ONLINE TACTILE MYOGRAPHY FOR SIMULTANEOUS AND PROPORTIONAL HAND AND WRIST MYOCONTROL

Christian Nissler, Mathilde Connan, Markus Nowak and Claudio Castellini
German Aerospace Center (DLR), Institute of Robotics and Mechatronics, Wessling, Germany

ABSTRACT

Tactile myography is a promising method for dexterous myocontrol. It stems from the idea of detecting muscle activity, and hence the desired actions to be performed by a prosthesis, via the muscle deformations induced by said activity, using a tactile sensor on the stump. Tactile sensing is high-resolution force / pressure sensing; such a technique promises to yield a rich flow of information about an amputated subject's intent.

In this work we propose a preliminary comparison between tactile myography and surface electromyography enforcing simultaneous and proportional control during an *online* target-reaching experiment. Six intact subjects and a trans-radial amputee were engaged in repeated hand opening / closing, wrist flexion / extension and wrist pronation / supination, to various degrees of activation. Albeit limited, the results we show indicate that tactile myography enforces an almost uniformly better performance than sEMG.

INTRODUCTION

Dexterous myocontrol is the study of natural control of a dexterous prosthesis by (so far, mostly) upper-limb amputees. By "natural" it is here meant, that such a control should work transparently to the subject, enforcing simultaneous and proportional (s/p) activation of a multi-degree-of-freedom (DoF) prosthetic artefact, directly upon the subject's desire [Jiang et al. (2009)]. Surprisingly, even after 20 years of research, the problem is still open, from a number of points of view. First and foremost, upper-limb prosthetic devices are still heavy, noisy, power-consuming and cumbersome; second, non-invasively or minimally-invasively extracting enough information from the subject's body to drive up to ten DoFs is a challenge; last but definitely not least, enforcing reliability of such a control proves to be hard due to the inherently statistical nature of machine-learning approaches used to enforce it, as well as to the changing nature of the signals yielded by surface electromyography (sEMG). Extensive surveys (e.g., [Micera et al. (2010), Peerdeman et al. (2011), Ison and Artemiadis (2014), Engdahl et al. (2015)]) show that solving these three problems would lead to greater acceptance and more extensive usage of such costly devices.

Among the proposed avenues to solve them, we here focus on *multi-modal sensing* [Jiang et al. (2012), Fang et al. (2015)]; in particular, force myography (FMG) and its high-resolution counterpart, tactile myography (TMG) are showing very promising results. Almost 20 years have now gone by since Kenney and Craelius's seminal works [Kenney et al. (1999), Curcie et al. (2001)] on the detection of stump deformations as an alternative to sEMG [Merletti et al. (2011)]; and the applications are now out in the academic world [Cho et al. (2016), Radmand et al. (2016)]. In particular, TMG has the advantage of providing a more stable signal than sEMG [Connan et al. (2016)] and, due to its high spatial resolution (up to 5mm), a richer image of the underlying muscle activity.

In this specific work we describe an experiment in which TMG was compared as fairly as possible with sEMG, during an online target-reaching task aimed at hand and wrist s/p control. We fitted six intact subjects and a trans-radial amputee with a shape-conformable tactile bracelet, and induced them to reach predetermined graded activations of the hand opening / closing, wrist flexion / extension and wrist pronation / supination; the experiment was then repeated using 20 commercially available sEMG sensors. Using several performance measures, TMG showed superior results with respect to sEMG: it enforced a higher Success Rate (SR), shorter Times to Complete each Task (TCT) and longer Time In the Target area when the tasks would fail (TIT). The results obtained by the amputated subject are quantitatively worse than those obtained by the intact subjects, but he still completed more than twice as many tasks successfully with TMG than with sEMG.

As far as we know, this is the first time that TMG-based full online s/p control of the hand and wrist is enforced; the encouraging results we obtained let us claim that TMG should be used as an alternative to, or as a companion of, sEMG in dealing with dexterous myocontrol.

MATERIALS AND METHODS

Experimental setup

TMG data was gathered using a custom-made shape-conformable tactile bracelet based upon the resistive principle [Kõiva et al. (2015)] consisting of 320 tactile sensors (taxels) distributed on ten rigid submodules evenly distributed around the proximal end of the subject's forearm or stump. For further details about the device, please refer to the above-mentioned paper.

sEMG data were gathered using 20 commercially available myoelectric sensors (*MyoBock 13E200* by Ottobock GmbH), arranged on two bracelets, covering approximately the same surface and location of the subject's forearm as the TMG device did (see Figure 1). The sensors were wirelessly connected to the PC using a custom-built wireless ADC device [Connan et al. (2016)].

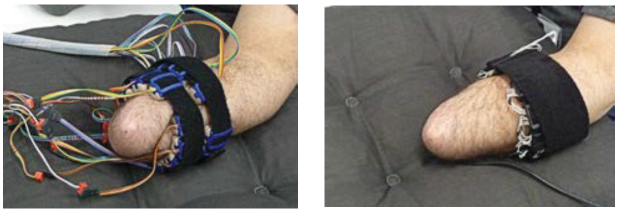

Figure 1: the amputated subject wearing the two sEMG bracelets (left) and the tactile device (right).

To test the approach we used a realistic 3D hand model displayed on a computer screen. Although the model has about 20 DoFs and roughly represents a human hand (including polygon-based 3D rendering and shading), most DoFs were coupled to one another. In the end only three DoFs were considered, namely wrist rotation, wrist flexion / extension and hand opening / closing. More in detail, five specific configurations of the model *(actions)*, namely hand opening / closing, wrist pronation, wrist supination, wrist flexion and wrist extension, were used, each one corresponding to coordinated, graded motions of the three DoFs.

S/p control was enforced using three parallel instances of, in turn, Ridge Regression (RR) applied to the 320 TMG signals and Ridge Regression with Random Fourier Features (RR-RFF) applied to the 20 sEMG signals (both signals were previously mildly low-pass filtered, but no feature extraction was enforced). RR is a well-known linear regression method – essentially least-squares regression plus a regularisation term [Hoerl and Kennard (1970)]. RR-RFF is a non-linear extension to RR, finitely approximating a Gaussian kernel, already successfully employed in myocontrol several times [Gijsberts et al. (2014), Strazzulla et al. (2016)]. Notice that the three DoFs of the model were always operated simultaneously and proportionally, since both RR and RR-RFF are pure regression approaches (i.e., no classification involved).

Subjects and experimental protocol

The experiment was joined by six intact subjects (30.7±7.2yrs old, five males, one female) and one left-hand trans-radial amputated subject (35yrs old male, amputation in 2005, routinely using a *Variplus* hand by Otto Bock GmbH with standard two-electrode control since 2012). All subjects signed an informed consent form; the experiment was performed according to the declaration of Helsinki, and it was previously approved by the DLR Work Safety Committee.

The subjects would comfortably sit in front of the screen displaying two 3D hand models; one of the model would act as a visual stimulus, i.e., the subjects were asked to do what that hand was doing, while the other would show the predicted intended action. The experiment consisted of two identical parts, one performed using the TMG device and one performed using the sEMG sensors. Half of the subjects started with TMG then proceeded to the sEMG part; the order was reversed for the other half. Figure 2 shows an intact subject while performing the experiment.

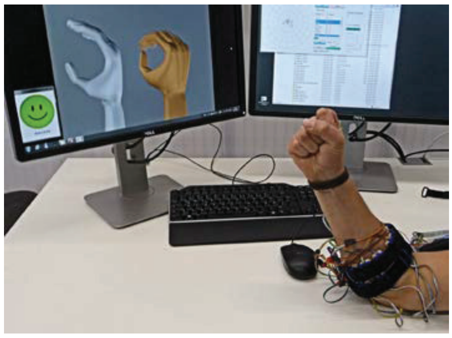

Figure 2: an intact subject performing the experiment with sEMG sensors. The grey hand is the visual stimulus, while the orange one is the prediction. A smiling face indicates that the current task was accomplished.

Initially each subject performed three repetitions of each required action (plus a "rest" position) while following the visual stimulus; data collected during this phase were used to train the control method at hand (RR for the TMG part, and RR-RFF for the sEMG part); training took not more than 300ms. Subsequently, 30 *tasks* in randomised order were administered to the subjects, as follows: the visual stimulus would perform an action to either full, two-third or one-third activation; the prediction model would then be activated, and the subjects were simply asked to have the prediction model mimic what the stimulus was doing. Intermediate levels of activation were used to determine whether proportional control could actually be achieved, e.g., that the wrist could be flexed at two thirds of the maximum activation. Each task was successful if the subject could match and keep the desired action at the desired activation level for 1.5s; "matching" was defined as remaining within 15% of each target DoF value. If she/he was not able to do so within 15s, the task was declared failed. A visual cue (smiling or sad face) was given as the result of a successful / unsuccessful task.

To evaluate the performance of each method we calculated the ratio of successful tasks over 30 (Success Rate, SR), the time it took the subject to accomplish the successful tasks (Time to Complete a Task, TCT) and the total time spent within the goal for unsuccessful tasks (Time In the Target, TIT). In the latter case (unsuccessful tasks), at this stage we did not differentiate the two sub-cases in which either the required DoF activation could not be reached, or other DoFs would be unwillingly activated at the same time.

The amputated subject was administered exactly the same procedure, executing first the sEMG part.

EXPERIMENTAL RESULTS

Intact subjects. SR was evaluated statistically using a paired Student's t-test – Figure 3 shows the SR comparison. The t-test returned $p = 0.0952$), which means that the difference is not significant ($\alpha = 0.05$). However, the average performance of the tactile bracelet ($75.56\% \pm 21.26\%$) was around 20% better than the performance of the sEMG sensors ($55.56\% \pm 16.42\%$). Furthermore, in case of TCT and TIT the tactile bracelet outperformed the sEMG sensors with $TCT_{TB} = 4.93s \pm 0.95s$, $TCT_{sEMG} = 6.28s \pm 0.58s$, $TIT_{TB} = 1.33s \pm 1.38s$ and $TIT_{sEMG} = 1.91s \pm 0.36s$. These results are summarised in Figure 4.

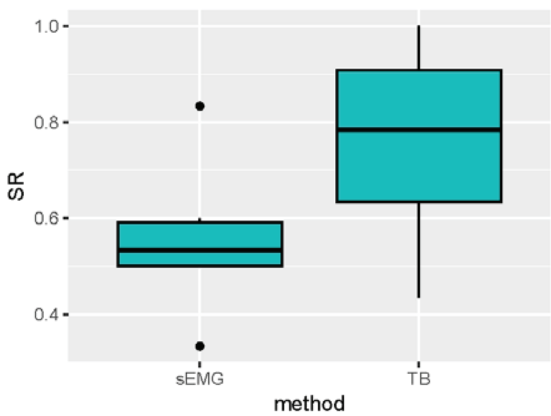

Figure 3: boxplot of the performance comparison between TMG and sEMG sensors.

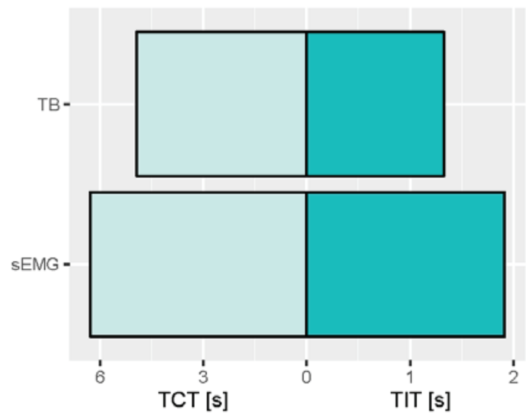

Figure 4: results of the comparison between TMG and sEMG in terms of task completion time (TCT) and Time In the Target (TIT).

Amputated subject. The amputated subject obtained the following results for each method:

sEMG:

$SR = 20\%$
$TCT_{sEMG} = 6.04s \pm 4.37s$
$TIT_{sEMG} = 0.84s \pm 1.48s$

TMG:

$SR = 43.33\%$
$TCT_{TB} = 4.80s \pm 2.38s$
$TIT_{TB} = 0.32s \pm 0.63s$

His success rate is more than double with TMG than with sEMG; as well the required TCTs are on average 20% better (shorter) with TMG. As opposed to this, the TITs obtained with TMG are considerably shorter. (Notice: the larger the TIT, the better.)

DISCUSSION AND CONCLUSIONS

Although preliminary since we tested only six intact subjects and one amputated subject, the experimental results we presented look very promising. For the comparison with TMG (which we enforced using a custom-built device with 320 sensors), we used 20 commercially available sEMG sensors, a very high amount if compared with relevant literature, which potentially poses serious challenges for the embedding in a prosthetic socket. Still, for intact subjects, TMG outperformed sEMG from all points of view considered (SR, TCT and TIT), although statistical significance is still under question (but notice the relatively low number of subjects tested). The amputated person obtained similarly better results with TMG for SR and TCT, but this result must be taken with two important considerations: first, the subject was totally untrained to activate his wrist; second, sEMG was administered first, which might have caused a competitive bias in favour of TMG. (The first remark explains his low overall performance.) Interestingly, his TIT is on average *larger* when using sEMG than TMG; this might indicate that some specific actions were almost unfeasible with TMG, as opposed to sEMG. Further analysis is required to shed light on this issue.

In the only direct reference to a competitor approach we are aware of, namely [Radmand et al. (2016)], a rigid cylindrical encasing fitted with 126 taxels was used to classify eight activation configurations performed by ten intact subjects; body postures were also taken into account by having the subjects perform the tasks in eight different positions in front of them. Since classification was used in this experiment, we cannot offer any direct comparison; their excellent results (classification rates uniformly close to 100%) further indicate the potentiality of TMG.

Lastly, let us remark that in this work linear regression (in the regularised form of Ridge Regression) *directly applied to the mildly filtered tactile values* was sufficient to obtain the results shown. On one hand, this opens up the immediate possibility to embed the whole approach in a prosthetic socket; on the other hand, we will explore in the near future several different sets of features extracted from the tactile image, possibly inspired by image processing, in order to reduce the dimensionality of the input space, and to exploit the reciprocal proximity of the adjacent taxels.

The final proof of feasibility of TMG is obviously to be drawn out of real-life experiments, in which the subject's body posture, the weight of the grasped objects, and the artefacts induced by bumping and accelerations, will need to be taken into account.

ACKNOWLEDGEMENTS

This work was partially supported by the German Research Agency project *TACT-HAND: improving control of prosthetic hands using tactile sensors and realistic machine learning* (DFG/SNSF Sachbeihilfe CA1389/1-1).

REFERENCES

[Cho et al. (2016)] Cho, E., R. Chen, L.-K. Merhi, Z. Xiao, B. Pousett, and C. Menon (2016). Force myography to control robotic upper extremity prostheses: A feasibility study. *Frontiers in Bioengineering and Biotechnology 4*, 18.

[Connan et al. (2016)] Connan, M., E. Ruiz Ramírez, B. Vodermayer, and C. Castellini (2016). Assessment of a wearable force- and electromyography device and comparison of the related signals for myocontrol. *Frontiers in Neurorobotics 10*(17).

[Curcie et al. (2001)] Curcie, D. J., J. A. Flint, and W. Craelius (2001). Biomimetic finger control by filtering of distributed forelimb pressures. *IEEE Transactions on Neural Systems and Rehabilitation Engineering (TNSRE) 9*(1), 69–75.

[Engdahl et al. (2015)] Engdahl, S. M., B. P. Christie, B. Kelly, A. Davis, C. A. Chestek, and D. H. Gates (2015). Surveying the interest of individuals with upper limb loss in novel prosthetic control techniques. *Journal of NeuroEngineering and Rehabilitation 12*(1), 1–11.

[Fang et al. (2015)] Fang, Y., N. Hettiarachchi, D. Zhou, and H. Liu (2015, Nov). Multi-modal sensing techniques for interfacing hand prostheses: A review. *IEEE Sensors Journal 15*(11), 6065–6076.

[Gijsberts et al. (2014)] Gijsberts, A., R. Bohra, D. Sierra González, A. Werner, M. Nowak, B. Caputo, M. Roa, and C. Castellini (2014). Stable myoelectric control of a hand prosthesis using non-linear incremental learning. *Frontiers in Neurorobotics 8*(8).

[Hoerl and Kennard (1970)] Hoerl, A. E. and R. W. Kennard (1970). Ridge regression: Biased estimation for nonorthogonal problems. *Technometrics 12*, 55–67.

[Ison and Artemiadis (2014)] Ison, M. and P. Artemiadis (2014). The role of muscle synergies in myoelectric control: trends and challenges for simultaneous multifunction control. *J. Neural Eng. 11*.

[Jiang et al. (2012)] Jiang, N., S. Dosen, K.-R. Müller, and D. Farina (2012). Myoelectric control of artificial limbs: is there the need for a change of focus? *IEEE Signal Processing Magazine 29*(5), 149–152.

[Jiang et al. (2009)] Jiang, N., P. Parker, and K. Englehart (2009). Extracting simultaneous and proportional neural control information for multiple degree of freedom prostheses from the surface electromyographic signal. *IEEE Transactions on Biomedical Engineering 56*(4), 1070–1080.

[Kenney et al. (1999)] Kenney, L., I. Lisitsa, P. Bowker, G. Heath, and D. Howard (1999). Dimensional change in muscle as a control signal for powered upper limb prostheses: a pilot study. *Medical Engineering and Physics 21*(8), 589–597.

[Kõiva et al. (2015)] Kõiva, R., E. Riedenklau, C. Viegas, and C. Castellini (2015). Shape conformable high spatial resolution tactile bracelet for detecting hand and wrist activity. In *Proceedings of ICORR - International Conference on Rehabilitation Robotics*, pp. 157–162.

[Merletti et al. (2011)] Merletti, R., A. Botter, C. Cescon, M. Minetto, and T. Vieira (2011). Advances in surface EMG: Recent progress in clinical research applications. *Critical reviews in biomedical engineering 38*(4), 347–379.

[Micera et al. (2010)] Micera, S., J. Carpaneto, and S. Raspopović (2010, October). Control of hand prostheses using peripheral information. *IEEE Reviews in Biomedical Engineering 3*, 48–68.

[Peerdeman et al. (2011)] Peerdeman, B., D. Boere, H. Witteveen, R. H. in 't Veld, H. Hermens, S. Stramigioli, H. Rietman, P. Veltink, and S. Misra (2011). Myoelectric forearm prostheses: State of the art from a user-centered perspective. *Journal of Rehabilitation Research and Development 48*(6), 719–738.

[Radmand et al. (2016)] Radmand, A., E. Scheme, and K. Englehart (2016). High-density force myography: A possible alternative for upper-limb prosthetic control. *J Rehabil Res Dev. 53*(4), 443–456.

[Strazzulla et al. (2016)] Strazzulla, I., M. Nowak, M. Controzzi, C. Cipriani, and C. Castellini (2016). Online bimanual manipulation using surface electromyography and incremental learning. *IEEE Transactions on Neural Systems and Rehabilitation Engineering 25*, 227–234.