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On the control of a robot hand by extracting neural signals from the PNS: preliminary results from a human implantation

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Abstract—**The development of hybrid neuroprosthetic systems (HBSs) linking the human nervous system with artificial devices is an important area of research that is currently addressed by several groups to restore sensorimotor function in people affected by different disabilities. It is particularly important to establish a fast, intuitive, bi-directional flow of information between the nervous system of the user and the smart robotic device. Among the possible solutions to achieve this goal, interfaces with the peripheral nervous system and in particular intraneural electrodes can represent an interesting choice. In the present study, thin-film longitudinal intra-fascicular electrodes were implanted in the median and ulnar nerves of an amputee. The possibility of restoring the bidirectional link between the subject and the external world was investigated during a 4 week trial. The result showed that both the extraction of motor information and the restoration of sensory function are possible.**

I. Introduction

A continuous challenge for scientists and engineers is to replicate the sensory-motor function of the human hand, a complex and adaptable system capable of both delicate and precise manipulation and powerful grasping of heavy objects which results by the combination of a large number of degrees of freedom (DoFs), proprioceptive and exteroceptive sensors, and a complex hierarchical architecture control [1]. However, despite this complexity, the real efforts required to the user during the daily activities are usually modest, provided that the performed task is carried out after an appropriate conscious and often unconscious training. Restoration of limb-controlling sensorimotor functions to those who lost limbs due to acute amputation is a very important and interesting field of research. External devices -namely artificial limbs- progressively more complex and technically sophisticated are available, but their use in a real world is still lacking due to several unsolved limitations. One of the crucial aspects toward effective results which needs solution is the development of suitable interfaces between the nervous system of the user and the external devices. Several approaches are possible and are currently investigated by different groups [2-4]. Among them, Kuiken et al. developed a new method based on the transferring of residual nerves of amputees to other muscles in or near the residual limb [5-6]. This approach has the interesting advantage that the nerve function correlates physiologically to the function it is controlling in the prosthesis. Therefore, the user operates in a more natural context in a logic which is easier than current EMG-based control paradigms. Moreover, the delivery of sensory feedback by using external stimulation seems to be possible [7].

However, the approach seems most suitable for subjects with a proximal amputation (shoulder or near axillary level) and it requires the use of external devices to record and stimulate without the advantage to be completely non-invasive. At the same time the use of invasive neural interfaces directly connected to the peripheral nervous system (PNS) is potentially appealing because it may provide in most cases a nearly “physiological” condition in which efferent and afferent fibers previously connected with the natural hand return to their role for limb/hand control. Several invasive PNS interfaces have been developed in the past [8]. Although most devices were originally developed for functional electrical stimulation (FES) in spinal cord injured persons [9], they can also be the key component of neuro-controlled hand prostheses. In this case, they are used to record efferent motor signals and to stimulate afferent nerves (i.e., in a complementary way with respect to FES systems) [10]. A scheme of the different PNS interfaces is given in Figure 1.

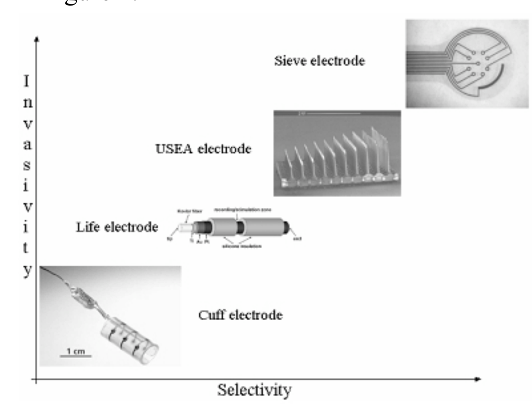

Figure 1: The characteristics of the different neural interfaces in terms of invasiveness and selectivity.

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Among them, Longitudinal intra-fascicular electrodes (LIFEs), intraneural electrodes inserted longitudinally into the nerve tissue [11], are potentially very interesting because of their selectivity of contact with specific nerve fibers and a relatively low level of invasiveness. In fact, they have been already used in the past to develop a bidirectional control of artificial devices [12-13] with very promising results during short term clinical trials with amputees. In particular, it was shown that the subjects were able to control a one degree of freedom prosthesis by processing efferent neural signals and to get a robust and reliable sensory feedback by stimulating the afferent nerves.

However, there are some important things which are not yet clear and which have to be investigated to fully understand the risk/benefits of this approach. For example it is not clear how many degrees of freedom (or different grip tasks) can be reliably extracted and controlled from efferent neural signals and whether an increased number of contact sites can improve the performance of the classifier.

To this aim, a new version of LIFEs was implanted in a right-handed male (P.P.) who suffered left arm trans-radial amputation due to a car accident 2 years ago. Results indicate that the combined used of tf-LIFEs and advanced signal processing/stimulation techniques allow to identify different grip types usable to control a prosthetic device and to deliver sensory feedback. Moreover, training and learning capabilities of human-interface interaction, together with a progressive reorganization of the input/output characteristics of the sensorimotor areas previously governing the lost limb were demonstrated.

It is important to point out that this is the first time this new version of LIFEs and the classification algorithms developed by these authors are tested with efferent ENG signals recorded from human volunteers. Previous experiments were related to afferent ENG signals recorded from anesthetized animals.

II. Materials and Methods

A. Thin-film LIFEs

A new version of the LIFEs, named the thin-film LIFEs (tfLIFE) was used in the experiments [14]. These electrodes were developed on a micropatterned polyimide substrate which was chosen because of its biocompatibility, flexibility and structural properties (see Fig. 2). tfLIFEs allow multi-unit peripheral nerve recordings at eight recording sites per structure. A tungsten needle linked to the polyimide structure is used for implanting the electrode and is removed immediately after insertion.

B. Experimental protocol

Electroneuropgraphic (ENG) and electromyographic (EMG, biceps/triceps, surface belly-tendon recordings) signals were recorded via four integrated 4-channel amplifiers (Grass QP511 Quad AC; ENG amplified: 10.000, filtered: 100 Hz - 10 kHz; EMG amplified: 5.000, filtered 30Hz - 3 kHz) and a 16 channels, 16 bit, 1 Ms/s analogue-to-digital converter. A two-channel stimulator (Grass S88X Dual Output Square Pulse Stimulator) delivered trains of cathodic 300-500 ms long pulses, with 3-250 pulses/train (10Hz to 500Hz frequency). Current intensity (10-100 µA) and duration (10-300 µs) were set in accordance with tf-LIFEs safety limits. P.P. was trained to image to perform three individual movements as shown in videos: (i) power grip; (ii) pinch grip; (iii) flexion of the little finger, each being identified by an individual trigger used during signal processing in order to discriminate voluntary activities only in the expected parts of the signal. Videos alternated immobile (2-4 s) with moving hand (movement executed in about 1 sec), and were synchronized with the recording system. Signals both from the tf-LIFEs and EMG electrodes were simultaneously recorded, sampled at 48 kHz, and mean rectified in data-windows of 1000 samples.

Immediate off-line signal evaluation identified best contacts for repeatability and high signal-to-noise ratio. Then, P.P. was asked to control its online modulation -this resulted the most efficient training protocol- and to maintain EMG activity as low as possible.

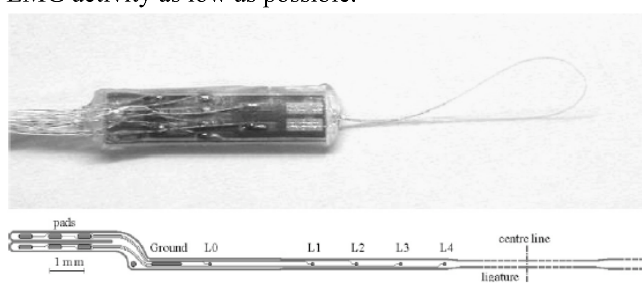

Figure 2: A tf-LIFE electrode

C. Processing algorithms

Wavelet denoising is a set of techniques for removing noise from signals and images [15]. The main idea is to transform the noisy data into an orthogonal time-frequency domain. In that domain, thresholding is applied to the coefficients to remove the noise, and the coefficients are finally transformed back into the original domain denoised. A decomposition scheme based on the translation-invariant wavelet transform [16] was used as shown in [17]. After this preliminary step an algorithm for spike detection and sorting was developed similarly to [18].

D. Classification

For each trial, the different epochs related to the different classes (e.g., grip types and rest) were labeled. Each epoch was a template that was used to train the classifier or to test its generalization skills. The feature vector was made of the ratios between the number of spikes matching each template and the total number of spikes in the epoch [19]. Therefore, the absolute spike rates were not used, but rather the relative spike rates of each waveform w.r.t. the others. This should prevent classification of the epochs based on the "quantity of activity" and favor the use of the "quality of activity" intended in terms of different waveforms for different stimuli. In order to infer the type of stimulus applied during a given epoch from the feature vector F, a classifier based on support vector machines (SVMs) [19] was used making use of the open source library LIBSVM [20]. To allow SVMs, and other binary classifiers, to handle multiclass problems, the latter must be decomposed into several binary problems. In this work we used a one-against-one approach [21]. The reason why spike sorting of signals recorded with LIFEs can produce measures which correlate with the grasping type is because it allows to identify spikes generated by different axons (or small group of axons). The signals related to different nerve fibers can be identified and extracted on the basis of the shape recorded from a multiunit recording. As different nerve fibers carry different information (e.g. which motor units to activate to perform a given grasp), spike sorting can be used to infer the grasp selected by the user.

III. Results

A. ENG processing and extraction of motor commands

The use of the walevet denoising algorithm allowed to significantly improve the quality of the signals before the spike sorting and classification. In Figure 3 an example of the effects of the denoising is given.

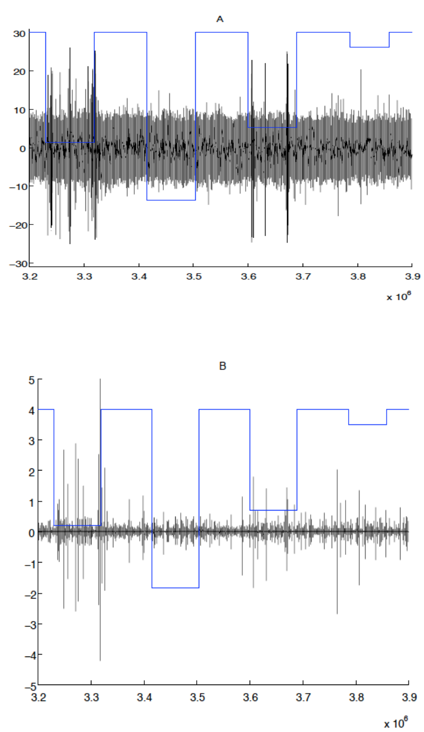

Figure 3: The ENG signals (black lines) recorded during the voluntary activities before (A) and after (B) the wavelet denoising. The blue lines represent the different classes of grips shown to the subject.

The spike sorting algorithm allowed the extraction of several classes of spikes from the neural signals. Some examples are given in Figure 4.

The occurrence of the different classes of spikes for the different grip types was used to extract the features for the classification similarly to what has been done in animal models [16].

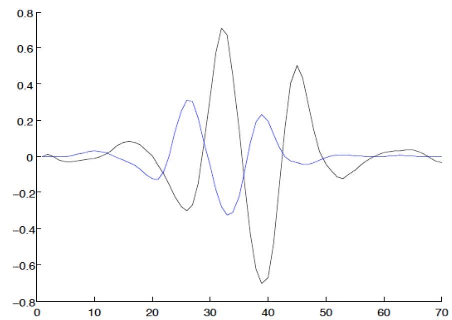

Figure 4: Two classes of spikes extracted from the motor ENG signals.

An example of this scatter plot is given in Figure 5.

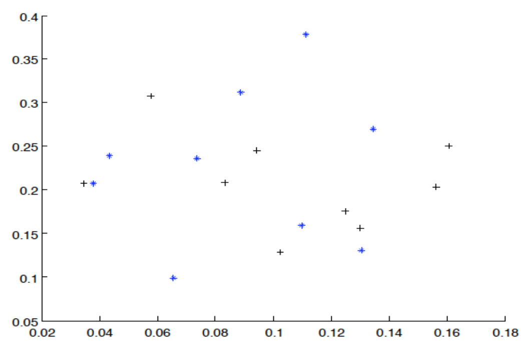

Figure 5: A scatter plot obtained by using the occurrence of the two classes of spikes for the different grip types (two in this case).

Finally, these classes of spikes were used to identify the different grip types. The results are shown in Table I.

Classes to be identified	Correct classification with the best single channel (%)	Correct classification with the best combination of channels (%)
Rest vs fist vs pinch (3 classes)	86	86 (1 channel)
Rest vs fist vs pinch vs little (4 classes)	45	**85** (12 channels)

Table I: Percentage of correct classification with one and all the channels.

B. Sensory feedback

It was also possible to deliver a sensory feedback to the user thanks to the stimulation of the afferent nerves interfaced by the tfLIFE electrode. In particular, P.P. referred tactile sensations in different parts of the phantom hand. However, it was possible to elicit these sensations only during the first week of experiments.

IV. Discussion and Conclusions

The implantation of intraneural interfaces into the PNS can allow the development of a bidirectional link between the nervous system and external devices such as artificial hand prostheses. This can be very important especially for amputees when an implantation into the CNS seems to be not acceptable (at least so far) for the limited benefits when compared with the costs. At the same time, the use of EMG signals even if interesting useful is limited by the lack of sensory feedback which can be delivered and by the possible problems connected to an unnatural use of muscular activities.

The results achieved with the implantation of tfLIFEs into the PNS of a selected amputee not only confirmed what previously achieved in terms of sensory feedback but also showed that some grip types can be identified by processing the motor neural signals. This is very interesting because it shows that a state control can be implemented asking the subject to imagine the movements without any specific (and not natural) coding of other muscular activities. It is important to point out that only three grip types were selected to avoid an excessive cognitive burden to the subject. However, because it was evident in our results some kind of learning (i.e., an improvement of the classification performance) it could be possible that more grip types could be achieved with a longer implantation period. It was also shown that an increased number of electrical contacts could be particularly important when the number of grip types to identify increases.

One of the main problems was that the delivery of sensory feedback by stimulating sensory nerves was not possible during all the 4 week implantation. This could be related to the limited charge density of the electrodes showing that microtechnology can allow the development of less invasive electrodes but with a more limited usability when compared with more standard solutions. This is an issue which needs to be investigated in the future to assure a chronic usability of this approach. A more thorough analysis of the data recorded is in progress with a particular attention also to the possible effects of the implantation in terms of cortical plasticity.

References

[1] M. Carrozza, G. Cappiello, S. Micera, B. Edin, L. Beccai, and C. Cipriani, "Design of a cybernetic hand for perception and action," Biol. Cybern, vol. 96, pp. 629–644, 2006.

[2] G. R. Muller-Putz, R. Scherer, G. Pfurtscheller, and R. Rupp, "EEGbased neuroprosthesis control: A step towards clinical practice," Neurosci. Lett., vol. 382, no. 1–2, pp. 169–174, 2005.

[3] M. A. Nicolelis, "Actions from thoughts," Nature, vol. 409, no. 6818, pp. 403–407, 2001.

[4] A. Ajiboye and R. Weir, "A heuristic fuzzy logic approach to emg pattern recognition for multifunctional prosthesis control," IEEE Trans. Neural Syst. Rehabil. Eng., vol. 13, no. 3, pp. 280–291, Sep. 2005.

[5] T. Kuiken, L. Miller, R. Lipschutz, B. Lock, K. Stubbefield, P. Marasco, P. Zhou, and G. Dumanian, "Targeted reinnervation for enhanced prosthetic arm function in a woman with a proximal amputation: A case study," *Lancet*, vol. 369, pp. 371–380, 2007.

[6] P. Zhou, M. Lowery, K. Englehart, H. Huang, G. Li, L. Hargrove, J. Dewald, and T. Kuiken, "Decoding a new neural machine interface for control of artificial limbs," J. Neurophysiol., vol. 98, pp. 2974–2982, 2007.

[7] T. Kuiken, P. Marasco, B. Lock, R. Harden, and J. Dewald, "Redirection of cutaneous sensation from the hand to the chest skin of human amputees with targeted reinnervation," in *Proc. Natl. Acad. Sci. USA*, 2007, vol. 104, pp. 20061–20066.

[8] X. Navarro, T. Krueger, N. Lago, S. Micera, T. Stieglitz, and P. Dario, "A critical review of interfaces with the peripheral nervous system for the control of neuroprostheses and hybrid bionic systems," *J. Periph. Nervous Syst.*, vol. 10, no. 3, pp. 229–258, 2005.

[9] D. Popovic and T. Sinkjaer, *Control of Movement for the Physically Disabled*. Berlin, Germany: Springer-Verlag, 2000.

[10] S. Micera, M. Carrozza, L. Beccai, F. Vecchi, and P. Dario, "Hybrid bionic systems for the replacement of hand function," *Proc. IEEE*, vol. 94, no. 9, pp. 1752–1762, Sep. 2006.

[11] K. Yoshida, K. Jovanovic, and R. Stein, "Intrafascicular electrodes for stimulation and recording from mudpuppy spinal roots," *J. Neurosci. Methods*, vol. 96, pp. 47–55, 2000.

[12] G. Dhillon, S. Lawrence, D. Hutchinson, and K. Horch, "Residual function in peripheral nerve stumps of amputees: Implications for neural control of artificial limbs," *J. Hand Surg.*, vol. 29A, no. 4, pp. 605–615, 2004.

[13] G. Dhillon and K. Horch, "Direct neural sensory feedback and control of a prosthetic arm," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 13, no. 4, pp. 468–472, Dec. 2005.

[14] K. P. Hoffmann and K. P. Koch, Final report on design consideration of tLIFE2 Fraunhofer Institute for Biomedical Engineering (IBMT), St. Ingbert , Germany, Tech. Rep., 2005.

[15] Coifman RR, Donoho DL. Translation-invariant de-noising. In: Wavelets and statistics, lecture notes in statistics. Springer-Verlag; 1995. p. 125–50.

[16] L. Citi, J. Carpaneto, K. Yoshida, K. Hoffmann, K. Koch, P. Dario, and S. Micera, "On the use of wavelet denoising and spike sorting techniques to process eng signals recorded using intra-neural electrodes," J. Neurosci Methods 2008

[17] Cortes C, Vapnik V. Support-vector networks. Mach Learn 1995;20(3):273–97.

[18] Chang CC, Lin CJ. LIBSVM: a library for support vector machines, 2001.