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Feasibility of Using Neuro-Fuzzy Subject-Specific Models for Functional Electrical Stimulation Induced Hand Movements

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Abstract: Functional Electrical Stimulation (FES) is a technique that artificially elicits muscle contractions and it is used to restore motor/sensory functions in both assistive and therapeutic applications. The use of multi-field surface electrodes is a novel popular approach in transcutaneous FES applications. Lately, hybrid systems that combine artificial neural networks and fuzzy logic have also been proposed for many applications in different areas. This paper presents the possibility of combining both approaches for obtaining subject-specific models of FES induced hand movements for grasping applications. Data of the hand and finger motion from two subjects affected by acquired brain injury were used to train two different approaches: coactive neuro-fuzzy inference system and recurrent fuzzy neural network. Preliminary results show that these approaches can be considered in modelling applications for their ability to learn and predict main characteristics of the system, as well as providing useful information from the original system that could be interpreted as subject-specific knowledge.

Keywords: Biological and medical system modelling, Neuro-prosthetics, Functional Electrical Stimulation, Fuzzy Neural Networks

1. INTRODUCTION

Functional Electrical Stimulation (FES) provides the possibility of achieving functional movements by externally delivering electrical pulses to the nervous system and eliciting muscle contractions. The main applications of FES are within the rehabilitation field, in which this technique is used to aid recovery or to restore lost or damaged sensory/motor functions (Popović et al. 2003, Kimberley et al. 2004). Unlike implanted electrodes, which require surgery to be placed and attached to the target nerves, surface electrodes are placed over the skin. They can present selectivity issues due to the complex composition of the layers between the electrodes and target nerves. Nevertheless, lately multi-field surface electrodes have become popular as they attend to reduce some of the disadvantages that surface stimulation carries, such as poor selectivity as shown by Popović-Bijelić et al. (2005) and Malešević et al. (2012). Although FES is extensively used in rehabilitation applications, its use as an assistive technology for restoring completely lost functions is still challenging in many cases, especially to reproduce complex tasks such as grasping. The main cause of this is the high complexity inherent to the human biological system and the large inter-subject physiological and pathological variances.

A wide variety of mathematical models to describe electrically stimulated musculoskeletal behaviour has been proposed throughout last decades for diverse applications such as the ones proposed by Lemay and Crago (1996), Dorgan and O'Malley (1997), or Blana et al. (2008) among others. However, most of them are complex models using many physiological parameters which are difficult to obtain in real world cases. In addition, most models are designed for very specific applications. Thus, lack of generic models for diverse FES applications and the difficulty of defining many parameters make mathematical models not very practical for real world applications.

As an alternative to mathematical models, Artificial Neural Networks (ANN) have been successfully implemented in many FES applications (Chang et al. 2009, Hincapie and Kirsch 2009, Yu et al. 2002, Malešević et al. 2010), due to their ability to learn from and predict the behaviour of complex systems. Similarly, Fuzzy Systems (FS) or Expert Systems for modelling and control have also been proposed in many FES applications, in which previous knowledge from human experts can be transferred to the FS by means of membership functions and fuzzy rules (Abdulla and Tokhi 2013, Miura 2011, Davoodi and Andrews 2004). Finally, hybrid systems that combine the advantages of these latter strategies are being proposed, taking advantage of the learning ability of ANNs and providing an intuitive manner of converting expert knowledge in terms of fuzzy rules (Micera et al. 2001, Qi et al. 1999, Hussain et al. 2011). These hybrid approaches, known as Fuzzy Neural Networks (FNN) involve different architectures. Many of them include a membership layer, as the first layer shown in Fig. 1, where the input space is divided into a predefined number of fuzzy sets. In these cases, fuzzification of input terms is carried out through membership functions (represented by A_{ij} in Fig. 1), which most common ones include triangular or Gaussian functions. During training, the parameters of such functions

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are modified in order to obtain fuzzy sets and rules that adapt to the system as explained by Jang et al. 1996.

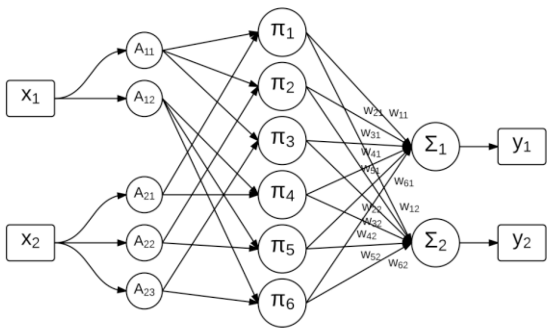

Fig. 1. Example of FNN with 2 inputs, 2 outputs and 6 rules.

In this work, we propose the possibility of using fuzzy neural networks to obtain subject-specific models of FES induced movements, in particular wrist and finger movements. For this purpose, data of the hand and finger motion from two subjects affected by acquired brain injury were used. With this hybrid approach we intend to merge the advantages of both ANN and fuzzy systems by creating models that are able to learn specific characteristics of the system while providing linguistic interpretability of fuzzy systems.

2. MATERIAL

2.1 Stimulator and electrodes

The FES device used in the trials was an enhanced version of the system presented by Velik et al. (2011) called *FES:a*, which was designed to activate 2 surface multi-field electrodes with 16 fields each and it was remotely controlled via Bluetooth. Regarding electrodes, two identical multi-field electrodes, shown in Fig. 2, were used for the stimulation of dorsal and volar sides of the forearm. Two standard single electrodes of size 50x50mm were also used as common anodes, one for each electrode matrix. The adaptation sessions were carried out by therapists, so conventional single electrodes (50x50mm) and Compex stimulator were used in these sessions as therapists were more familiar to handling this technology.

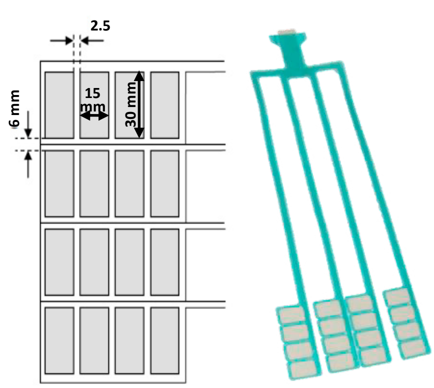

Fig. 2. Multi-field surface electrode sizes.

2.2 Sensor system

The sensor system for measuring hand motion and position consisted of a combination of two separated systems based on inertial sensors and optic fiber based sensors. For the measurement of finger flexion/extension the 5Data instrumented glove from Fifth Dimension Technologies was used. It contains 5 optic fiber sensors, one for each finger, which provided the percentage of curvature of both metacarpophalangeal and proximal interphalangeal joints with respect to a previously defined maximum value. In these trials, the maximum and minimum values were defined by the passive range of motion (PROM) measured at the beginning of the trials.

Wrist flexion/extension was measured with two 3-space wireless inertial sensors from YEI Technology, mounted on top of the glove as can be seen in Fig. 4. One of them was mounted on top of the dorsal side of the palm and the other one was mounted on the dorsal side of the forearm, close to the wrist. Euler pitch angles were collected from these sensors and their difference was taken as an approximation of wrist joint angle.

Data from all sensors were collected at 20Hz and they were all calibrated at the beginning of the session as described in next section.

3. METHODS

3.1 Data collection protocol

The objective of this pilot study was to collect data from hand movements of hemiplegic patients upon application of FES on the forearm. For this purpose, experiments were carried out in two volunteer chronic stroke patients at ADACEN (Brain Injury Association of Navarra) centre. The protocol consisted of an adaptation week to become familiar with FES and a main session held at ADACEN centre. Both participants signed the informed consent to carry out the experiment and had the cognitive ability to understand and follow the study without any difficulties. Both subjects were left side affected and time from stroke was 3 and 4 years for subject 1 and subject 2 respectively.

Adaptation sessions were held a week before the main session and consisted on daily sessions of 30 minutes of electrical stimulation carried out on dorsal (channel 1) and volar (channel 2) sides of the forearm. Electrode pairs were placed longitudinally on the forearm, with the anodes placed on the wrist and cathodes placed covering extensor/flexor muscles. Each session followed a sequence of 5s of stimulation on dorsal side of forearm, 5s on volar side of forearm and 5s of rest. All this was carried out in three phases consisting of: a) 5 minutes at 25Hz, 150μs and amplitude below motor threshold (MT); b) 20 minutes at 25Hz, 250μs, and amplitude over MT; and c) 5 minutes at 5Hz, 250μs and amplitude below MT.

After the adaptation week, a main session of around 60 minutes was carried out at the centre. A first stage consisted in donning the electrodes and sensor system on patients' arm. Electrode placement is shown in Fig. 3. One matrix electrode and its corresponding anode were placed on the dorsal side of the forearm taking the olecranon as a reference. Similarly, the second matrix electrode and its correspondent anode were placed on the volar side of the forearm taking the medial epicondyle as a reference. An elastic sleeve was put on top of the electrodes to ensure hydrogel-skin contact throughout the experiment. Finally, the instrumented glove was donned.

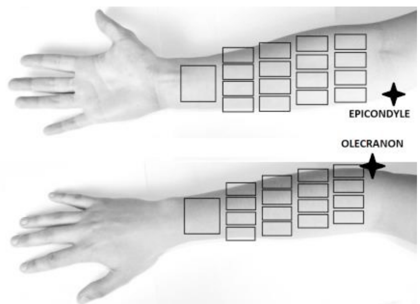

Fig. 3. Electrode placement.

After the donning stage, the calibration stage took place. At this point, the subject was seated in a chair and rested his arm on top of a table with an elbow angle of 90 degrees. The forearm was kept in neutral position and rested on top of a pillow. Firstly, PROM ranges were registered by collecting maximum extension/flexion of wrist angles and maximum and minimum flexion percentages of fingers. Correspondingly, active ranges of motion (AROM) were recorded afterwards. Finally, maximum tolerated amplitudes were registered for flexor and extensor areas by activating a single field in each area and increasing the amplitude until subject's tolerance.

The final stage consisted of data collection, for which FES parameters were fixed at 25Hz frequency and 200µs pulse width. In this phase the subject was asked to not make any voluntary movements and to relax the forearm and hand while the forearm was kept in neutral position. Stimulation consisted of 4 repetitions of randomly activating all the fields of the two electrode matrices. Each field started at 20 mA and increased in steps of 1 mA and 1 s of duration until the amplitude limit for that subject was reached. The sequence followed an order, which was activation of fields located over the extensors first and activation of fields located over the flexors next with approximately 10 seconds of rest between each field, and 1 minute of rest between the repetitions. These frequent and long resting periods were applied to avoid fatigue interfere in this preliminary study. If the subject felt discomfort at any time during the experiment, the stimulation was stopped for the corresponding forearm area and stimulation continued in the next stage.

3.2 Model training

Two different structures were trained with the same data: co-adaptive neural fuzzy inference system (CANFIS) and recurrent fuzzy neural network (RFNN). The first method is a modification of the adaptive neural fuzzy inference system (ANFIS) to allow its use in multiple output applications. It constructs fuzzy rules by adjusting Gaussian membership function parameters learned by means of an adaptive network as described by Jang et al. (1996). Similarly, RFNN also merges both FS and ANN techniques, but its architecture includes an internal recurrence in the second layer, which brings the ability of temporarily storing information, and, therefore, it is possible to deal with dynamic system applications with smaller structures than other FNNs (Lee and Teng 2000).

In order to train the fuzzy neural networks, data was codified in 3 inputs and 6 outputs. One of the inputs represented the amplitude, which was scaled to the maximum value tolerated by the subject. The other two inputs represented the position of the activated field on the arm in two planes, which were proximal-distal and medial-lateral dimensions. Proximal-distal dimension was represented by being zero the closest row to the elbow. In the case of lateral-medial dimension, data was scaled to the range (-1,1), where negative values represented fields over extensor muscles and positive values fields over flexor muscles. Zero value or reference value represented the ulna area. Regarding the outputs, 5 outputs represented each finger flexion percentage over the PROM, whereas the wrist was scaled to the range (-1,1) over the PROM, where negative and positive values represented extension and flexion angles respectively.

Once data was codified and scaled, model training was carried out with an error backpropagation learning strategy using Matlab/Simulink. Data was trained with 80% of the samples and was validated with the remaining 20%. Regarding fuzzy partition, grid partition was used, where input space term number was selected in a previous stage as 10 input terms for Subject 1 and 7 input terms for Subject 2. Membership functions consisted on Gaussian functions and they were uniformly distributed throughout the input space on initialization. Additionally, an approach with an output feedback was tested with both structures, where an additional input was added for providing previous output information to the network. In this case, only one output feedback was used to avoid network size increase, and wrist feedback was selected as it was considered to carry the most important information regarding hand kinematics. The scheme showing the tested approaches is shown in Fig. 4.

4. RESULTS

4.1 Identification without feedback

Training the CANFIS and RFNN systems without any feedback information resulted in the behaviour shown in the examples in Fig. 5 and Fig. 6, which represent training and validation periods respectively. In order the figures to be understandable, only two of the five outputs, and a portion of the data sets are shown. Both approaches were able to reproduce the system outputs properly, although some peaks were present during the learning phase, and were much more prominent in the CANFIS case. Regarding the validation case, RFNN showed higher variation than CANFIS, as shown in Fig. 6, and although these variations were overestimated, it can be said that in overall RFNN captured the system characteristics slightly better than the CANFIS. Table 1 and Table 2 show the mean square errors (MSE) of the scaled values of CANFIS and RFNN results respectively. We can see that higher peak values of CANFIS in the learning period resulted in higher MSE errors, whereas differences in terms of error were small and dependent on subject and output type in the case of validation phase.

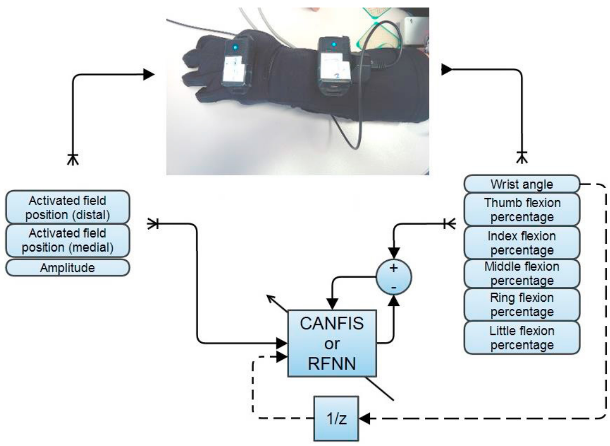

Fig. 4. Identification approach scheme, with dashed line representing wrist output feedback.

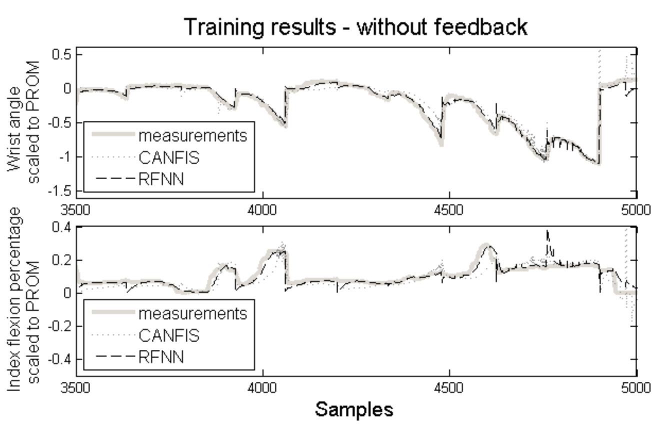

Fig. 5. Training outputs of wrist and index with Subject 1.

4.2 Identification with wrist feedback

Training the CANFIS and RFNN systems with the wrist feedback information resulted in the behaviour shown in the examples in Fig. 7 and Fig. 8, which represent training and validation periods respectively. Once more, training phase was properly reproduced by both structures, and the peak values produced by CANFIS had lower values than before. Regarding validation phase, in this case RFNN presented small variation and did not represent the system characteristics properly, whereas, CANFIS showed greater variation but it was either overestimating or underestimating the outputs, especially in the latest periods of the validation phase. Table 3 and Table 4 show the MSE values of the scaled values of CANFIS and RFNN results respectively. Once again, peak values of CANFIS in the learning period resulted in higher MSE errors. In the validation period, RFNN showed smaller MSE values for all outputs and both subjects, however, as already mentioned, it was not able to capture the system characteristics properly.

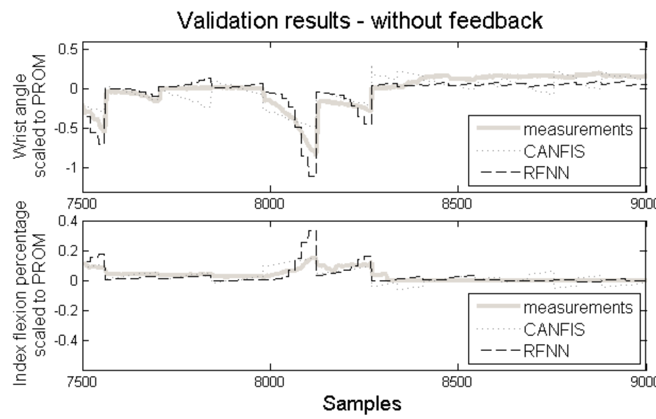

Fig. 6. Validation results of wrist and index with Subject 1.

Table 1. MSE errors of CANFIS system

Subj.	Wrist	Thumb	Index	Middle	Ring	Little
Training						
1	1.0166	0.0154	1.0665	0.0160	0.0625	0.5526
2	0.0796	0.3702	2.2323	4.923	0.7771	4.2618
Validation						
1	0.0143	0.0004	0.0012	0.0001	0.0035	0.0058
2	0.0169	0.0005	0.0056	0.0004	0.0009	0.0015

Table 2. MSE errors of RFNN system

Subj.	Wrist	Thumb	Index	Middle	Ring	Little
Training						
1	0.0041	0.0004	0.0031	0.0011	0.0014	0.0017
2	0.001	0.0009	0.0013	0.0038	0.0004	0.0018
Validation						
1	0.0123	0.0005	0.0014	0.0003	0.0005	0.0034
2	0.0238	0.0003	0.0082	0.0024	0.0003	0.0059

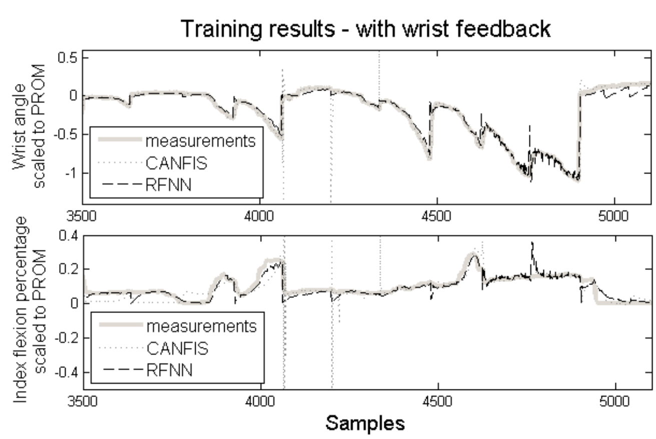

Fig. 7. Training outputs of wrist and index with Subject 1 with wrist feedback.

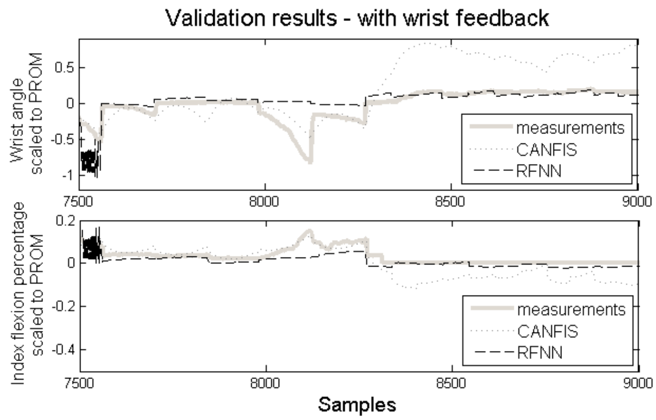

Fig. 8. Validation outputs of wrist and index with Subject 1 with wrist feedback.

Table 3. MSE errors of CANFIS system

Subj.	Wrist	Thumb	Index	Middle	Ring	Little
Training						
1	0.0108	0.0634	0.5291	0.2514	0.1791	0.1721
2	0.0007	0.0024	0.2550	1.3505	0.2805	1.5714
Validation						
1	0.1411	0.0036	0.0028	0.0003	0.0024	0.0061
2	4.96	0.1113	0.0041	0.0050	0.0228	0.0535

Table 4. MSE errors of RFNN system

Subj.	Wrist	Thumb	Index	Middle	Ring	Little
Training						
1	0.0029	0.0003	0.003	0.001	0.0011	0.0016
2	0.001	0.0008	0.0011	0.0032	0.0004	0.0016
Validation						
1	0.0356	0.0005	0.0008	0.0002	0.0004	0.0045
2	0.0136	0.0004	0.0126	0.0067	0.0005	0.0082

4.3 Membership functions

As described in the introduction section, FNNs have the ability to adjust membership function parameters to adapt them to the system. In this case, means and standard deviations of initially uniformly distributed Gaussian functions were adjusted in order to adapt to this specific case. This type of information can bring clues and knowledge about the system that is being analysed.

Membership functions will tend to expand in order to wrap those values which lead to similar results, whereas they will tend to become narrower to differentiate between values that lead to distinct results. As an illustration, the resulting 10 membership functions for each input after training with Subject 1 are shown in Fig. 9. For example, one of the membership functions that represent distal position has extended almost from elbow to middle forearm, which can mean that similar movements are achieved when any field located in this area is active. Lateral position shows similar behaviour on the extensors side. Conversely, membership functions that represent distal position from middle forearm to wrist and lateral position on the flexors side are slightly narrower. This fact tells us that Subject 1 has higher selectivity of FES induced movements on flexors than on extensors and, similarly, on the distal part of the forearm than on the proximal part of the forearm. In the case of stimulation amplitude, different membership functions tend to merge and become narrower around the motor threshold, whereas one of the membership function becomes very wide, representing the lack of movement that is common to these lower values. It should be noted that membership functions that represent amplitudes from 0 to 20mA (0-0.5) do not change because those values were not present in the data used for training.

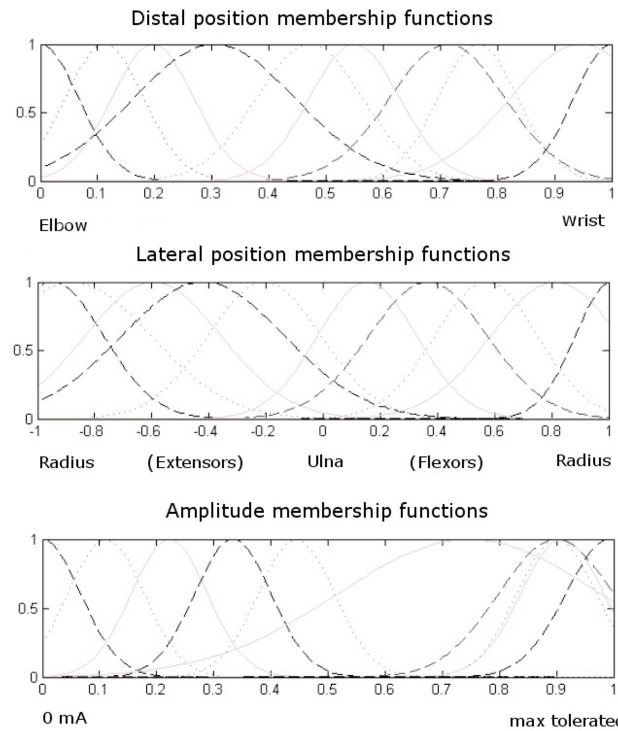

Fig. 9. Membership functions after training Subject 1.

5. DISCUSSION

The aim of this paper was to suggest the use of fuzzy neural networks in the identification and modelling of FES applications, in particular those involving hand movements. Two approaches and two structures were tested and although wrist feedback structure showed worse results on the validation phase, in these preliminary results, all cases showed the ability to learn main characteristics from data recorded from subjects, at least on the training phase. The main advantage of the presented systems is the ability to extract combined physiological and stimulation features and to transform them into membership functions that can be interpreted in an easy manner. Like this, subject-specific models and knowledge can be acquired from a single data-recording session, which can later be analysed or used as a support for the design of subject-specific neuroprostheses, design of control systems, simulations, etc. Additionally, it can be useful for visually and easily comparing inter-subject, inter-session or inter-pathology variability among others. Although this study has focused on hand movements, the presented approach could easily be adapted to elbow and shoulder movements for FES reaching and grasping applications.

These preliminary results show that fuzzy neural networks in combination with novel multi-field electrodes can be a promising branch that could help in the development of surface neuroprostheses. Future work should include a deeper analysis on the architecture, feedback approaches, parameter tuning and learning strategies and their effect into the different models' performance. Next steps could also involve fatigue induced trials, and inter-session trials, to study the ability of the system to learn these dynamic properties.

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