A Low-Cost Lightweight Prosthetic Arm with Soft Gripping Fingers Controlled Using CNN

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***Abstract*— In this paper, a low-cost prosthetic arm design approach is introduced through a non-invasive technique for amputees. The arm is controlled by brain signals using electroencephalography (EEG) data obtained from an EEG headset. The prosthetic arm is fabricated from two different materials: a soft elastomer material for fingers which provides the arm with a high power-to-weight ratio and PLA 3D printing material for the limb. The driving force is a pneumatic circuit that helps to avoid the vibrations and noise induced by the servo motors in the currently existing commercial prosthetic limbs. A commercial headband (OpenBCI) was used to capture brain signals from the amputee's motor cortex via the headset's GUI and controlled using Raspberry Pi 4. Subsequently, two different learning algorithms were adopted, Support Vector Machine (SVM) and Convolutional Neural Network (CNN) to classify brain signals and transmit them to the prosthetic arm. The fingers are designed from elastomer material with a length of 70 mm and a wall thickness of 2 mm to increase the strength of the actuator and reduce the applied air pressure. A finite element analysis using ABAQUS software is conducted to investigate the stress on the soft-gripping fingers. A bending angle of 90 degrees was achieved while applying a pressure of 3.3 Pa.**

***Keywords*— Soft pneumatic actuator, Electroencephalography, Convolutional neural network**

I. INTRODUCTION

Human limbs can be relied on to perform multiple tasks every day. However, in some cases, these limbs are exposed to severe injury whether it is caused by war, working hazards, diseases, or congenital deficiencies [1-3]. These injuries may sometimes lead to the amputation of one or more limbs.

Advanced replacements for lost limbs are very technologically advanced nowadays. Several researchers have presented solutions to replace the amputee arm with a 3D printed prosthetic arm controlled by Electroencephalography (EEG) [4-9]. However, they used different control algorithms and additional sensors for instance the authors in [5] have introduced 3D printed arm equipped with various types of sensors to provide the arm with normal hand functionality, and smart and smooth reflex response. The authors in [6] presented a deep learning model that combines Long short-term memory (LSTM) with a Genetic algorithm (GA) to improve the accuracy however, this model has added computational complexity to the control algorithm. Mohamad Amlie Abu Kasim et al. [7] presented an integration between the EMOTIV EEG headset and LabVIEW GUI. Despite that, implementing these algorithms within the LabVIEW GUI may add complexity to the software design and increase processing overhead. More recently, Haider Abdullah Ali et al. [8] have integrated both the EMOTIV cortex API package and Python programming to reduce the noise and the artifacts on the raw extracted signals from the headset. The processed signals are wirelessly passed from the computer to Raspberry Pi 4 to control the stepper motor. The prosthetic hand has two commands: opening and closing. Nevertheless, transmitting signals wirelessly from the computer to the Raspberry Pi 4 may introduce latency, impacting the real-time responsiveness of the prosthetic hand which might affect functionality. Teban et al introduced a myoelectric-based control approach with Recurrent Neural Network (RNN) models [9]. They used the Proportional-Integral-Derivative (PID) controllers to provide real-time control for the prosthetic hand. The study reveals how RNN may mimic the nonlinear workings of a real human hand. However, prosthetic hand delays are neglected while the dynamics of finger flexion are somewhat considered.

According to the literature study, several studies have proposed prosthetic arms however, none of them have considered suitable material to achieve a lightweight arm as well as mentioning the total cost, as shown in Table 1. To ensure the stability in the function of the prosthetic arm a comprehensive approach that addresses the suitable material for arm fabrication and control algorithm are required. Consequently, this paper emphasises designing a lightweight arm by utilising a soft elastomer material for fingers which provides the arm with a high power-to-weight ratio, and PLA 3D printing material for the limb.

This paper presents a novel low-cost soft prosthetic hand that has been developed using a lightweight soft elastomer material and controlled using an EEG headset and Raspberry Pi 4. Support Vector Machine (SVM) and Convolutional Neural Network (CNN) algorithms are used to achieve the required function with relatively high accuracy. The prosthetic hand has a high power-to-weight ratio that can avoid the vibrations and noise induced by the servo motors in the commercial existing prosthetic limbs. The developed prosthetic limb targets different types and levels of amputation; however, it is mainly for people who suffer severe biomedical damage in the peripheral nerve. These cases have no choices other than surgical intervention by placing electrodes in the motor cortex of the brain, as Electromyography electrodes cannot be easily used to control the prosthetic limbs in conditions of damaged nerves. The soft actuators forming the prosthetic arm either inflate or deflate according to the brain signals. The gripping force and the stresses acting upon the soft prosthetic hand are calculated by a finite element analysis using ABAQUS software.

TABLE I. SUMMARY OF THE EXISTING STUDIES IN THE LITERATURE

Ref.	Sensor	Prosthetic Type	Control algorithm	Weight	Cost	Experimental Validation
[4]	EEG	3D-printed right-hand prosthetic arm	Arduino Microcontroller and Neurosky Mindwave 2	N/A	N/A	No experimental results
[5]	EEG	3D-printed smart prosthetic arm	Raspberry Pi III microcomputer, interfaced with an Arduino Mega microcontroller	N/A	N/A	Experimental validation
[6]	EEG	Virtual robotic arm	LSTM with Genetic algorithm	N/A	N/A	No experimental results validating the simulation accuracy
[7]	EEG	Commercial prosthetic hand	EMOTIV	N/A	N/A	N/A
[8]	EEG	3D-printed prosthetic hand	Signal processing (EMOTIV cortex API and Python)	N/A	N/A	Experimental validation, grasping force of 3 kg
[9]	Myoelectric	Prosthetic hand	Recurrent Neural Network (RNN)	N/A	N/A	Prosthetic hand delays and finger flexion dynamics considered
Current research	EEG headset and	Soft elastomer material for fingers and PLA 3D printing material for the limb	Raspberry Pi 4 using CNN and SVM	400 grams (total weight)	700 $	Stresses simulation and experimental validation

II. MATERIALS AND METHODS

A. Mechanical Design

The designed prosthetic arm consists of a forearm, palm, and five fingers. The forearm and the palm were 3D printed PLA and the five fingers were fabricated from soft robotic materials. The soft actuator finger's chamber morphology was designed based on a research study that focused on measuring the required bending torque (Ma) to overcome the internal bending moment of the chamber walls [10]. The geometrical design parameters are the chamber cross-section, length, wall thickness, extent of the actuator orientation, and patch of the winding. Based on the study mentioned previously [10], the length of the finger was designed to be 70 mm. The wall thickness is selected to be 2 mm to increase the strength of the actuator and reduce the applied air pressure.

B. Mold Design

The mold consists of four main parts, mold base with wrapping feature, top cover, steel half-rounded rod, and mold cap as shown in Figure 1. The mold base is designed with a length of 90 mm and a hole at the end for fixing the steel rod in the middle of the mold. The diameter of the hole is designed to be 6 mm to fit inside the air pipe in the palm taking into consideration the dimensions of the inner chamber of the actuator. These dimensions have been selected to resemble real human fingers.

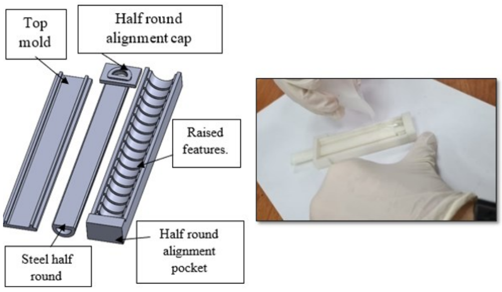

Figure 1 Mold parts design pouring process.

C. Soft Material

Four materials are investigated for the finger's soft design regarding their uniaxial tensile stress–stretch to select the most material that resembles the human hand. The materials are Ecoflex with a shore hardness of (00-10 to 00-50), Dragon skin with a shore hardness of (10-30 A), Elastosil M4601 with a shore hardness of (28 A), and smooth-Sil with a shore hardness of (36-60A). The Dragon Skin 20 was the most suitable type to be used due to its super flexibility without tearing and return to the original shape without deformation and has a safety certificate for dealing with human skin. The fabrication process is adopted from a previous study [11].

III. CONTROL SYSTEM

Two different learning algorithms were utilized to control the prosthetic arm which are SVM and CNN. This should be able to effectively enable the prosthetic arm to interpret the user`s intentions and respond accordingly. The neural network features 16 layers, with 14,000 neurons in the Conv2D layer, 3,500 in the DepthwiseConv2D layer, 434 in the SeparableConv2D layer, and 4 in the final Dense layer, totaling 17,938 neurons.

The data is gathered from the amputee using a commercial OpenBCI EEG Headband Kit. This kit has eight electrodes capable of gathering 1200 datasets at once. There is a channel for each electrode. The kit has a Cyton board to stream the gathered data from the headset's electrodes to the model. Also, the data, as a preprocessing stage, passes by a 50 Hz filter to eliminate the noise from the electronics. The signal monitoring and live streaming are conducted through the kit's OpenBCI software package. The dataset which is extracted from the EEG eight electrodes represents the brain activity at specific time intervals, with features corresponding to the electrical signals measured by the electrodes, enabling classification of movements which are "open hand," "close hand," "rotate wrist clockwise," and "rotate wrist counterclockwise" based on the user's neural activity as shown in Figure 2. The control technique is implemented using an EEG headset that reads the analog electric signals from the brain, digitises them, and sends them to Raspberry Pi 4 which is connected to the solenoid of the pneumatic pump to control the arm fingers.

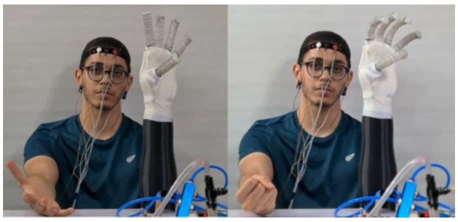

Figure 2 Testing the prosthetic arm shows the hand opened and closed

IV. Simulation and Experimental Results

A. *Finite Element Analysis (FEA) simulations*

FEA simulation is conducted using ABAQUS software for the soft actuator to test maximum stress on the wall chamber and the achievable bending angles while applying different pressures. It was found that the maximum pressure that can be applied is 3.3 Pa with a response time of 900 ms to achieve the required bending angle of 90 degrees as shown in Figure 3.

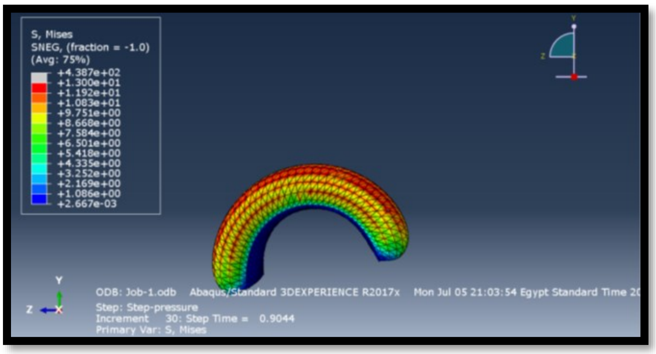

Figure 3 FEA for the soft robotic finger

B. *Experimental results*

Comprehensive experiments were conducted to test the developed prosthetic arm's functionality and performance. The inference time is calculated for the CNN model, revealing an average inference time of 17 ms, crucial for real-time control response. The accuracy achieved by SVM and CNN algorithms are 28% and 48% respectively, providing insights into their performance for gesture recognition tasks. The higher accuracy achieved by the CNN model demonstrates its ability to extract complex features from EEG signals, resulting in more precise prediction. The proposed material used in the design of the prosthetic arm leads to cost and weight reduction where it costs $700 and achieves a weight of 400 grams, showcasing significant advancements compared to commercial alternatives and ensuring accessibility for wider adoption.

V. Conclusion

A newly developed prosthetic arm design is implemented using soft robotics. The soft actuators forming the prosthetic arm either inflate or deflate according to the brain signals through the EEG headset. Two different algorithms are used which are SVM and CNN for controlling the prosthetic arm yielded distinct accuracies of 28% and 48% respectively. The developed prosthetic arm has the advantage of high accuracy, lightweight, and high power-to-weight ratio of the soft pneumatic actuator. The total cost of the developed prosthetic arm was 700 US dollars which is a low cost compared to commercial arms. Introducing the prosthetic arm with the concept of soft gripping fingers has reduced its total weight to 400 grams (about 14.11 oz). A Finite element analysis using ABAQUS software confirms the strength and functionality of the soft-gripping fingers, achieving a bending angle of 90 degrees with a pressure of 3.3 Pa. Consequently, this design can be used for children as they need a prosthetic arm that is lightweight, accurate, and without surgical intervention. This research can be extended to enhance the prosthetic arm by considering multiple solenoids to control each finger individually.

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