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Concept of Using the Brain-Computer Interface to Control Hand Prosthesis

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Abstract:
This study examines the possibility of implementing intelligent artificial limbs for patients after injuries or amputations. Brain-computer technology allows signals to be acquired and sent between the brain and an external device. Upper limb prostheses, however, are quite a complicated tool, because the hand itself has a very complex structure and consists of several joints. The most complicated joint is undoubtedly the saddle joint, which is located at the base of the thumb. You need to demonstrate adequate anatomical knowledge to construct a prosthesis that will be easy to use and resemble a human hand as much as possible. It is also important to create the right control system with the right software that will easily work together with the brain-computer interface. Therefore, the proposed solution in this work consists of three parts, which are: the Emotiv EPOC + Neuroheadsets, a control system made of a servo and an Arduino UNO board (with dedicated software), and a hand prosthesis model made in the three-dimensional graphic program Blender and printed using a 3D printer. Such a hand prosthesis controlled by a signal from the brain could help people with disabilities after amputations and people who have damaged innervation at the stump site.

Keywords: *BCI, EEG, hand prosthesis, hand, prosthesis, 3D printing*

1. Introduction

Brain testing uses several methods, one of which is the measurement of brain waves. These brain waves can be collected in the form of electrical signals. The acquisition of brain signals can be done invasively and non-invasively. The invasive method involves placing sensors inside the scalp, but this is a risky course of action. The other method is non-invasive, and the sensors are implanted above the skin. However, this method is noisy, making it difficult to extract useful information. The connection between the brain and an external device is called the brain-computer interface (BCI) [1-3]. Currently, the most popular data source for BCI is EEG signals from surface brain activity. This is because these types of measurement are non-invasive [4, 5]. BCI can improve the quality of life for people with severe motor disabilities. BCI captures the user's brain activity and translates it into commands that control an effector such as a computer cursor, a robotic limb, or a functional electrical stimulation device [6]. BCI has many applications, such as in medicine. RuiNa et al. [7] in their paper presented the control of an electric wheelchair using BCI. In their design they used visual evoked potentials: SSVEP. The wheelchair consists of a hybrid visual stimulator that combines the advantages of liquid crystal display (LCD) and light emitting diodes (LED). M. Vilela and L. R. Hochberg [6] described new developments to improve the user experience of BCI with effector robots. Full efficient manipulation of robots and prosthetic arms via a BCI system is challenging due to the inherent need to decode multidimensional and preferably real-time control commands from the user's neural activity. Such functionality is fundamental if BCI-controlled robotic or prosthetic limbs are to be used for daily activities.

BCI also has applications in rehabilitation, such as BCI-controlled robots. They are designed for motor assistance to help paralyzed patients to improve upper and lower limb mobility [8]. Different algorithms are used to classify brain signals.

Channel selection is a key topic in BCI. Imagining hand movement is a frequently used component of the learning data set for algorithms. For example, Milanović [9] used a sequence of 70 tasks involving alternating imagining a right-hand movement and a resting hand movement. S. Soman and B. K. Murthy [10] created a design based on a BCI system for generating synthesized speech that operates on a blinking eye detected from the user's electroencephalogram signals. Khan et al. [11] developed a broad overview of the applications of BCI interfaces in the context of the upper extremity. Gubert et al. [12] analyzed left- and right-hand motion imagery. They used publicly available databases and the CSP (Common Spatial Patterns) algorithm. Hernández-Del-Toro et al. [13] used the Emotiv EPOC interface. As a test sequence, they used a set of repetitions of imagined words spoken in Spanish (up, down, left, right, choice) repeated randomly 100 times each by 27 individuals. Fourteen EEG channels were used; the sampling rate was 128 Hz. Discrete wavelets transform (DWT) and fractal methods, among others, were used to analyze the signals. The nearest neighbor method (decision tree

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method) and support vector machine (SVM) were used for classification, among other tools.

Task irrelevant and redundant channels used in BCI can lead to low classification accuracy, high computational complexity, and application inconvenience. By choosing optimal channels, the performance of BCI can improve significantly. B. Shi et al. [14] in their paper proposed a novel binary harmony search (BHS) to select optimal channel sets and to optimize the accuracy of the BCI system. BHS is implemented on learning datasets to select optimal channels, and test datasets are used to evaluate the classification performance on the selected channels. The authors proposed a BHS method for selecting optimal channels in MI-based BCI. Their results validate the BHS algorithm as a channel selection method for motor imaging data. The BHS method, costing less computation time, gives better average test accuracy than steady-state genetic algorithms. The proposed method can improve the practicality and convenience of BCI system.

F. M. Noori et al. [11] proposed a new technique for determining optimal feature combinations and obtaining maximum classification performance for BCI-based functional near-infrared spectroscopy (fNIRS). The results of the proposed hybrid GA-SVM technique, by selecting the optimal feature combinations for fNIRS-based BCI, provide opportunities to enhance classification performance.

Janani et al. [15] applied a deep learning neural network algorithm to classify motion imagery based on infrared signal. Functional near-infrared spectroscopy (fNIRS) was used, in which infrared light passes through a hemodynamic system. The phenomenon of change in absorption of infrared radiation depending on the wavelength of radiation was used. The principle of operation is like the blood oxygen saturation meter.

BCI will also find application in neuro-prosthetics. Neuroprosthetics is a combination of neuroscience and biomedical engineering. Implantable devices can significantly improve quality of life due to their unique performance. The combination of biomedical engineering and neuro-prosthetics has led to the development of new hybrid biomaterials that meet the needs of ideal neuroprosthetics. The site of implantation of the prosthesis determines the type of material and method of fabrication. P. Zarrintaj et al. [16] in their article described the types of biomaterials used for bionic neuroprostheses. The diversity of neuroprosthetics necessitates the use of a wide range of materials from organic to inorganic. However, using only metals, due to incompatibility with soft tissues, can cause inflammation. Metal-polymer hybrids can reduce the disproportion between soft tissues and electrodes, where the polymer part can regulate the modulus of the metal. Moreover, different types of electrodes should be selected for different types of signal recording. Therefore, the selection of biomaterials for neuroprostheses is crucial and requires knowledge of the electrode implantation site and material characteristics.

2. Examples of Implementation Concept in the Field of Artificial Hand

This article describes the concepts of a proprietary BCI-controlled hand prosthesis. The hand prosthesis controlled by the signal from the brain enables people with disabilities without a hand or after amputations, and people with damaged innervation at the stump site. This solution uses a non-invasive method, so people who are not entirely convinced of this method can test whether it suits them without interfering with their body. The main goals are to select an EEG device, design and construct a prototype of a hand prosthesis, select and program an appropriate control system.

A prosthesis is a tool that supports or replaces an amputee in carrying out their daily tasks. Instead of passive devices that are purely aesthetic, the current devices have im-proved functionality using robotic technology. M. A. Abu Kasim et al. [17] presented their conceptual idea to use a non-invasive Emotiv headset to control a prosthetic hand using LabVIEW. This design is intended for the use of cost-effective upper limb prostheses controlled by signal artifacts and uses facial expressions. This device can be used and controlled by paralyzed persons with limited communication skills via a graphical user interface (GUI). It is worth noting that the non-invasive BCI method was used to create the project. The GUI is created with LabVIEW software connected to the Ar-duino board via a serial USB data connection.

The use of body-powered prostheses can be tiring and lead to further compliance and prosthetic problems. BCI makes it possible to inspect dentures for patients who are otherwise unable to operate such devices due to physical limitations. The problem with BCIs is that they usually require invasive logging methods where surgery needs to be performed. G. Lange et al. [18] presented a study to test the ability to control the movement of an upper limb prosthetic terminal device by classifying electroencephalogram data from the actual grasping and releasing movement. Thus, they developed a novel EMG-assisted approach to classifying EEG data from hand movements. This demonstrates the possibility of a more intuitive control of the prosthetic end device of the upper limb with a low-cost BCI without the risk of invasive measurement.

R. Alazrai, H. Alwanni, M. I. Daoud [19] described a new EEG-based BCI system that they used to decode the movements of each finger in the same hand. It is based on the analysis of EEG signals using the quadratic time frequency distribution (QTFD), or Choi-William distribution (CWD). In particular, CWD is used to characterize the various components over time of spectral EEG signals and to extract functions that can capture motion-related information. The extracted CWD-based functions are used to create a two-tier classification structure that decodes the finger movements in the same hand.

J. E. Downey, J. Brooks, S. J. Bensmaia [20] described technologies designed to sense the state of the hand and contact with objects and connect with the peripheral and central nervous systems. The skillful manipulation of objects is based not only on a sophisticated motor system that moves the arm and hand, but also on the accumulation of sensory signals that convey information about the consequences of these movements. The development of a skillful bionic hand therefore requires the restoration of both control and sensory signals. It is important that the bionic hand is well constructed and allows for freedom of movement: to do this you need to properly attach the sensors. Research aims to create artificial sensory feedback through electrical nerve stimulation in amputees or electrical brain stimulation in tetraplegic patients. While artificial sensory feedback, still in its early stages, is already giving bionic hands more dexterity, ongoing research to make artificial limbs more natural offers hope for further improvements.

Guger et al. [21] presented a system that uses EEG for hand prosthesis control. The digital input / output channels are used to control a remote control that is connected to a microcontroller to control the prosthesis. The microcontroller receives commands from the remote control and regulates the speed of the grip. The technique of imagining the movement was used to control the hand. After the appropriate beep was heard, the user had to imagine the movement of his left or right hand depending on the arrow that was displayed on the monitor. It all took a few seconds, and then for the next time the EEG signal was properly classified and used to control the prosthesis. One session required the authors to make as many as 160 attempts. The authors performed three sessions. The operation of the system is based on the BCI software and hardware. Matlab Simulink is used to calculate various parameters that describe the current EEG state in real time. Matlab also supports data acquisition, synchronization, and presentation of the experimental paradigm.

In their article, G. R. Müller-Putz and G. Pfurtscheller [22] presented a prototype of a two-axis electric hand prosthesis control, which uses an asynchronous four--class BCI based on static and visual evoked potentials (SSVEP). The authors constructed a stimulation device. For the experiment with the prosthetic device, they modified the prosthesis of the hand in such a way that, in addition to the gripping function (opening and closing the fingers), it was also possible to rotate the wrist (left and right). Four red LEDs are mounted at specific locations on the armature. The authors used four healthy participants for their research. They performed four sessions of 40 attempts, and the participants had to follow the instructions given to them by a beep. Users also had to focus on the appropriate flashing lights attached to the prosthesis to trigger the appropriate prosthetic action. The LED lights were not attached accidentally. Each was attached precisely to make the right movement: one LED on the index finger to turn right, and one LED on the fifth finger to turn left. There were also two LEDs attached to the forearm. The first lamp was used to open the hand, and the second to close it. The authors proved that an SSVEP-based BCI, operating in asynchronous mode, is feasible for the control of neuroprosthetic devices.

In this article, T. Beyrouthy et al. [23] presented a preliminary design of a mind-controlled, intelligent, 3D-printed prosthetic arm. The arm is controlled by brain commands received from the headset via an EEG. The arm is equipped with a network of intelligent sensors and actuators. This smart network provides the arm with normal hand functionality and smooth movements. The arm has different types of sensors, including temperature sensors, pressure sensors, ultrasonic proximity sensors, accelerometers, potentiometers, strain gauges, and gyroscopes. EEG signals are recorded using the Emotiv EPOC wireless headset. The EEG signals provided by the input unit are sampled and processed by the processing unit. The arm is equipped with a special servo and an Arduino microcontroller, which ensures an appropriate interface between the mechanical and processing units. Multiple sensors allow the arm to interact with and adapt to the surrounding environment and to command the arm and provide feedback to the patient.

In Constantine et al.'s application [24], they used a comprehensive model structure, from feature construction to classification, using a technological neural network. The process of starting from the beginning meant that the initial solution of the team was put together by the tools, starting from the beginning of the initial instantiation of the computer solution (CCI). The proposed architecture is complemented by the design and implementation of a hand prosthesis with Google Degree of Freedom (DOF). This incorporates a Field Programmable Gate (FPGA) that converts electroencephalographic (EEG) AR gates into prosthetic movement. They also proposed a new subject selection and grouping technique that is available with the subject's motor intentions. The model implemented with the proposed architecture showed a successful pattern of 93.7% and a classification time of 8.8 years for FPGA. Their implementation allows the application of BCI for the technique used in FPGA practice.

In their article, J. W. Sensinger, W. Hill, and M. Sybring explore the many aspects that influence the ability of an upper limb prosthesis to affect a person's daily life. They argue that these influences can be categorized into four domains: aspects intrinsic to the person; factors focused on the design, control, and sensory feedback of the prosthesis; facets external to the person; and outcome measures used to evaluate devices, activities, or quality of life. The purpose of a prosthetic device is to improve a person's quality of life [25].

3. Materials and Methods

The methodology has three stages: acquisition of EEG data from the selected BCI device, design and printing of a 3D-printed prosthesis hand, and programming of the control system. The EEG signal acquisition device is the Emotiv EPOC+ NeuroHeadset and has the following specifications [26]:

- 14 recording electrodes and 2 reference electrodes, offering optimal positioning for accurate spatial resolution.
- the channel names based on the international 10-20 electrode location system are: AF3, F7,

F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4, with CMS / DRL references at locations P3 / P4.
- uses sequential sampling method, single ADC, at 256 SPS (2048 Hz internal) - sample rate per second.
- operates at 16-bit resolution per channel with a frequency response of 0.16 - 43 Hz.
- supports Bluetooth Smart 4.0 LE.
- has high resolution (14-16 bit)
- typical operating time of the device from a full charge is 12 hours.

The control system is a microcontroller (Arduino UNO) and servo (Feetech servo FT6335M standard). Arduino is an open-source electronics platform based on easy-to-use hardware and software. The Arduino UNO is a microcontroller board that has 14 digital input/output pins (6 of which can be used as PWM outputs), 6 analog inputs, a 16 MHz ceramic resonator (CSTCE16M0V53-R0), a USB connector, a power jack, an ICSP jack, and a reset button. It is based on the ATmega328P. It is a low-power, 8-bit CMOS microcontroller type based on AVR® with an enhanced RISC architecture. By executing instructions in a single clock cycle, the device achieves processor throughput approaching one million instructions per second per megahertz, optimizing power consumption compared to processing speed. The Arduino UNO board is 5V. It has 32 kB of Flash memory, 2 kB of RAM, 14 digital I/Os of which 6 can be used as PWM channels, 6 analog inputs, and popular communication interfaces [27]. The prosthetic hand model was designed in Blender. Blender is a free and open-source 3D modeling software. It was developed by NeoGeo but has been developed by the Blender Foundation since 2002. From the beginning, Blender's main programmer was Ton Roosendaal. It is available for various hardware and software platforms, including Microsoft Windows, macOS, and many others. The program caters to all the needs of 3D graphic designers. It can model, animate, simulate, render, compose and track motion, edit video, and create 2D and 3D animation [28].

4. Results

It is reasonable to assume that as a result of the loss of the hand (no hand), the brachial plexus is not functioning or may be damaged. This is a bundle of nerve fibers running from the spine all the way to the hand. It is important for the patient with the artificial hand to be able to control the prosthetic hand independently with the help of EEG signals. The task of such a prosthesis will be therefore the ability to execute the commands in correlation with Emotiv EPOC+ NeuroHeadset device. This solution will allow the patient to fully control his hand even if the nerves in the amputated limb are not fully functional.

4.1. EEG Signal Acquisition Device

In the global market, there are many companies producing Brain-Computer Interface devices. However, two companies play a key role: Emotiv Systems and NeuroSky. The device that we chose to acquire EEG signals is the Emotiv EPOC+ NeuroHeadset. It allows communication with a computer based on brain activity, facial muscle tension, and emotions. It has 14 recording electrodes and 2 reference electrodes. This amount is sufficient in this case. It connects wirelessly to the computer and mobile devices and has 9-axis motion sensors. It stands out for its long working time (up to 12 hours). The device sets up quickly. It is also important to remember to properly moisten the reference sensors with saline solution so that signal reception occurs properly.

In the box of the EPOC+ Headset (Fig. 1) are:

- Brain-Computer Interface with built-in lithium battery,
- universal USB receiver,
- humidifier packet,
- saline solution,
- USB charger with Mini-B connector,
- quick start guide.

4.2. Expressiv Suite Functions

The Expressiv Suite app in the Emotiv Control Panel features an avatar that mimics facial expressions and shows teeth clenching, left and right eye movements (Fig. 2), eye blinking, left or right eye blinking, eyebrow raising and smiling.

Fig. 1. Basic components of Emotiv EPOC+ Neuroheadset

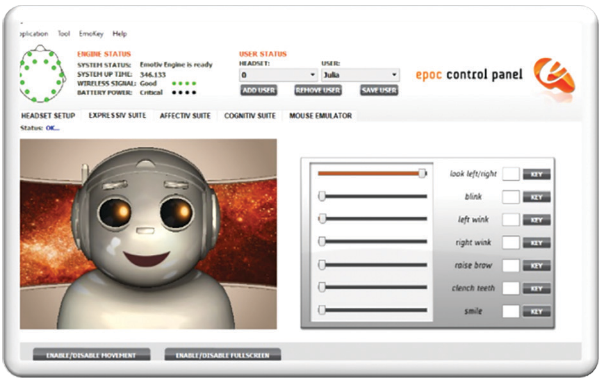

Fig. 2. Screenshot of the application Expressiv Suite during looking right

In this app, there is a control panel next to the avatar that allows you to adjust the sensitivity with sliders. For each facial expression, you can check its effectiveness. If the Expressiv Suite app does not respond easily to a particular facial expression, use the slider to increase the sensitivity. If the stimulus is triggered too easily, causing an unwanted result, then use the slider to decrease the sensitivity. You can increase or decrease the sensitivity by moving the sensitivity slider to the right or left respectively. Each of the seven types of facial expressions can also be assigned any action in the form of calling any combination of keys or mouse buttons. This makes it possible to operate applications, play games or control a device such as a wheelchair or prosthesis using facial expressions. The EmoKey is used for this (Fig. 3). Next to each slider is a key button, which is used to configure facial expressions for EmoKey. EmoKey combines Emotiv's technology with applications, converting detected events into any combination of keystrokes. EmoKey runs in the background but is safe for your device and allows you to create mappings. EmoKey's mappings are relatively simple, like linking the detection of teeth clenching to a mouse key press, for example. The app then immediately captures the moment when the user clenches their teeth. To configure facial expressions for EmoKey, you need to select the appropriate expression you want to link and click the Key button next to the description of, for example, clench teeth, which will bring up a configuration dialog. You can also set the facial expression to be continuous by selecting Hold in the key box. There are also options for further configurations, such as key hold time and key trigger delay; using these, only actions to which key presses are assigned are sent to the active application window. Some expressions have the option "occurs" and others have "is equal to," "is greater than," "is less than." For example, when you type "0.3" in the condition field it will cause clench teeth to be shown when a clench greater than 30% of full scale is detected. You can also manage and save Emokey mappings using the EmoKey menu at the top of the Control Panel window. Mappings can be loaded or saved and can be suspended.

4.3. Methods of Prosthesis Design

The hand prosthesis was modeled in Blender. Many features of the rich software were used to create the hand. Among others, scaling, extrude function and Bevel function were used. Two solids were used to create the prosthesis: a cylinder and a cube. To enable the hand to have the right proportions Rotate and Move tools were used. The joints were created using cylinders, which were placed and scaled accordingly. The holes in the joints were made using the Boolean modifier. The fingers in the hand have two joints and resemble hinge joints. They consist of three parts, but the latter part is part of the metacarpus (Fig. 4).

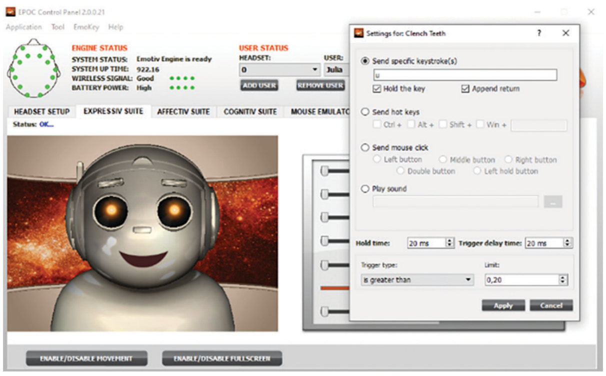

Fig. 3. Screenshot of the application Expressiv Suite with used EmoKey for clenching teeth

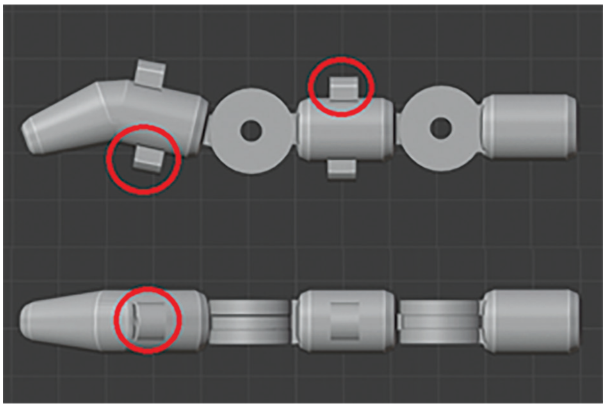

Fig. 4. Index finger design - side and top view (the red circle marks the hooks to which thin lines resembling tendons are attached)

The saddle joint of the thumb is too complicated, so it was replaced by a hinge joint in the hand model. The thumb consists of 2 parts (Fig. 5). The latter part of the thumb connects immediately to the metacarpus, as in the other fingers. In addition, the thumb, so that it can replicate the behavior of the human hand, has been placed at an angle.

The largest part of the hand and the prosthesis is the metacarpus (Fig. 6). It has a special depression at the bottom. At the top are parts that are supposed to reflect the tendons.

The hand prosthesis resembles a human hand in appearance. However, its mobility is much less, as it has only 11 degrees of freedom and includes 9 movable joints. For the purpose of this project, however, this amount is sufficient. The final design of the hand prosthesis is shown in Fig. 7.

4.4. Final Model of Hand Prosthesis

The entire model consists of 10 parts that were printed on a 3D printer using PLA filament. PrusaSlicer software was used for 3D printing. The parts of the prosthesis were printed in two stages using the Creality Ender 3 printer. The parts of the fingers were printed together with proper spacing, and the metacarpals were printed separately. The

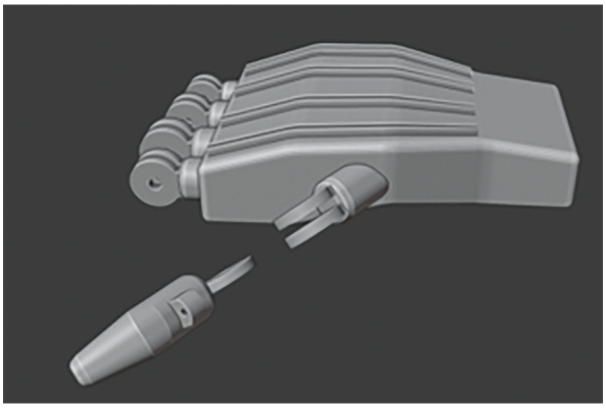

Fig. 5. Thumb design

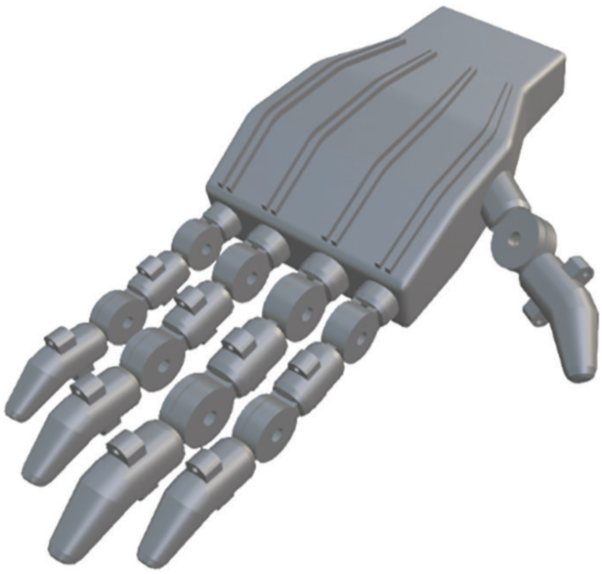

Fig. 7. Final design of hand prosthesis

metacarpal took the longest time to print: 10 hours. PLA filament in black and gray was used for printing. The prototype hand prosthesis consists of 10 parts. The parts were properly sawn after printing so that they could fit well. The parts of the prototype prosthesis were connected using 3 mm diameter screws. Figures 8 and 9 show the printed hand before and after assembly.

4.5. The Signal Transmission to the Prosthesis Hand

When performing a movement, the user does not need to make a muscle movement directly, but simply clenches his teeth or blinks his eye or raises his eyebrows. In creating an appropriate effective activity matrix, it is important to differentiate a given facial expression, and the movement should be appropriately assigned to a given facial expression. This provides the opportunity to properly classify the user's intentions and thus build the executive system. Using Emotiv's EPOC+ device, the EEG signal is acquired from the patient's head surface using electrodes placed on the device. Using the Expressiv Suite

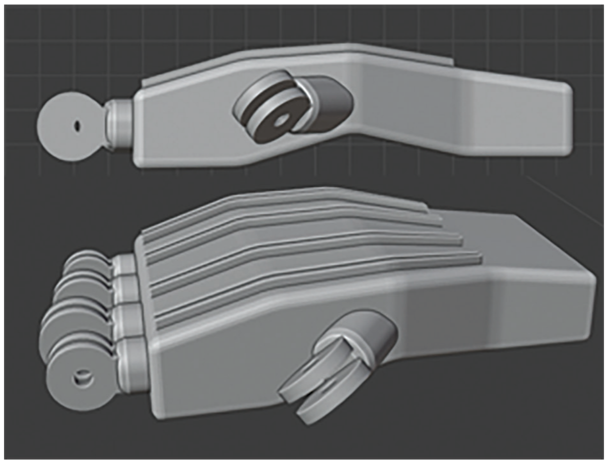

Fig. 6. Metacarpus design

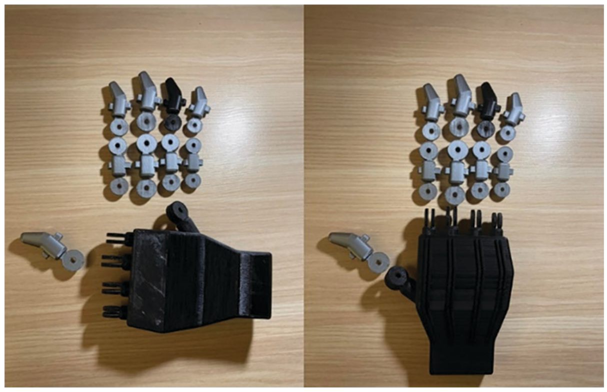

Fig. 8. 3D printed hand prosthesis – before assembly

Fig. 9. 3D printed hand prosthesis – after assembly

app included with the Emotiv EPOC+ NeuroHeadset hardware, it is possible to identify the facial expressions of the user using the device. The application uses EmoKey to assign the appropriate keys from the keyboard (i.e., time in μs of servo rotation) to a specific facial expression. The serial port monitor is a tool available to the Arduino software that allows the servo to be controlled. The minimum and maximum servo rotation time in μs is stored for a particular

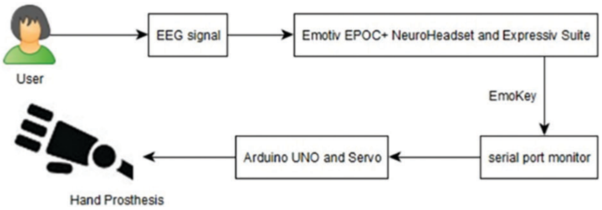

Fig. 10. Diagram of signal transmission to the prosthesis

facial expression. Depending on the particular facial expression, the servo rotation time that was previously assigned to the particular facial expression is entered on the serial port monitor. This causes the servo to rotate, for example, by its maximum angle, which gives the effect of a hand movement. The acquisition of the EEG signal from the user's head to the Expressiv Suite application is based on wireless communication using a Bluetooth connection. Receiving the signal from the computer by the control system, for the time being, is done by wire. A schematic of signal acquisition and transmission to the prosthetic hand is shown in Figure 10.

4.6. Communication

In the Expressiv Suite app, the user selects given facial expressions to which he assigns specific numbers using the EmoKey. These numbers are the corresponding rotation time of the servo. Two servo positions are demonstrated in the project: a 0-degree position and a 180-degree position. The 0-degree position corresponds to a time of 0 µs, and the 180-degree position corresponds to a time of 2400 µs. Table 1 shows the relationships, for example, of facial expressions to the finger movement of the prosthetic hand. A time of 2400 µs was assigned to the teeth clench expression and a time of 0 µs was assigned to the raised brow expression. When the user performs a given facial expression, this servo time is outputted on the serial port monitor, causing it to rotate and move the prosthetic hand. Facial expressions can be customized to the user's liking, i.e., instead of a clench teeth, there can be a blink of the eye or a smile.

Tab. 1. Relationship of facial expression to hand finger movement

Facial expressions	Servo rotation time	Movement
clench teeth	2400 µs	finger bends
raise brow	0 µs	finger bends

4.7. Tests

The using of the hand prosthesis prototype was tested for a selected finger and for selected facial expressions. Cables were attached to the prototype and to the servo. For the test, the hand prosthesis was placed in such a position that it could be moved only through brain waves. It was also necessary to properly place the servo. Then the program dedicated to the microcontroller used was turned on along with the necessary tool — the monitor of the serial port, to be able to control the servo. The next step was to properly prepare the Emotiv EPOC+ NeuroHeadset. After preparing the device on the computer, the Expressiv Suite app was selected, to which appropriate servo rotation times were assigned to the given facial expressions using EmoKey. Lifting the eyebrows was assigned "2400" and "0" was assigned to the clenched teeth. The finger is bent when clamping with the teeth and when the eyebrow is lifted, the finger is straightened. Facial expressions can be adjusted depending on the user's preferences; therefore, performance tests were also performed during sideways movement of the eyeballs and blinking. It is important to concentrate properly when performing a given facial expression. User can trace facial expressions by looking at the avatar in the Expressiv Suite app. It is also advisable that the user, before attempting to make movements of such a prosthesis, which is controlled by facial expressions, should practice the given facial expressions using the Expressiv Suite application itself. Fig. 11 shows the user during the prototype performance test.

4.7. Artifacts

The most common BCI is based on EEG signals, and there are a number of interferences during the electroencephalographic test. Artifacts can be divided into technical and biological. The sources of interference are artifacts introduced by physiological processes, i.e., muscle activity, facial expression, heart rate, and technical solutions, such as the power grid. Therefore, the signal must be significantly amplified and must also consider the voltages generated at the skin-electrode interface. After filtering out mains frequency interference and performing the filtering and feature extraction the signal should be clean. The result of these actions will be the expected signal properties. Undoubtedly, during diagnostic testing of EEG signals, artifacts are eliminated as much as possible. Normal signal EEG (no artifacts) shows in Fig. 12.

Facial expressions, as already mentioned, are also among the artifacts, but for the purposes of using the Expressiv Suite in Emotiv Control Panel artifacts are as desirable as possible. In this application, therefore, there is a built-in algorithm for the detection of artifacts, or signal interference. Figures 12-15 show artifacts during different facial expressions.

5. Discussion

Some difficulties were encountered during the prototype development. The control problem was that initially in the concept implementation, the Congnitiv Suite app in Emotiv Control Panel could be used for control. However, this application requires a very high level of concentration and trained senses to be able to use it freely. Therefore, it was concluded that it would be better to control using the Expressiv Suite app, which is more intuitive and simpler for the user. It is worth noting that, therefore, control by facial expressions is significant for this solution. When modeling the prosthetic hand, instead of using 14 joints as in the human hand, it was decided that 9 moving parts would be sufficient for the purpose of this prototype, and the thumb saddle joint, which has too complicated a structure, was replaced by a hinge joint in the hand model.

Fig. 11. Test of using hand prosthesis

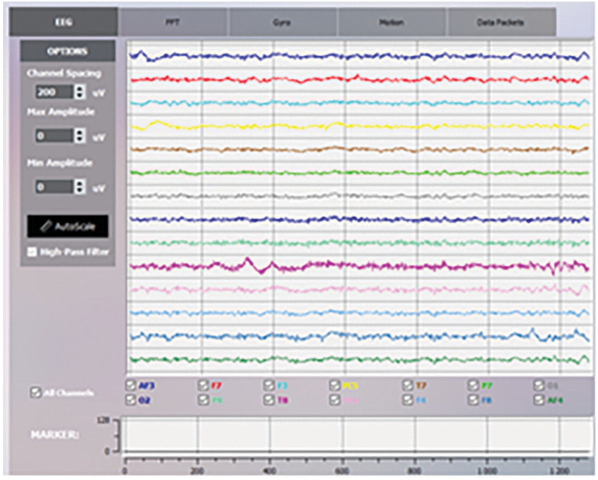

Fig. 12. EEG signal – no artifacts

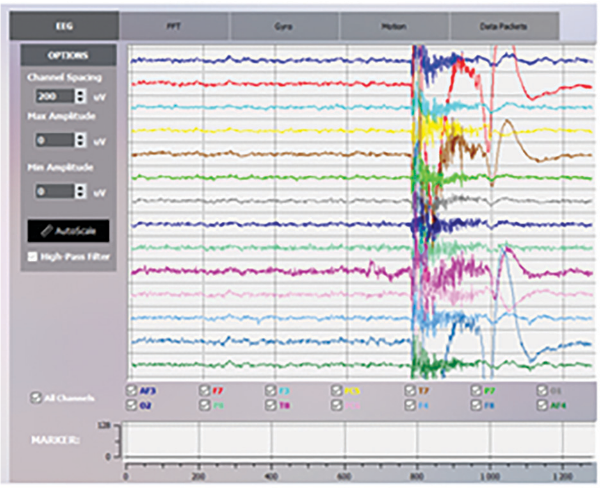

Fig. 13. Artifact – EEG signal during clenching teeth

Fig. 14. Artifact – EEG signal during raising brows

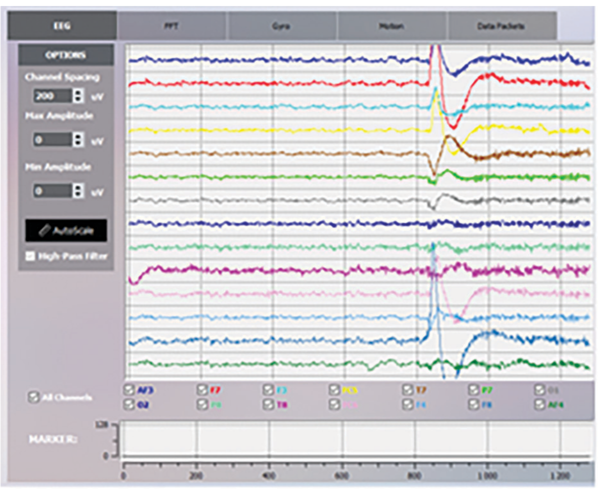

Fig. 15. Artifact – EEG signal during smiling

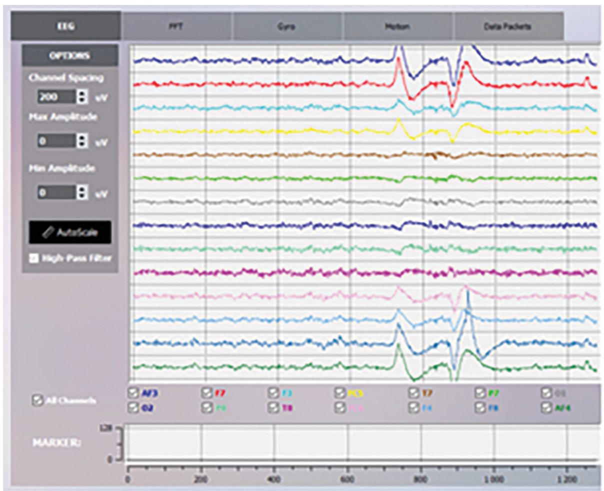

Fig. 16. Artifact – EEG signal during blinking eyes

6. Conclusion

This article shows one of the many proposed solutions for improving the functioning of people without an upper limb. This proposal is to control a prosthetic arm using brain waves. The use of such a prosthesis is very important for disabled people. Such a hand prosthesis controlled by facial expressions can help amputees and people who have damaged innervation in the stump area. This solution uses a non-invasive method, so people who are not fully convinced by this method can test it for themselves without interfering with their bodies.

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