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# Personalized Movement Algorithms for Neural Forearm Prostheses Using Convolutional Neural Networks

Sorin LAZARESCU[1], Florin ISTUDOR[2,*], Octavian IONESCU[3,4], David DRAGOMIR[4], Marian ION[4], Ladislau SZÉKELY[5], Szilárd OLASZ[5], István TÜSEZ[5], Gabriela IONESCU[3], Stefanos P. ZAOUTSOS[6], Cătălin NICULAE[7], and Bogdan SINATOMA[7]

[1]University of Medicine and Pharmacy "Carol Davila", Bd. Eroii Sanitari 8, Bucharest, Romania
[2]National University of Science and Technology Politehnica, Bucharest, Romania
[3]Faculty of Mechanical and Electrical Engineering, Petroleum-Gas University of Ploiesti, Romania
[4]IMT Bucharest, Str. Erou Iancu Nicolae 126A, Bucharest, Romania
[5]Osteopharm, Târgu Mureș, Romania
[6]University of Thessaly, Str. Argonauts & Filellinon, 38221 Volos, Greece
[7]AREUS Technology, Bucharest, Romania

Email: sorin.lazarescu@drd.umfcd.ro, florin.istudor@upb.ro*, octavian.ionesc@imt.ro, david.dragomir@imt.ro, marian.ion@imt.ro, szekely.laszlo@osteopharm.ro, szilard.olasz@osteophram.ro, istvan.tuzes@osteopharm.ro, gabriela.ionescu@upg.ro, szaoutsos@uth.gr, catalin.niculae@areusdev.ro, bogdan.sintoma@areusdev.ro
* Corresponding author

**Abstract.** The article presents personalized movement algorithms for neural forearm prostheses equipped with AI module. The implementation of personalized motion algorithms is done by using a glove with finger flexion sensors mounted on the patient's healthy hand, a neural interface with plug electrodes implanted in the motor fascicles of the median and ulnar nerves from the patient's amputation stump and an AI module based on a convolutional neural network (CNN). For each prosthesis movement selected by the patient, the glove will detect the movement parameters of the fingers from the healthy hand, the neural interface will detect the motor neural signals from the median and ulnar nerves, and the CNN will identify the specific pattern of motor neural signals. The AI module will thus learn to recognize the patient's commands for the prosthesis and will command its natural movements.

**Key-words:** Convolutional neural networks; implantable neural interface; movement algorithms; neural prostheses.

# 1. Introduction

Arms are essential for healthy humans in most activities. The distinct movement a healthy human performs with his arms proves such motion to be coordinated by half of the brain motor centres. Total or partial amputation of an upper limb is one of the most devastating situations a human being can face [1]. At international level, the number of people who had undergone forearm amputations is not precisely known, but 2018 statistics from disability patient organizations in the US estimate that 185,000 amputations are performed in the United States each year [2].

Statistics in recent years show that the number of people with amputated arms worldwide is alarmingly high and it is constantly increasing: 450,000 people in 2018 in the U.S. [2], 45,000 people in the UK [3]. Advanced Amputee Solutions forecasts that the number of people with amputated limbs in USA will reach 3,600,000 by 2050 [4]. The actual situation of such numerous people is difficult and constitutes a real concern. The high and ever-growing number of people with amputated arms [4] indicates both an acute global problem, and a potentially high market demand [5]. Such patients are confronted with great difficulties both in finding a job, for getting themselves reintegrated into society, and in performing daily personal hygiene activities, nutrition, etc., being often dependent on the financial support of their family and the government.

Many of the movement skills are lost during amputation and cannot be restored to the patients even by the most advanced prostheses on the market. The movements of the fingers of a healthy hand are controlled by 22 muscles, and only 8 muscles usually remain during a forearm amputation surgery. The muscles remaining after the amputation could only control a limited range of finger movements, and it is difficult for the patient to learn to use them to control other movements of the fingers of the prosthesis this time. For each movement of the prosthesis, the patient must generate two different signals each time he wants to perform that movement with the prosthesis: a myoelectric signal from one muscle group to start the motors and another myoelectric signal from another muscle group to stop the motors and return the fingers to their original position [6, 7]. With only a few muscles remaining in the amputated stump (after the amputation surgery), the patient cannot generate too many distinct myoelectric signals in order to be able to use all the movements available with myoelectric prostheses. Some myoelectric gates offer 20 movements, but patients can use only 4 or at most 5 of these movements. Because of the atypical muscle contractions they use, the patients have also some difficulties in passing from one movement of the prosthesis to another. Signals acquired from the existing muscles in the stump can be used to control the movements of the prosthesis only after the amputee has developed new skills in associating the old neural commands (which were used for other movements) with the new desired movements of the prosthesis. This training is difficult and takes a long time, because amputees have to develop new neural maps in the brain and neural reflexes in the spinal cord, etc. Unlike myoelectric prostheses, neural prostheses are intended to be controlled by the patient with neural motor signals acquired from the stump nerves (which remain the same after amputation). These signals are not completely affected by the amputation, as they are directly related to the brain activity that controls the movements. Therefore, the neural signals of an amputated limb contain all the information related to a movement: range, speed, direction, etc. If one has have access to this information, one may reconstruct a wide variety of movements.

These aspects formed the basis for the design and manufacture within the NerveRepack project of a neural forearm prosthesis, which offers patients more motor functions compared to myoelectrical prostheses. In the following section it is described the neural controlled prosthesis from the NerveRepack project.

## 2. The NerveRepack Neural Prosthesis

The NerveRepack prosthesis is different from all existing prosthesis on the market, because it is controlled with neural signals from the patient's stump. The general concept of the NerveRepack neural prosthesis is presented in Fig. 1.

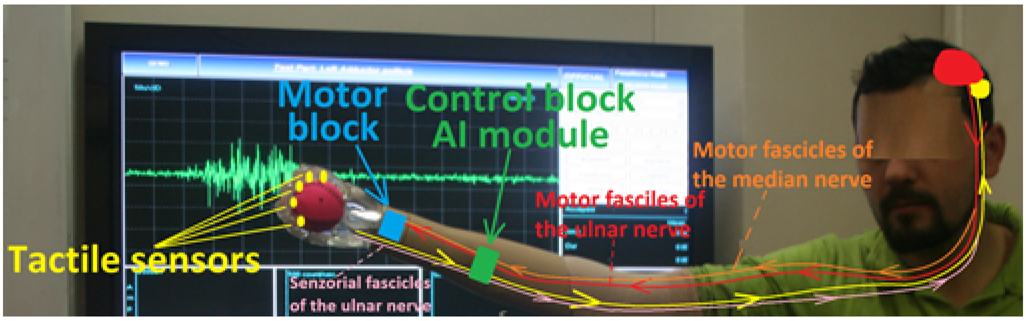


**Fig. 1.** The neural command chain for controlling the neural-exoprosthesis.

The NerveRepack prosthesis has a bidirectional connection with the peripherical nervous system of the patient, ensured by plug electrodes implanted in the patient's stump. The plug electrodes contain two types of needles:

- Motor needles for acquiring neural signals from the motor fascicles of the median and ulnar nerves from the patient stump; these signals are sent via wifi to the prosthesis control system and will control the movements of its finger;
- Sensorial needles for stimulating the sensorial fascicles of the patient's median and ulnar nerves with signals from the pressure sensors mounted on the prosthesis fingers, and generating tactile sensations to the patient.

The plug electrodes and neural interface from the NerveRepack project are presented in detail in [8]. What is specific about the plug electrodes is that they contain several 50-micron diameter needles that are surgically inserted into the motor fascicles of the median and ulnar nerves from the patient's amputation stump and collect his motor signals, which then are transmitted via wifi by the neural interface to the prosthesis to control its movements [8]. The neural signals from the patient's stump will be acquired with the implanted electrodes and are used for the movement algorithms.

## 3. The Module for Generating Movement Algorithms

The NerveRepack neural prosthesis is equipped with a module for generating personalized movement algorithms. This module contains a Convolutional Neural Network (CNN) that is trained with neural signal patterns that are acquired from the median and ulnar nerves from the patient's stump. This module learns to recognize the commands from the patient's brain for each type of movement of the prosthetic fingers. It requires special learning sessions for the patient to adapt to the new prosthesis.

Each type of movement of a healthy arm is controlled by specific trains of signals from the median and ulnar nerves. The characteristics of these trains of signals are different for each type of movement. The train of signals from the median and ulnar nerves are the same every time the patient makes the same movement with his healthy arm (palm and fingers). After amputation, the train of signals from the stump's nerves are the same as before amputation, when the arm was healthy. The neural signals from his both arms nerves (median and ulnar nerves) will have the same characteristics and will be specific for each selected movement for prosthesis.

The patient performs this training after the neural interface implantation surgery in his/her amputation stump. During this training, the patient uses a special glove (5DT Data Glove Ultra) equipped with flexion sensors for fingers, that is mounted on his/her healthy hand. The patient triggers in his brain the same movement simultaneously for the fingers of both hands. Data about the movement of the fingers of the healthy hand are collected by the glove mounted on this hand, and the motor neural signal patterns from the median and ulnar nerves from the amputation stump are collected by the plug electrodes, implanted in the amputated forearm. During this training session, the movements of the patient healthy fingers must be performed with the same speed. If the patient changes the speed of the fingers' movements, the data (trains of signals) that are acquired with the implanted electrodes from the median and ulnar nerves, are not included in the data base for CNN (Fig. 2). The CNN can be trained properly only if it receives at its entries correct labeled data for each movement. After this training session, the module is able to recognize the patient brain command for that movement, and commands the motors of the prosthesis in such way that its fingers perform the selected movement like the patient healthy fingers.

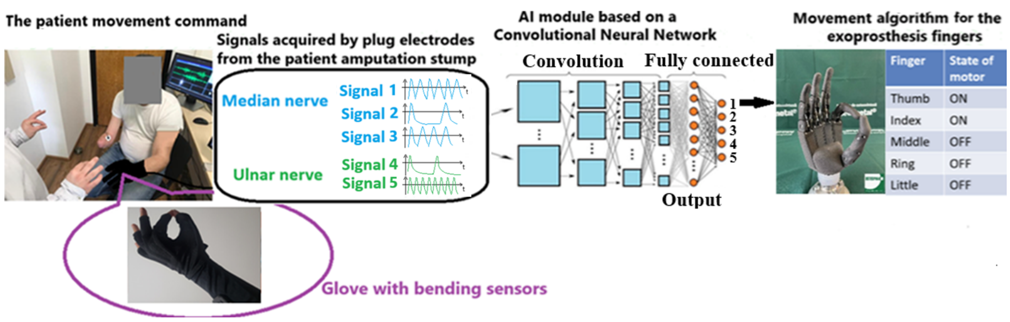


**Fig. 2.** The training session of the CNN with specific neural signals pattern for each prosthesis movement.

The number of movements that the neural prosthesis can provide to the patient depends on the configuration of the plug electrodes that will be implanted in the patient's median and ulnar nerves. For the NerveRepack neural prosthesis, the plug electrodes for the median nerve have 3 needles and the plug electrodes for the ulnar nerve have 2 needles (Fig. 3).

For the plug electrodes configuration mentioned in Fig. 2, Fig. 3 and Fig. 4, the total number of distinct movements that can be implemented in the AI module of the NerveRepack neural prosthesis is given in the next formula:

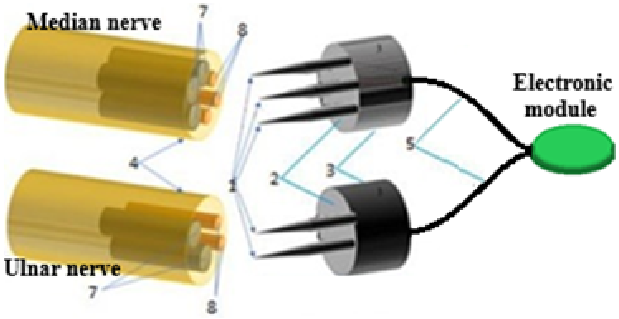


**Fig. 3.** Schematic representation of the plug electrodes, median and ulnar nerve; (1) needles electrodes for motor neural fascicles; (2) support for fixing the needle electrodes; (3) guide tube; (4) epinerve; (5) conductive wires covered with biocompatible material; (6) electronic module of the implantable system; (7) motor neural fascicles; (8) sensorial neural fascicles.

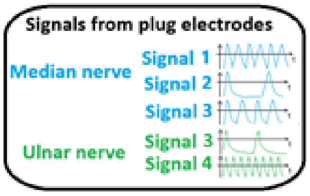


**Fig. 4.** General representation of the signals acquired from median and ulnar nerves.

$$N_{mvm} = \sum_{i=1}^{5} C_5^i = 31 \tag{1}$$

It is observed that a neural interface with only 3 motor needles for the median nerve and 2 motor needles for the ulnar nerve offers the neural prosthesis 31 different movements that the patient can command with his natural brain commands that he had before the amputation and which he can also use to command the prosthesis. The patient therefore does not have to learn how to generate other neural commands to command the prosthesis but uses the commands that he knows and has in his memory.

## 4. Tests and Results

The AI module implementation was done on an FPGA platform Basys3and a 5DT Data Glove Ultra was used (Fig. 5). The glove has the following specifications: 5 Sensors in total; 1 Sensor per finger, measures average of knuckle and first joint; Full-speed USB 1.1; RS-232 (via serial interface kit); Via USB Interface; Minimum 75Hz [8]. The board Basys3, contains XC7A35T-1CPG236C FPGA, ARTIX-7 FPGA with great specifications for the task at hand. Being a computationally heavy task, the most important devices are the DSPs (Digital Signal Processors). The FPGAs contains 90 such DSPs, that can perform up to 929 GMAC/s (for ideal symmetrical filter implementation). Realistically, in any general application, the DSP may perform between 2 to 8 MFLOPS, which is still an acceptable rate. The implementation of this architecture, on the FPGA, results in an inference time of approximately 20ms, for the aforementioned input image size (5 x 3000).

**Fig. 5.** The glove's interface for acquiring the fingers' movements parameters.

The neural network contains a single convolutional layer, followed by a feature map activation layer and a classification layer. The implemented version has two hidden layers and 32 output classes (one for each possible combination finger flex / extension). The glove sends the angular position of each finger through a USB interface, thus allowing us to determine if a finger is either flexed or extended, by setting up a threshold. In the following images, the variation of the glove data can be observed through the real time plots. Fig. 6 shows the signals generated by the glove for 2 distinct movements (grabbing a spherical object and gripping a pen).

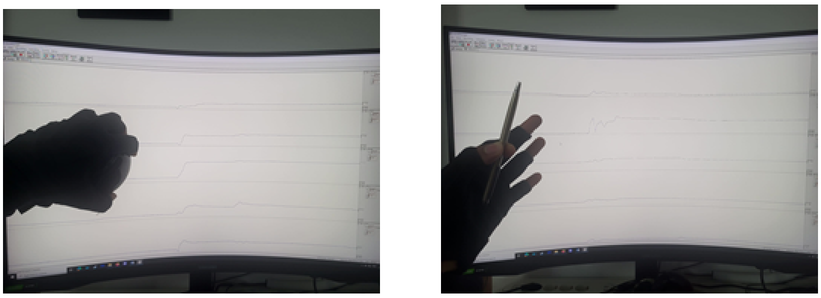

**Fig. 6.** Signals generated by the glove for grasping two different objects: a glass and a pen.

Each of the five sensors generate an analog voltage level, which is converted and transmitted through a serial interface to the controller. The raw angular position of each finger is a 12bit value, where 0 represents complete extension and 4095 represents complete flexure. Fig. 6 shows this behavior, as flexing a finger causes its raw value to increase. The algorithm continuously reads the angular position of fingers through the serial interface and saves each value to an internal register. Because the anatomy of the hand differs greatly from user to user, the authors have also implemented an autocalibration system, which records the minimum values and maximum values for each finger and stretches this interval to [0,4095], to make use of all available values. To determine whether a finger is flexed or not, the respective angular position was compared with a threshold. This threshold can be modified depending on the user. If the angular position

**Table 1.** Different configurations of finger state depending on the movement

| Movement | | State (Movement direction) | | | | |
|---|---|---|---|---|---|---|
| | | Thumb | Index | Middle | Ring | Little |
| Pinch |  | 1 (1) | 1 (1) | 0 (-1) | 0 (-1) | 0 (-1) |
| Fist |  | 1 (1) | 1 (1) | 1 (1) | 1 (1) | 1 (1) |
| Extension |  | 0 (-1) | 0 (-1) | 0 (-1) | 0 (-1) | 0 (-1) |

of finger is greater than this threshold, then the respective finger is considered to be flexed, otherwise it is considered to be extended. The state of a certain finger is represented through a 1bit value (0 – extended; 1 – flexed). If the state changes at any point, this triggers the movement of the prosthesis: the finger whose state was changed will move according to the new state. For example, if the index finger was previously flexed and is extended, then the prosthesis will extend the index finger. Movement of the exo-prosthesis is done through setting two parameters for each finger: the direction of movement (which is directly correlated to the state mention in the previous paragraph) and the speed of the movement (angular velocity of the motors). In this first iteration of the algorithm, the authors have used constant angular speed. The configuration of the finger state variables and the direction of movement can be observed in Table 1.

Upon realizing a command, it is saved in the available command list. This list will help the exo-prosthesis user in shaping personalized movements, by practicing the same movement, in both the healthy and the amputated arm. By correlating the position of the glove with the parameters extracted from the neural signals, the user can associate certain neural activity in the ulnar and median nerve with a certain movement of the glove, which will be mimicked by the exo-prosthesis, through the proposed algorithm.

# 5. Conclusions

The results presented in this article show that neural prostheses offer patients a greater range of movement functions compared to that provided by myoelectric prostheses. The number of these functions can also be increased by modifying the configuration of the plug electrodes that provide the connection with the motor fascicles of the nerves from the patient's stump. Neural prostheses also offer to the patient, thanks to the bidirectional connections with the patient's nervous system offered by the neural interfaces, many tactile feedback functions, functions that are not offered by the myoelectric prostheses. The research presented in this article shows that in the coming years, implantable neural interfaces together with neural prostheses, will be exponential developed and will help amputees to regain many of the motor and sensory functions lost during the amputation. The neural interface fabricated in the NerveRepack project has been successfully tested both in vitro and in vivo and will be implanted for the first time in a human patient in March 2027, as the process of obtaining approvals from ethics committees takes many months. The implantation of this neural interface in a human patient will open and support many new research directions regarding the pattern of motor neural impulse trains for each fingers' movement, and also the pattern of the neural signals suitable for generating to the patient, tactile and other feedback sensations.

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