really need to be improved for good and natural control (some prosthesis are controlled with the arm/shoulder, so body-powered and non-natural). On this topic several research projects exist with varying objectives, from invasive methods to using additional signals such as cameras in the prostheses, which is described in this text.

This article summarises several years of research executed in the MedGIFT research group in two projects funded by the Swiss National Science Foundation in collaboration with national and international partners. It starts with the descirption of a basic acquisition setup that uses mainly electromyography and acceleration sensors and finishes with the current multi-sensor integration that also includes a scene camera, object recognition and gaze tracking of the person using a prosthesis combined with surface Electromyography and acceleration sensors on the forearm. The text finishes with a short outlook into future research challenges for controlling hand prostheses.

*Index Terms*—multi-sensory information, gaze tracking, prosthesis control, electromyography

### I. INTRODUCTION

A hand amputation is not one of the most frequent injuries but it is one that can have a strong personal impact, as many daily activities can become difficult to perform. It was estimated that around 41,000 people were living with a major upper limb loss in the USA in 2005 [1]. There are cosmetic prostheses, for example a simple hook without any active functionality. Then there are body-powered prostheses, where a non-natural moment is used for opening and closing a hand. This is usually only possible for a single movement and not for more complex parts. surface Electromyography (sEMG) allows to measure the electrical activity of the remnant muscles and it constitutes the third large group of professional prostheses Most often this is also only used for one movement or a

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very small number of movements but more complex prostheses with single fingers and up to 50 movements exist as well. A review of hand prostheses can be found in [2].

In research environment also invasive methods that do not only use muscles but also connected directly to the nerves have been implemented, as well as brain-computer interfaces, both as invasive and non invasive methods, for example via EEG (Electro-EncephaloGram) [3].

Unfortunately commercial prostheses are frequently rejected by the users and so only a minority of amputated persons uses prostheses. Critical points are for example linked to heat and the wight of prostheses [4]–[6]. Most commercial prostheses are also very expensive [7], [8]. Addition of video streams for the analysis of grasps has also been done in research work [9].

Comparing quality of prosthesis control has been difficult, as the number of movements and subjects varies strongly form one publication to another.

## II. METHODS EMPLOYED AND RESULTS OBTAINED IN THE PROJECTS

This section describes the main results obtained in the MeganePro and NinaPro<sup>1</sup> projects, from the standardised acquisition setup developed to the obtained classification results of the tests with amputated persons and healthy controls. Ethics approval for the project was obtained both in Switzerland and in Italy (at the University hospital of Padova, Italy), where most data acquisitions were done.

#### A. Acquisition setup

Figure 1 shows one example setup for the MeganePro and NinaPro project. Usually sEMG electrodes are placed around the forearm, with several types of electrodes having been used in the project, from Otto Bock, to the Myo armband and Delsys Trigno wireless electrodes that are all compared in [10]. After an analysis for an acquisition protocol described in [11] first tests were performed with an amputated subject [12] to make sure that good signal quality could be obtained and

<sup>&</sup>lt;sup>1</sup>http://ninapro.hevs.ch/

also to measure how difficult and stressful such tests are for amputees. Based on the first experiences the protocol was slightly simplified and more breaks were included to limit the amount of stress and the impact of fatigue. The objective of the protocol was clearly to favour natural control of the prosthesis [13]. In several setups, tests were also run using a CyberGlove and echoing the movement from one hand on the other. Force measurements were also used in some of the tests, also to possibly synchronise movements. Several slightly different setups were used for the acquisitions, usually with a large number of around 50 movements, exceeding in complexity what was commonly used in the field and to allow for a maximum of possible uses.



Fig. 1. Acquisition setup in the MeganePro project including the description of movements to execute on a screen and data acquisition with electromyography and acceleration tracking and in addition the gaze tracker that includes a scene camera for analysing the field of view of the person.

Several of the data sets produced in the NinaPro project were published and are also publicly available for other researchers to use them [14], [15]. In the setup of the MeganePro project [16] a gaze tracking device from Tobii (Tobii 2 glasses) was added, as can be seen in Figure 2. This adds information for making a decision on the movement to be taken by recognising objects in the images [17] and also by analysing the gaze point prior to starting a new movement and adapting the movement to the object that was selected. An overview of such gaze trackers with more technical information of the devices can also be found in [18].



Fig. 2. The Tobii glasses that were used in opur experiments.

One of the major challenges in recording data from several sources is the synchronisation of the data sources, from the sEMG stream of 12 electrodes, to 12 acceleration sensors in 3 directions, the video stream and gaze point in the video recorded. Participants were following a video showing the movements to before, and a delay in starting the movement after it is shown on video can vary from one movement to another and also between repetitions of the same movement. Frequencies of the devices are not at all the same and there are possibilities for up- or down-sampling the devices, which can both have an impact on the classification results. It is important to well identify the onset of a movement to then be able to react quickly. In general the maximum amount of time for starting a movement that the prosthesis user initiated

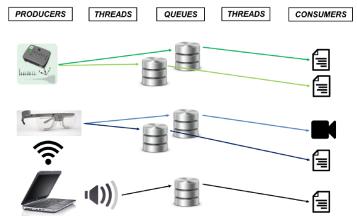


Fig. 3. Several data sources need to be combined for the final decision making, including complex synchronisation of data acquired with varying frequencies.

Most of the data acquisition were performed without an actual prosthesis but wit the help of a 3D printed prosthesis it was in the end possible to also have such visual feedback for the participants in the study [19], [20], as such feedback also allows the amputees to have visual feedback on the movements detected and thus possible the participants can adapt their behaviour, leading to much better classification results.

#### B. Outcomes of the NinaPro and MeganePro projects

Based on the initial NinaPro data acquisitions [11] and several studies that were done later with the same protocol but different electrodes, for example [10] much research was made possible both in our research group but also in several other researcher groups that obtained access to the data set. Many techniques have been applied for the data classification, for example deep learning approaches [21].

One outcome has been the important correlation of some of the clinical parameters with the performance of amputees in [22]. It was shown that remaining forearm percentage is clearly correlated with performance. More surprising also personal, subjective phantom limb sensation was correlated with performance, which has so far no clear explication. The time since the amputation is also positively correlated with classification accuracy of movements and this independent on whether the persons use a prosthesis or not, which was surprising A possible explication is that natural re-innervation increases the quality if the signal that is available for movement recognition. Neuroscience experiments on the other hand show that the brain area responsible for a missing limb decreases over time. The general accuracy of movement recognition of persons who use or who do not use prostheses can be found in [23].

An important aspect of such experiments and data acquisitions is whether the results can be repeated and for this s protocol was defined where the same ten persons were recorded for five straight days twice per day, once in the morning and once in the afternoon [24]. The results show that there are significant differences in the data and that it is hard to lear across sessions even for the same persons. This can be linked to the exact electrode position but also to fatigue in the afternoon and external factors.

The availability of the large amount of recorded data of muscle activities for many movements also allowed further analyses. In [25], several synergies of the muscles were identified and this can have an important possible impact for the analysis of neural diseases or rehabilitation beyond prosthesis control- I can also help to build better prostheses by using the detected synergies.

Another project that was made possible via all the acquired data is the creation of a new hand taxonomy that is not based on subjective human analysis but on experimental quantitative data [26]. Such a taxonomy can equally have an important impact on the domains of prosthesis control and more general in rehabilitation involving the hand, also for example after stroke.

#### **III. CONCLUSIONS AND FUTURE WORK**

Within the NinaPro project the foundations for a protocol for data acquisition with many amputees and also non-amputees was created with a large number of movements that allow to cover most movements for activities of daily living in a realistic scenario. This created a benchmark for performance analysis of movement control and sharing the benchmark data with the community was valuable, thus allowing to compare the many approaches on the same bases. Links between clinical data and movement quality were made but also several shortcomings were found in the repeatability experiments meaning that transfer learning was very difficult and might be impossible in the current setup. The difference between amputees and healthy subjects is significant and when using many movements the quality of classifying movements fully correctly is somewhat limited in amputees. Some information, for example of the thumb muscle is simply absent in amputees. Additional information can be obtained with the gaze tracker and a scene camera, which allows to identify objects in a scene and which of the objects is likely to be used via the gaze information. This has the potential to partly leverage the missing information and might improve the classification accuracy particularly for amputees. These differences can also be explained by other parameters. In most studies the amputees are patients with a large variety in age and socioeconomic status. The control group are most often volunteers from the university campus who are usually of a higher socioeconomic class and thus healthier and usually quite young compared to amputees. This can already make an important difference in acquisition quality and in the MeganePro project a data set will soon be released that contains 20 amputees and a control group that is matched by age, gender and partly the education status. Another difference is that healthy persons have feedback on the movement with their hands whereas amputees do not have any feedback in the experiments. In a small test [20] with a real, 3D printed prosthesis showed that amputees are able to adapt to the system, possibly leading to higher results. Showing results in augmented reality for training can also help with thus basic sensory feedback.

As a conclusion, both the NinaPro and MeganePro projects have created an open environment for research in hand prosthetics by making data and source code available ands sharing openly with the research community.

#### REFERENCES

- K. Ziegler-Graham, E. J. MacKenzie, P. L. Ephraim, T. G. Travison, and R. Brookmeyer, "Estimating the Prevalence of Limb Loss in the United States: 2005 to 2050," *Archives of Physical Medicine and Rehabilitation*, vol. 89, no. 3, pp. 422–429, 2008.
- [2] M. Atzori and H. Müller, "Control capabilities of myoelectric robotic prostheses by hand amputees: A scientific research and market overview," *Frontiers in Systems Neuroscience*, vol. 9, no. 162, 2015.
- [3] I. Iturrate, R. Chavarriaga, M. Pereira, H. Zhang, T. Corbet, R. Leeb, and J. del R. Millán, "Human EEG reveals distinct neural correlates of power and precision grasping types," *NeuroImage*, vol. 181, pp. 635– 644, 2018.
- [4] S. Ritchie, S. Wiggins, and A. Sanford, "Perceptions of cosmesis and function in adults with upper limb prostheses: a systematic literature review." *Prosthetics and orthotics international*, vol. 35, no. 4, pp. 332– 41, 2011.
- [5] F. Cordella, A. L. Ciancio, R. Sacchetti, A. Davalli, A. G. Cutti, E. Guglielmelli, and L. Zollo, "Literature Review on Needs of Upper Limb Prosthesis Users," *Frontiers in Neuroscience*, vol. 10, p. 209, may 2016.
- [6] E. Biddiss, D. Beaton, and T. Chau, "Consumer design priorities for upper limb prosthetics," *Disabil. Rehabil. Assist. Technol.*, vol. 2, no. 6, pp. 346–357, 2007.
- [7] D. K. Blough, S. Hubbard, L. V. McFarland, D. G. Smith, J. M. Gambel, and G. E. Reiber, "Prosthetic cost projections for servicemembers with major limb loss from Vietnam and OIF/OEF," *Journal of rehabilitation research and development*, vol. 47, no. 4, pp. 387–402, 2010.
- [8] D. Van Der Riet, R. Stopforth, G. Bright, and O. Diegel, "An overview and comparison of upper limb prosthetics," *IEEE AFRICON Conference*, 2013.
- [9] I. González-Díaz, J. Benois-Pineau, J. Domenger, D. Cattaert, and A. de Rugy, "Perceptually-guided deep neural networks for ego-action prediction: Object grasping," *Pattern Recognition*, vol. 88, pp. 223–235, 2019.
- [10] S. Pizzolato, L. Tagliapietra, M. Cognolato, M. Reggiani, H. Müller, and M. Atzori, "Comparison of six electromyography acquisition setups on hand movement classification tasks," *Plos One*, 2017.
- [11] M. Atzori, A. Gijsberts, S. Heynen, A.-G. Mittaz-Hager, O. Deriaz, P. van der Smagt, C. Castellini, B. Caputo, and H. Müller, "Building the NINAPRO Database: A Resource for the Biorobotics Community," in *Proceedings of the IEEE International Conference on Biomedical Robotics and Biomechatronics (BioRob)*, 2012, pp. 1258–1265.
- [12] M. Atzori, M. Baechler, and H. Müller, "Recognition of Hand Movements in a Trans–Radial Amputated Subject by sEMG," in *Proceedings* of *IEEE International Conference on Rehabilitation Robotics (ICORR)*, 2013.
- [13] M. Atzori, A. Gijsberts, B. Caputo, and H. Müller, "Natural Control Capabilities of Robotic Hands by Hand Amputated Subjects," in Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2014.

- [14] M. Atzori, A. Gijsberts, I. Kuzborskij, S. Elsig, A.-G. Mittaz Hager, O. Deriaz, C. Castellini, H. Müller, and B. Caputo, "Characterization of a benchmark database for myoelectric movement classification," *Neural Systems and Rehabilitation Engineering, IEEE Transactions on*, vol. 23, no. 1, pp. 73–83, 2015.
- [15] M. Atzori, A. Gijsberts, C. Castellini, B. Caputo, A.-G. M. Hager, S. Elsig, G. Giatsidis, F. Bassetto, and H. Müller, "Electromyography data for non-invasive naturally-controlled robotic hand prostheses," *Scientific Data*, vol. 1, 2014.
- [16] F. Giordaniello, M. Cognolato, M. Graziani, A. Gijsberts, V. Gregori, G. Saetta, A.-G. M. Hager, C. Tiengo, F. Bassetto, P. Brugger, B. Caputo, H. Müller, and M. Atzori, "Megane pro: myo-electricity, visual and gaze tracking integration as a resource for dexterous hand prosthetics," in *IEEE International Conference on Rehabilitation Robotics*, 2017.
- [17] M. Cognolato, M. Graziani, F. Giordaniello, G. Saetta, F. Bassetto, P. Brugger, B. Caputo, H. Müller, and M. Atzori, "Semi-automatic training of an object recognition system in scene camera data using gaze tracking and accelerometers," in *International Conference on Computer Vision Systems (ICVS)*, Jul. 2017.
- [18] M. Cognolato, M. Atzori, and H. Müller, "Head-mounted eye gaze tracking devices: An overview of modern devices and recent advances," *Journal of Rehabilitation and Assistive Technologies Engineering*, vol. 5, Jun. 2018. [Online]. Available: http://journals.sagepub.com/doi/10.1177/2055668318773991
- [19] M. Cognolato, M. Atzori, C. Marchesini, S. Marangon, D. Faccio, C. Tiengo, F. Bassetto, R. Gassert, N. Petrone, and H. Müller, "Multifunctional control and usage of a 3d printed robotic hand prosthesis with the myo armband by hand amputees," *BioRxiv*, 2018.
- [20] M. Cognolato, M. Atzori, D. Faccio, C. Tiengo, F. Bassetto, R. Gassert, and H. Müller, "Hand gesture classification in transradial amputees using the myo armband classifier," in 7th IEEE International Conference on Biomedical Robotics and Biomechatronics (Biorob), Aug. 2018, pp. 156 – 161.
- [21] M. Atzori, M. Cognolato, and H. Müller, "Deep learning with convolutional neural networks applied to electromyography data: A resource for the classification of movements for prosthetic hands," *Frontiers in Neurorobotics*, vol. 10, 2016.
- [22] M. Atzori, A. Gijsberts, C. Castellini, B. Caputo, A.-G. M. Hager, E. Simone, G. Giatsidis, F. Bassetto, and H. Müller, "Clinical parameter effect on the capability to control myoelectric robotic prosthetic hands," *Journal of Rehabilitation Research and Development*, vol. 53, no. 3, pp. 345–358, 2016.
- [23] M. Atzori, A.-G. M. Hager, E. Simone, G. Giatsidis, F. Bassetto, and H. Müller, "Effects of prosthesis use on the capability to control myoelectric robotic prosthetic hands," in 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Aug. 2015.
- [24] F. Palermo, M. Cognolato, A. Gijsberts, B. Caputo, H. Müller, and M. Atzori, "Analysis of the repeatability of grasp recognition for hand robotic prosthesis control based on semg data," in *IEEE International Conference on Rehabilitation Robotics*, 2017.
- [25] A. Scano, A. Chiavenna, L. M. Tosatti, H. Müller, and M. Atzori, "Muscle synergy analysis of a hand-grasp dataset: a limited subset of motor modules may underlie a large variety of grasps," *Frontiers in Neurorobotics*, 2018.
- [26] F. Stival, S. Michieletto, M. Cognolato, E. Pagello, H. Müller, and M. Atzori, "A quantitative taxonomy of human hand grasps," *Journal* of NeuroEngineering and Rehabilitation, vol. 16, no. 28, 2019.