Grasp control of a prosthetic hand through peripheral neural signals

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Abstract. The use of neural electrodes to stimulate the Peripheral Nervous System (PNS) of upper limb amputees is giving promising results in restoring tactile feedback. The same interfaces could be used to record the motor activity originated from the brain and transferred to the muscles. In this paper, the possibility to control a prosthetic hand by means of neural signals acquired through tf-LIFE4 electrodes implanted in a human subject was investigated. A Support Vector Machine (SVM) algorithm was adopted to classify two common demanded grasps. The obtained classes were converted into reference positions for a position-and-slippage control strategy that guarantees to perform stable grasps with a prosthetic hand avoiding slippage events. The achieved results showed an accuracy of the classifier higher than 90% and a success rate of the control strategy equal to 100%.

1. Introduction
In the development of prosthetic hands, to take into account the prosthesis user needs is of paramount importance. The analysis of user priorities [1] revealed that two of the most desired features are an intuitive and reliable interface and to perform stable grasps avoiding slippage events.

The most commonly adopted interfaces between the user and the prosthetic device are the electromyographic (EMG) sensors. In fact, commercially available prosthetic hands operate under EMG signals without providing any type of sensory feedback to the user [1], [2]. Invasive neural interfaces allow to restore the bidirectional communication with the central nervous system and to re-establish a physiological control of prosthetic hand thanks to the high level of selectivity. The activity of the nerve fibers can be detected from the fascicle originally innervating the missing limb and used to control an artificial hand [3][4]. The main problems of using the neural signal (ENG) to control a prosthetic hand are related to the low amplitude of the signal, the crosstalk with the muscular activity and the electrical interference in such low amplitude source [5]. All these problems reduce the quality of the ENG signal and make it difficult to extract user intentions from it.

In the literature, force control approaches were proposed to ensure stability during grasp. For instance, in [6], a PI force control was used with a velocity inner loop, in [7] a force control based on a neural network was developed to compensate the non-linearity of hardware components. The main limitations of these approaches are that they cannot hinder the possible object slippage. It was proved that the introduction of slippage information improves the grasp stability [8], [9], [10].
This paper aims at i) investigating the use of ENG signals to control a prosthetic hand by adopting the same pattern recognition techniques applied to EMG signals; ii) proposing and testing on a real prosthetic hand, i.e. the IH2 Azzurra, a position-and-slippage control approach able to move the hand in the desired configuration managing slippage events. The motion commands (i.e. classes related to power and pinch grasps) obtained from the pattern recognition algorithm are converted into reference positions to be given in input to the control strategy.

The paper is structured as follows: in section 2, the methods adopted for collecting and processing data and the control strategy are described; in section 3, the results are shown and discussed. Finally, in section 4 conclusion and future work are reported.

2. Methods and materials

2.1. Data recording and ENG classification

ENG data were acquired from tf-LIFE4 intraneural electrodes inserted longitudinally in the median and ulnar nerve of a male amputee during a human experimentation that took place in Rome in 2009 [3]. The study was approved by the local Ethics Committee and the competent Ministry. Data were recorded by means of the Grass QP511 Quad AC, amplified by 10000 and filtered between 100 Hz and 10000 Hz. The sampling frequency was set to 48000 Hz. Data acquired during the execution of power and pinch grasps were used in the following analysis.

In order to compute the envelope of the neural recordings, the data were filtered with a 4-th order Butterworth filter between 700 Hz and 5000 Hz. The sampling frequency was set to 10000 Hz. Data acquired during the execution of power and pinch grasps were used in the following analysis.

To enhance the presence of spikes inside the recording, the energy E is computed as

\[ E[i] = \frac{1}{W} \sum_{i-W/2}^{i+W/2} (x_i - \bar{x}_m)^2 \]

where \( W \) is the length in samples of the window in which the energy is computed and \( \bar{x}_m \) is the signal mean value [11]. In this work, the window \( W \) is set to 120 samples. Secondly, an amplitude threshold was used to detect the spikes. It was computed by means of the standard deviation of the entire signal, calculated from the Mean Absolute Deviation [12], multiplied by a constant factor set to 9 [13]. The \( W \) and the constant factor values are experimentally retrieved to reduce false positives and false negatives thus improving the algorithm performance. Once the amplitudes A and the time bins T of the spikes were saved, they were used to compute the envelope of the ENG according to the formula

\[ e\text{ENG}[i] = \frac{\alpha A_i + \beta A_{i+1}}{2} e^{-\frac{T_{i+1}}{T_i}} \]

where \( \alpha \) and \( \beta \) are weight factors between 0 and 1. In [13] it was shown that, imposing \( \alpha = 0.5 \) and \( \beta = 0.4 \), it is possible to highly correlate the EMG and ENG envelope concurrently recorded. The ENG was classified by means of the Support Vector Machine (SVM) algorithm implemented in Matlab using the libsvm 3.22 library, available online. The Root Mean Square (RMS) features were extracted from a windowed portion of the recorded signals. The obtained vector of features was segmented in two sets, the Training (TRs = 75%) and the Cross-Validation set (CVs = 25%). The SVM was optimized varying the C and \( \gamma \) parameters from \( 2^0 \) to \( 2^{10} \) and from 0.1 to 3 respectively [14]. Every time the training is performed by means of the TRs with a defined pair (C, \( \gamma \)), the generated model is tested via the CVs. The pair (C, \( \gamma \)) that guarantees the highest accuracy is applied to the testing data.

2.2. Control law

A position-and-slippage control strategy was implemented. The control scheme adopted for each finger of the prosthetic hand is shown in Figure 1. The control aims at using the class from the
classifier for moving the hand fingers to reach the desired position (a priori known) [15] by online compensating for possible object slippage. The information about the object slippage are obtained by applying the slippage detection algorithm proposed in [10] on the voltage information obtained by Force Sensing Resistor (FSR) sensors positioned on the thumb and index fingertips. The control approach has been adapted for underactuated fingers. The voltage measured by the FSR sensors was converted in force values after an appropriate sensor calibration. These force signals were constantly monitored during the trials in order to avoid breaking the grasped object.

![Figure 1. Block scheme of the control strategy applied to one underactuated finger.](image)

In Figure 1, \( x_{d_i} \) represents the reference position to be reached by the \( i \)-th hand finger, \( e_{x_i} \) is the position error for the \( i \)-th finger slider obtained from a Proportional-Integrative (PI) position control

\[
e_{x_i} = x_{d_i} + e_{s_i} - x_i,
\]

\( x_i \) is the actual position derived from the hand position sensors, \( K_{p1} \) and \( K_{p2} \) are the controller gains, \( K_{p3} \) is a constant that regulates the weight a slip-dependent additional contribution \( e_{s_i} \) has in the control. This additional contribution has the aim of managing slippage events [8], and is expressed as

\[
e_{s_i} = K_{p1} \int_0^{t_f} \alpha \, dt.
\]

\( \alpha \) is the binary signal equal to 0 if slip does not occur and equal to 1 when slip occurs and \( t_f \) is the final integration time. The integration of this signal will guarantee a smooth increment of the applied grasping force in presence of slippage, as demonstrated in [8]. The obtained position error \( e_{x_i} \) should be led to zero by a Proportional-Derivative (PD) control in the slider space described by the equation

\[
u = r [K_{p4} e_{x_i} - K_{d1} \dot{x}].
\]

where \( r \) is the vector of the pulley radii, \( K_{p4} \) is the proportional gain, \( K_{d1} \) is the derivative gain and \( x, \dot{x} \) and \( \ddot{x} \) are the slider position, velocity and acceleration, respectively [16].

### 2.3. Setup and experimental protocol

The proposed architecture was tested on the IH2 Azzurra anthropomorphic robotic hand [17] (Figure 2a). The 5-finger robotic hand has 11 Degrees of Freedom (DoFs), 5 of which are active. A slider located in the hand palm is responsible for the Flexion/Extension (F/E) of each underactuated finger, whereas a universal joint is used for linking the thumb Adduction/Abduction (A/A) motor, positioned in the palm, to the TM joint. The finger position is measured by means of an incremental encoder.

FSR sensors were glued on the thumb and on the index fingertips that were covered with silicon material simulating a cosmetic glove (Figure 2a). In particular, the silicon material was molten on a 3D printed model of the fingers. The obtained silicon cups were placed onto each fingertip to cover and protect the surface of the FSRs. The slippage events were detected in real-time by applying the slippage detection algorithm proposed in [10] to the voltage signal acquired by the FSR sensors positioned on the thumb and index fingertips.

The testing sets are represented by 10 acquisitions (named T1 to T10) in which the power grasp and pinch grasp were randomly performed. To increase the performance of the classifier, a voting system was applied. Instead of classifying one sample per time, the predicted class is obtained by
counting the highest number of the predicted class in a span of 5 predictions. Even if it slows the classification, it is a way to improve dramatically the performance of the classifier.

The obtained classes are converted in reference position to be given in input to the prosthesis control. The control strategy was experimentally tested on the IH2 Azzurra prosthetic hand. The following objects were grasped by the hand with a pinch and a power grasp, respectively: a ball of 35mm diameter and a glass of 75 mm diameter. The objects to be grasped were located in front of the hand, which was positioned on a support. Once grasped, 4 slippage events were induced to the grasped object by applying an impulsive force to the objects. Ten repetitions of the same grasping action were performed. The starting A/A angle of the thumb was imposed on the basis of the human being behaviour [18]. In particular, for the pinch grasp, it was set to 1.656 rad and for the power grasp it was set to 1.845 rad. The finger controller was implemented in C programming language under Windows 10. The communication between the hand and the PC was performed by means of an USB port. The gains of the position control were imposed equal to \( K_{p1} = 1, K_{p2} = 4, K_{p3} = 80, K_{p4} = 0.1, K_{d1} = 0.004 \).

3. Experimental results

The training process of the classifier was able to identify a pair \((C, \gamma)\) that maximizes the accuracy of the CVs. In particular, the pair chosen and later used for the Testing set is \((2^{10}, 0.47)\). Once the model for the SVM was generated with these values, the classification algorithm was applied to the Testing sets. The accuracy ranged from 86.67% (T2) to 92.67% (T5). The total accuracy of the classifier across the tests is 90.13% ± 2.24%.

In Figure 2 and Figure 3, the results obtained on two representative grasping trials (corresponding to the two classified grasping configurations, i.e. pinch and power grasps) are shown.

In particular, the grasping configurations are shown in Figure 2a and in Figure 3a. In Figure 2b and in Figure 3b, the detected slippage events, the hand joint angles and the grasping class are reported for the pinch and the power grasp, respectively. It is important to outline that grasping forces are acquired from the sensors placed on both the fingers, i.e. thumb and index. From the reported plots it is possible to note that, when the object slippage is detected by the sensor embedded in the index and/or in the thumb fingertips (outlined in blue and in red in the top of Figure 2a and of Figure 3a, respectively), a variation of the F/E angle of the index Metacarpophalangeal (MCP) joint and of the thumb Trapeziometacarpal (TM) joint occurs, as evident in the zoomed part of the signal in Figure 3b and in Figure 4b. The 20 grasping trials were performed with a success rate (i.e. ratio between the number of
compensated slippage events and the number of trials) of 100%. Therefore, it is possible to conclude that the proposed control approach guarantees a stable grasp also in presence of unforeseen events.

![Figure 3](image.png)

**Figure 3.** (a) Grasping configuration. (b) Detected slippage events (the slippage event detected by the sensor positioned on the index finger is shown in blue, whereas the one detected by the thumb is in red), hand joint angles (the different colours correspond to the different fingers), grasping class (i.e. output of the classification algorithm).

### 4. Conclusion

In this paper the feasibility to use neural signals to control a prosthetic hand was demonstrated. The neural signals were processed to obtain their envelopes in order to reduce the variability of the raw signals. The proposed approach allows the ENG envelope to be treated as the EMG one, a signal that is more commonly used in pattern recognition. The classified gestures (i.e. power and pinch grasps) were given in input to a position-and-slippage control architecture applied on a prosthetic hand. The obtained results showed an accuracy of the classifier above 90% and a success rate of the proposed position-and-slippage control strategy of 100%. Future work will be devoted to increase the number of detected and classified hand gestures and to include the patient in the control loop by giving him/her the possibility to actively control the grasping force.

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