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Portable Fabric-Based Soft Glove Controlled with Single-Channel Electroencephalography

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Abstract—**Brain-computer interface (BCI) has been widely used to capture electrical signals generated from the brain. One of the most commonly used methods in the BCI system is the electroencephalogram (EEG). However, processing brain signals is challenging and requires a lot of computation processes. This study selected single-channel EEG as the input command for a portable soft exoskeleton glove system. This research aims to develop an affordable soft exoskeleton glove driven by single-channel EEG for people with impaired hand motion. We proposed an intuitive control method that feels more natural by imagining hand movements. Eighteen healthy participants underwent EEG data collection while their brain activity (attention level) was measured under four controlled conditions: listening to preferred music with lyrics, listening to disliked music, pre-workout state, and post-workout state. These variations in attention level, mood, and physical exertion influenced the measured EEG signals to drive the soft glove. T-test was applied to determine the significant difference for noise environment and physical variation tests. Those EEG signals are used to drive the linear actuator and provide mechanical assistance. Simple on/off control was embedded in the soft glove microcontroller to control the finger flexion/extension based on the EEG signal as a command. The result shows that the proposed wearable soft exoskeleton glove driven by EEG signal can be a potential assistive device for people with hand impairment. The speed for the soft glove was 3 seconds to close completely from a fully open. For optimal performance, this system needs to be used in a calm and distraction-free environment when the user is well-rested.**

Keywords—Embedded Control; Fabric; EEG; Soft Exoskeleton Glove; Brain-Machine Interface.

I. INTRODUCTION

A wearable exoskeleton robot is an assistive device that various researchers around the world have developed. Robot exoskeletons are widely used to provide mechanical support for both the upper and lower limbs. In the upper limb exoskeleton, this wearable robot assists hand movements such as the elbow or fingers of the user who cannot move normally. There are two types of exoskeletons based on the material used, i.e., hard exoskeleton and soft exoskeleton. Hard exoskeleton design technology has rapidly grown as a movement-assistive device and therapy kit. EksoVest is a passive upper-body exoskeleton with a moment and hinge mechanism developed by Ekso-BIONICS [1]. CAREX-7 was another hard exoskeleton supporting a total of 5 degrees of freedom (DOF) movement for the upper-limb torso with 3-DOF motion and shoulder and elbow with 2-DOF motion [2]. In addition to hard exoskeleton products as movement-assisting devices, there is also hard exoskeleton as a rehabilitation device. NEUROExos was a 4-DOF rehabilitation device for a motor disorder called spasticity [3]. Researchers utilized 3D printers for constructing the exoskeleton material and linkage system to minimize the weight [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16]. By applying it, a lightweight and affordable hard exoskeleton could be manufactured.

However, hard exoskeletons are challenging to attach and align, especially for different hand sizes of users. Therefore, researchers developed a soft exoskeleton hand for easy attachment and detachment to overcome this issue. It is safer and lighter compared to hard exoskeletons. Researchers employ pneumatic/hydraulic networks [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], motor-tendon [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], and shape memory alloys (SMA) [38], [39], [40], [41], [42], [43], [44], [45]. Most developed soft exoskeleton hands were utilized to support finger flexion and extension and rehabilitation [46]. Soft exoskeleton products are available on the market and are often used for physical training and rehabilitation. Exoskeleton actuated by the soft modules (EAsoftM) proposed an active exoskeleton with active and passive joints to compensate for gravity and a rotating shoulder [47]. Soft exoskeletons are typically made from textiles or other flexible materials, making them lighter and more comfortable to wear. They pose a lower risk of injury compared to hard exoskeletons. To enhance the user experience of exoskeletons, researchers are investigating sensors that can capture brain or muscle activity, enabling more intuitive and comfortable control.

Electromyography (EMG) sensors are commonly used in wearable robots such as prosthetic hands and exoskeleton hands. In prosthetic hands, EMG is applied to measure muscle activity in the remaining hand of a user whose hand has been amputated. The EMG reads muscle activity and generates signals according to hand movements. Researchers used machine learning to classify hand movements and provide classification results for hand movements in prosthetic hands [48], [49], [50]. The studies show that machine learning or deep learning can classify hand movement classification with high accuracy.

For people with hand disabilities such as hand paralysis, brachial plexus injury (BPI) or persons who cannot use their arm or hand, muscle movement is very challenging to measure using the EMG sensor because they cannot move their hand muscles. Therefore, the electroencephalography (EEG) sensor is suitable for patients who cannot move their hands. Exoskeleton robots can be used for patients with hand paralysis by using commands from the EEG sensor. Research related to the BCI system hand glove had been done with a product called the hand Exoskeleton for Rehabilitation Objectives (HERO), which incorporated a textile-associated 3D printing technique to produce a lightweight and wearable device [51]. This research utilized common spatial pattern (CSP) and linear discriminant analysis (LDA) classifiers to detect two classes where research volunteers were instructed to relax the Hand (Class 1) and perform a right-hand movement (Class 2). Other BCI-based soft exoskeleton gloves are used in stroke rehabilitation. The rehabilitation system is built like a visual game according to activities of daily living where participants move objects while EEG signals are being recorded [52], [53]. EEG sensors detect the brain waves categorized into delta, theta, alpha, beta, and gamma waves [54]. Delta wave is recognized during sleep with a frequency lower than 4 Hz, meanwhile, in the state of meditation and a relaxed mind, the EEG sensor detects the signal into theta and alpha waves. Beta waves are recognized when the brain is in full concentration mode [55].

Commonly, the EEG sensors that have been used previously are an EEG with more than one channel, and the price is relatively unaffordable for most people (around 1,000 USD). It can detect and measure delta, theta, alpha, beta, and gamma waves. In addition, machine learning or deep learning algorithms are needed to classify the hand movements desired by the user/wearer using their brain signal [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66], [67], [68], [69], [70], [71]. Online movement recognition with multi-channel EEG needs a high and complex computation process. However, personal computers/laptops or single-board computers (SBC) were widely added for EEG system recognition for driving the hand exoskeleton instead of embedded systems. These kinds of systems usually are large, and bulky, and need external computers for feature extraction and classification using online machine learning or deep learning. This large and complex exoskeleton system has two drawbacks: it's not portable and it's not user-friendly in terms of wearability.

Therefore, developing and integrating a soft exoskeleton glove and single-channel EEG with a low-cost and small-size microcontroller will be significant for the portable and lightweight exoskeleton glove system. By achieving a portable soft exoskeleton glove based on EEG, the user can wear it easily and comfortably. Recently, EEG devices have become more portable and user-friendly, allowing for real-time data collection, and robotic control. Single-channel EEG offers simplicity and portability for simple tasks, while multi-channel EEG provides spatial resolution and accuracy for more complex tasks.

The main contribution of this study is an intuitive control and simple method that allows for natural control through imagined hand movements based on single-channel EEG, which is applied to drive the soft exoskeleton glove. Fabric-based exoskeleton robots will be developed because it is easy to attach, detach, and align. Moreover, it is comfortable for the user to wear. The proposed fabric-based exoskeleton glove offers a compelling alternative for situations that prioritize comfort, affordability, and ease of use. The single-channel EEG is integrated with the developed soft glove using a custom Bluetooth communication device for a simple communication interface. Because EEG is vulnerable to noise, 18 study participants are involved in studying the effect of noise sound (music) and fatigue to find the optimum utilization environments. The soft glove is controlled using embedded on-off control based on the feedback from the linear potentiometer on the linear actuator. When the soft glove is controlled using single-channel EEG, the grasping force generated during flexion motion is measured for providing mechanical grasping assistance. This system allows a user to modulate grasping force during flexion/extension for improved mechanical assistance.

II. MATERIALS AND METHODS

A. Single Channel EEG

This study selected the Neurosky Mindwave headset as the affordable EEG sensor. It can measure 12-bit raw brainwave data (3-100 Hz) with a sampling rate of 512 Hz. Two signal values are generated from single-channel EEG, namely attention and meditation. Attention signal is the focus of this research to be extracted as a soft glove input signal command. Attention level is presented as a score/value from 0 to 100, indicating the intensity of the user's "focus" or "attention" level. The level of attention increases when the user focuses on a single thought or external object and decreases when he/she is not focused. Attention levels were categorized into five levels: poor attention, lack of attention, neutral, high enough attention, and full attention. Attention levels at neutral are considered normal concentration levels, while attention levels at less and poor are lower than normal. Attention levels above neutral levels indicate the person has a higher current concentration level. People with "full attention" levels ranging between 80 and 100 have very high concentration levels. These attention level categories are summarized in Table I.

TABLE I. ATTENTION LEVEL ON SINGLE CHANNEL EEG [72]

Attention level	Classification
1 - 19	Poor Attention
20 -39	Lack of Attention
40 - 59	Neutral
60 -79	High Enough Attention
80 - 100	Full Attention

Many external factors can affect the value of attention, such as age, gender, noise, background music, fatigue, illness, and many others. This study took several samples from several study participants who were tested for their attention level. The factors tested in this study include background music, noise, and fatigue after working out. The study participants consisted of 18 people, namely nine males and nine females (age = 24.3 years, SD=7.6). All study participants were physically and mentally healthy and had eaten before the EEG measurement. Tests were conducted between 10 a.m. and 2 p.m. in a closed, air-conditioned room to reduce external noise or interference. A day before the test, participants were advised not to drink alcoholic and caffeinated beverages first. This study utilized adult study participants to minimize the influence of factors such as incomplete brain development or age-related cognitive decline on the EEG. The list of study participants who participated in this research is summarized in Table II.

TABLE II. LIST OF PARTICIPANTS IN EXTERNAL FACTOR TESTING

Participant	Gender	Age	Occupation
A	Female	15	Student
B	Male	15	Student
C	Female	16	Student
D	Male	17	Student
E	Female	17	Student
F	Male	18	Student
G	Female	22	College student
H	Male	22	College student
I	Female	23	College student
J	Male	23	College student
K	Female	23	College student
L	Male	23	College student
M	Female	31	Worker
N	Male	35	Worker
O	Female	33	Worker
P	Male	34	Worker
Q	Female	36	Worker
R	Male	35	Worker

Music has a substantial effect on a person's behavior and attention. Many researchers have studied the impact of music on human behavior, such as eating, drinking, and psychological behavior. A study of work concentration levels and background music showed that people who listened to music during an attention test had highly variable scores on an attention test. This study explores how background music, with likes and dislikes, affects one's attention performance. In this test, participants were asked to listen to two songs. One song is a song the participants like, and the other is one that the participants do not like. While listening to the song, participants will be asked to work on math problems provided previously, and their attention value will be measured using a Mindwave headset for 80 seconds. This test is conducted for 1 trial for each study participant.

When people become tired due to work or daily activity, they will usually complain and find it difficult to concentrate and focus their attention on the tasks they have to do. The value of attention is affected explicitly by physical and mental fatigue, and attention is a key feature of dynamic human behavior. Therefore, the attention value measured by the EEG was tested after the study participants did some physical exercises. Participants were asked to run on a treadmill for 10 minutes in this test. After running on the treadmill, they were asked to work on the math problems while their attention was measured using the single-channel EEG. This measurement of EEG signal for pre-workout and post-workout was conducted for 1 trial for each study participant for 80 seconds.

B. Soft Exoskeleton Glove System and Control

In this study, the wearable assistive soft robotic glove aims to assist people with BPI or impaired hands in daily activities such as grasping and lifting objects. Compared to the hard exoskeleton, the advantage of this type of wearable assistive soft robotic glove is that it is more comfortable to use and can adapt well to wrap/align to the hands of users/wearers [17], [29]. Therefore, the glove does not injure the user in performing daily activities. In addition, because it is made of SR-10 fabric, this glove can be washed and cleaned. The prototype of the wearable assistive soft robotic glove can be seen in Fig. 1. The developed fabric-based soft exoskeleton glove system can be attached and detached easily from the user. The linear actuators are attached between the hand and elbow, while the battery and controller units are placed between the user's shoulder and elbow. Because it is lightweight and small and comprises actuators, batteries, and a controller, the user can wear the soft glove system comfortably.

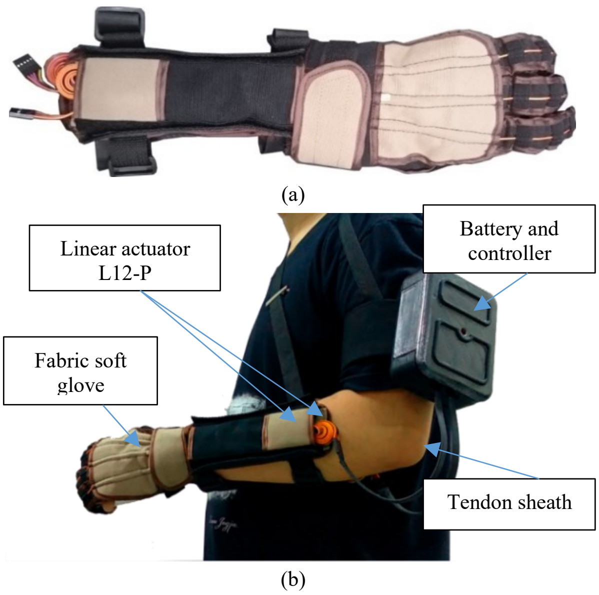


Fig. 1. Fabric-based soft exoskeleton glove, (a) Soft glove prototype, (b) The glove worn by a study participant

The prototype of the wearable assistive soft robotic glove that has been successfully developed will be given input in the form of an EEG signal (attention level). Linear actuator L12-P with a linear potentiometer position sensor with a closed length of 152 mm and the maximum voltage of 12 volts (Actuonix, Victoria, BC, Canada) was selected as the primary actuator for the soft glove due to it is relatively small compared to the pneumatic or hydraulic system. It converts rotational motion by an electric motor into linear motion to drive the soft glove. The maximal stroke of the linear actuator is 5 cm and the maximum speed (no load) is 24 mm/s. This stroke is sufficient to drive the developed soft glove for finger flexion and extension motion. The design of the soft glove can be seen in the previous research [73].

The schematic of the hardware from the EEG to the soft robotic glove can be seen in Fig. 2. The EEG signal was obtained by an Arduino microcontroller equipped with a Bluetooth receiver. It sent the signal to the soft glove controller through an analog signal. L293D driver motor was selected to provide bidirectional drive currents for extending and retracting the actuator stroke. This system employed two linear actuators on the soft glove to actuate the soft glove extension and flexion motion. The motions from the linear actuator were transferred using a tendon sheath to drive the soft glove fingers.

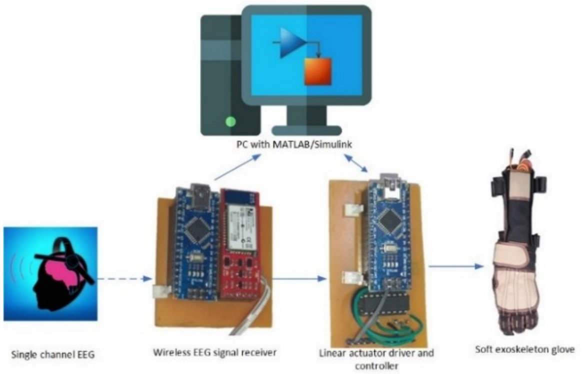


Fig. 2. Proposed hardware for the soft exoskeleton glove

This study implemented a modified on-off control with dead-zone value to extend or retract to the desired stroke displacement on the actuator. The proposed modified on-off control with a dead-zone value could increase the system's longevity, reduce the switching control (smoother response), and reduce power consumption. Because the signal coming from EEG was noisy, the attention signal as the linear actuator's input command was filtered using a discrete first-order low-pass filter to smooth the input signal as written in equation (1). It is easy to implement with basic mathematical operations and computationally efficient, making it suitable for real-time applications.

The signal conditioning input block diagram is depicted in Fig. 3. Simulink Support Package for Arduino Hardware was utilized for an embedded control system on the Arduino Nano microcontroller. The measured EEG signal was sent to the soft glove via Bluetooth device. The minimum (0) and maximum (100) values from the EEG were converted to the minimum (0 cm) and maximum (5 cm) displacement strokes for driving the finger flexion and extension. Modified on-off control, regulates the motion of the linear actuator stroke based on the EEG signal input. The overall block diagram of the modified on-off controller for the soft glove is presented in Fig. 4(a). The overall control block for the soft glove was developed under Simulink, as shown in Fig. 4(b). The speed for extending and retracting the linear actuator stroke was provided with a supply voltage of 6V (max PWM value of 255). The linear actuator was commanded to stop if the displacement error was between -0.05 cm and 0.05 cm, as depicted in Fig. 4(c) (dead-zone block), to reduce the oscillation in the on-off feedback control.

$$G(z) = \frac{0.8647}{z - 0.1357} \tag{1}$$

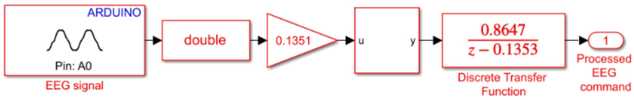


Fig. 3. Block diagram for EEG signal filtering

The figure for the soft exoskeleton glove worn by a user is depicted in Fig. 5. The glove is comfortable and lightweight; therefore, a user can wear the glove without fatigue for a long time usage. For the finger extension, the linear actuator stroke was set at 1.3 cm while the finger flexion was adjusted at 5.7 cm of linear actuator stroke. Each linear actuator was utilized for finger flexions/extensions (index, ring, and middle). The thumb was fixed at a particular position as shown in Fig. 5.

C. Grasping Performance Measurement

The grasp force test on the glove was carried out to determine how much force was generated on the fingertips when using a wearable assistive soft robotic glove. Before the grasp force test was carried out, several pieces of supporting equipment were developed for the test. A 10 k Ω resistor was selected to process the output voltage from a force-sensing resistor (FSR) sensor. The accuracy and reliability of the FSR sensor measurements are affected by nonlinearities and temperature. The output voltage (V_o) can be computed using Equation (2). R, Vin, and R_{FSR} are the selected resistor (10 k Ω), input voltage (5V), and measured FSR resistance value (Ω), respectively. The proposed measurement equipment to measure the generated force on the soft exoskeleton glove is shown in Fig. 6.

The grasp force test aims to determine the amount of grip force produced by the finger when using a wearable assistive soft robotic glove. The force generated by the linear actuator was reduced by the user's tendon-sheath friction and finger stiffness. The roughness of the surfaces and the tension in the tendon influence the amount of frictional force encountered in the soft glove. When the actuator applies force, this stiffness of the fingers leads to resistance to movement and reduces the force transmitted to the gripped object.

The shape of the force measurement was fabricated as shown in Fig. 6(a). The complete photo of the measurement system is presented in Fig. 6(b) to simplify the grasping force test. The measurement of the grip force on each fingertip was carried out as in Fig. 6(c). The input signal to move the finger comes from a potentiometer that is slowly rotated from an angle position of 0° to 270°. The angle of 0° equals a stroke of 1 cm of the actuator. Meanwhile, the angle of 270° equals a stroke of 5 cm. After giving the maximum input, the finger will press the FSR sensor (force-sensitive resistor) maximally and obtain the data grasp force on each fingertip during the grasping process.

$$V_o = V_{in}\frac{R}{R + R_{FSR}} \tag{2}$$

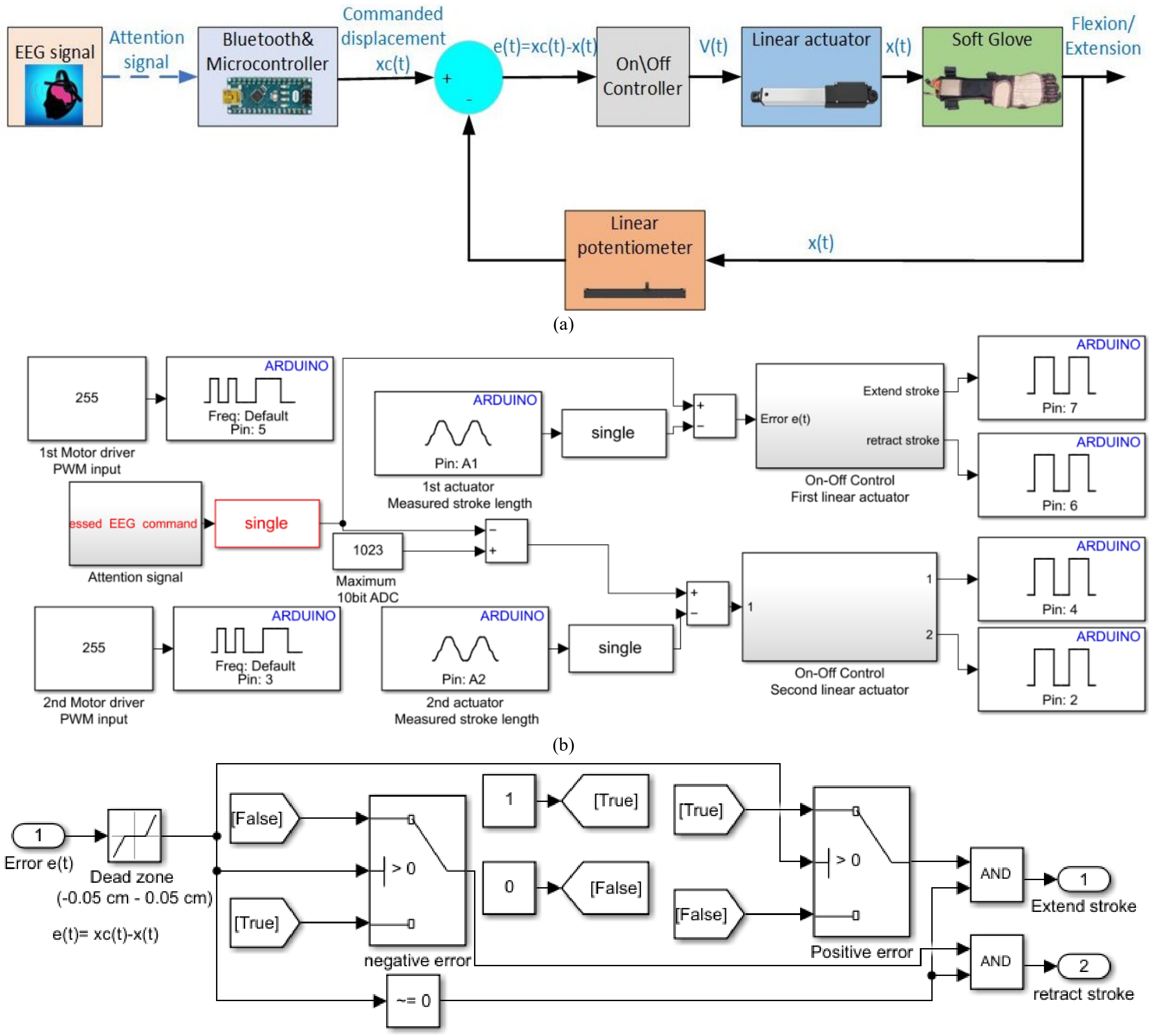
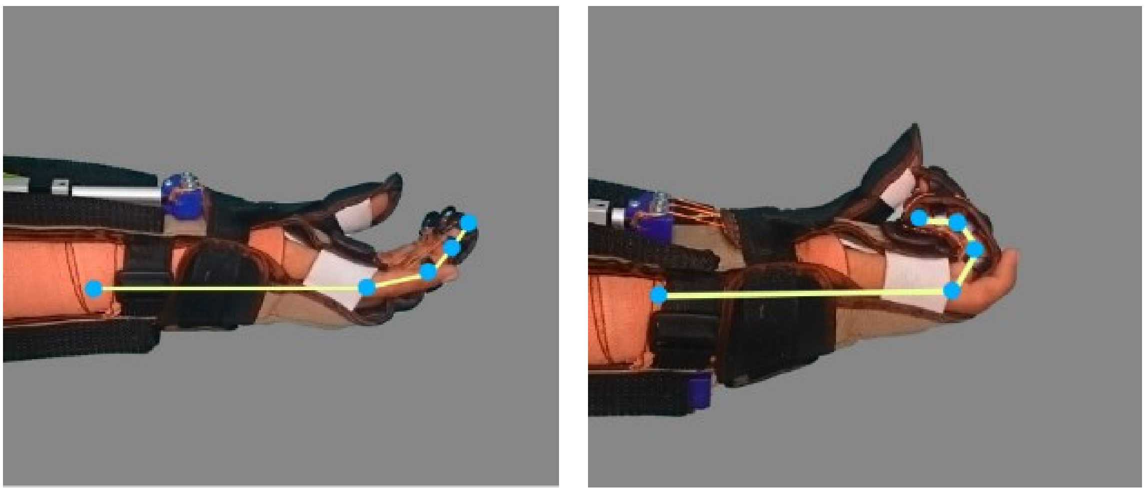
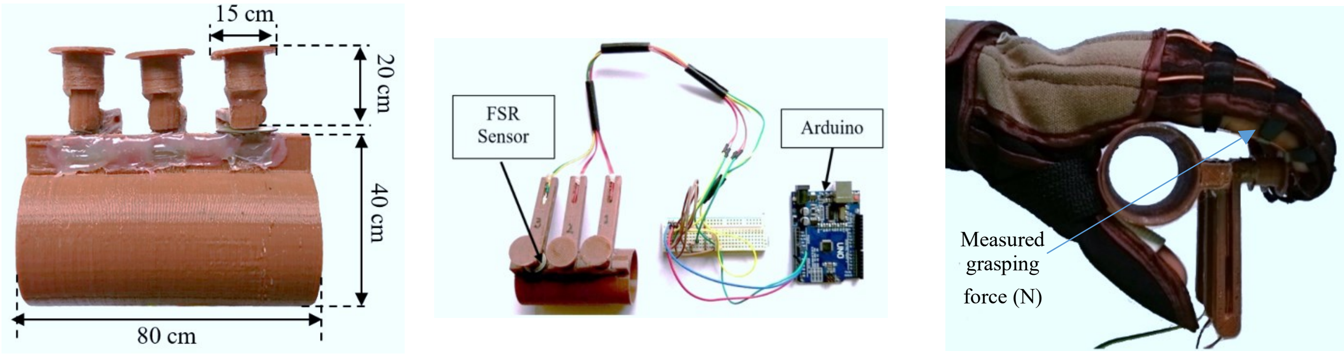


Fig. 4. Overall EEG control for soft exoskeleton flexion/extension motion assistance, (a) On-off control diagram block, (b) Embedded overall control on Arduino microcontroller, (c) Proposed on-off control on the soft glove motion



(a) (b)

Fig. 5. Mechanical assistance for hand motion, (a) Finger extension, (b) Finger flexion



(a) (b) (c)

Fig. 6. Grasping force measurement. (a) Proposed grasping measurement. (b) Overall grasping measurement system. (c) Grasping force. measurement

III. Results and Discussion

The results for the effect of music and working out are presented in Fig. 7. The measured attention signal for a study participant while listening to music and working out are plotted in Fig. 7(a) and 7(b). A T-test is conducted to determine the significant difference in the tested condition. Fig. 7(c) shows that background music with lyrics (do not like music) has a more significant adverse effect on attention values than music without lyrics (favorite music). Music with lyrics is a more complex stimulus than instrumental music alone, which explains the graph above that music with lyrics has a significant adverse effect on attention scores than music without lyrics (p-value < 0.05). Based on the test results, the utilized EEG will produce a higher attention value when a user listens to his/her favorite music. After a workout, the samples were selected from the male and female study participants' youngest, middle, and oldest. The results show that after doing exercise for 10 minutes, the study participant's attention values were decreased as shown in Fig. 7(d).

For the grasping force performance, the force generated by each finger is affected by the length of the tendon, finger stiffness, and tendon-sheath friction. The length of tendons used in the index, middle, and ring fingers varies, and the force is inversely proportional to the length of the tendons used. The following is the data on the grasp force test for each finger, which is presented in Table 3. The obtained grasping force vs. time is given in Fig. 8. The measured grasping force is obtained using the developed device as shown in Fig. 6. Providing sufficient tendon length for general users is difficult. Therefore, designing the glove with adjustable tendon length will be conducted in future study. Varying tendon lengths in a soft exoskeleton glove can have practical implications on its functionality. Excessive tendon length can lead to slack in the soft glove mechanical system, making precise control over finger movements difficult. Excessive tendon length can compromise control precision while a shorter length can provide higher tension but lead to discomfort during the use of the soft glove.

TABLE III. Measured Rasping Forces on Three Fingers

Finger	**Length of tendon (mm)**	**Maximum force (N)**
Index	19.5	5
Middle	20.0	4
Ring	19.0	3

To determine the response of the actuator in the soft glove, voltage with increments of 1 volt was given to the linear actuator from 1 volt to 12 volts. The results of the linear actuator response to voltage variations are shown in Fig. 9(a). The response graph which has experienced steady-state/constant shows that the linear actuator has moved fully to carry out a full extension movement. The results show that the greater the value of the electric voltage applied to the linear actuator, the faster the actuator response. Therefore, a voltage value of 12 volts was chosen as the working voltage for the soft robotic glove for the best response.

Meanwhile, the closed-loop response is shown in Fig. 9(b), and Fig. 9(c). Step input is given to the soft glove as an input command to determine the time constant of the soft glove (Fig.9(a)). The response without load and response with load lines indicate that the soft glove is not being worn and is being worn when the soft glove is tested. The test results on the input step show that the time constancy for the soft glove is 1.8 seconds using 12 volts of power. Fig. 9(c) shows that the soft glove can follow sinusoidal commands despite a slight delay of around 0.6 seconds. The time response for the previous silicone-based soft glove with a dual motor tendon actuator was 2.8 seconds when it is worn [30]. The measured time constant in this study is sufficient to provide the mechanical support from finger full open/extension to finger full close/flexion for grasping the object.

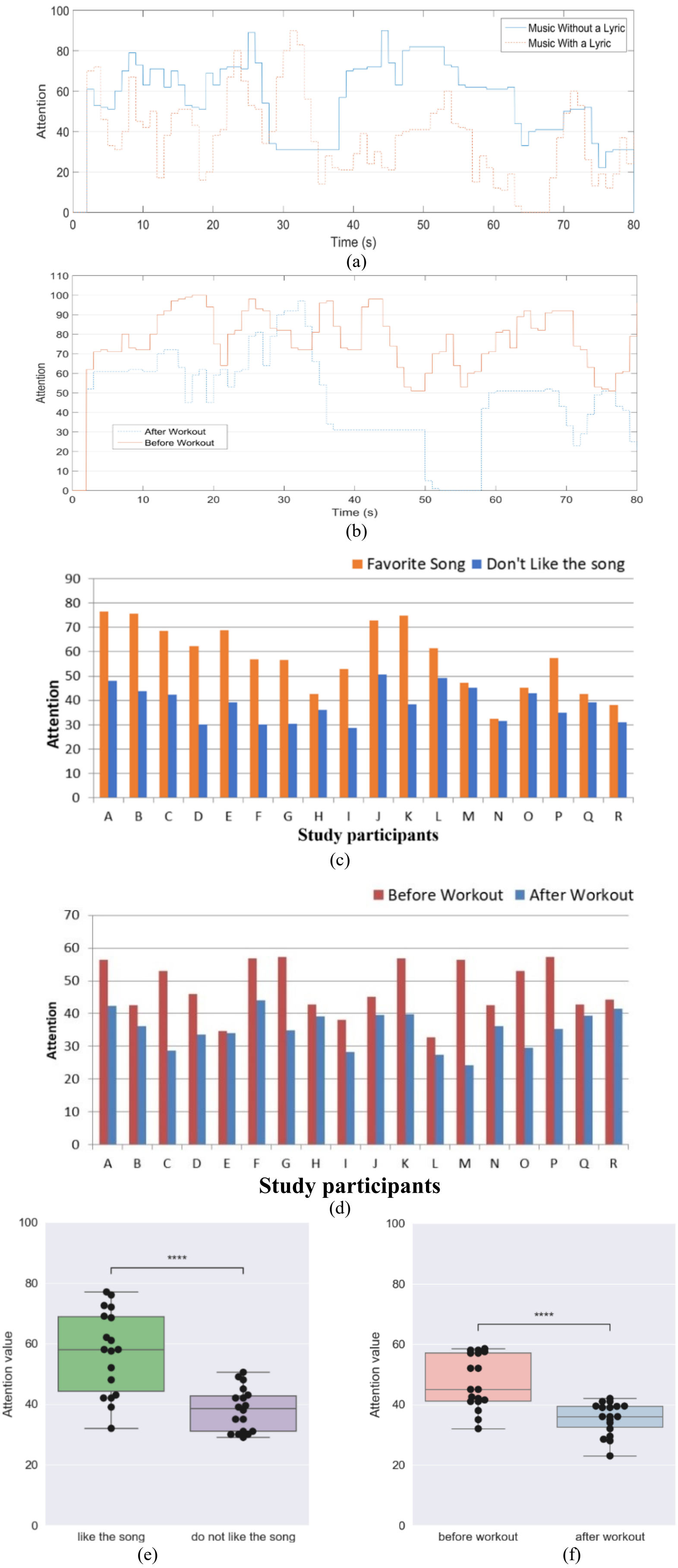


Fig. 7. Effect of listening to music and working out. (a) Music with lyrics and without lyrics for a study participant. Effect of workout for a study participant. (c) Average attention values for all participants with listening to music. (d) Effect of workout on average attention signal for all study participants. (e) Boxplot for music (noise) effect (p-value < 0.05). (f) Boxplot for the workout (fatigue) effect (p-value < 0.05).

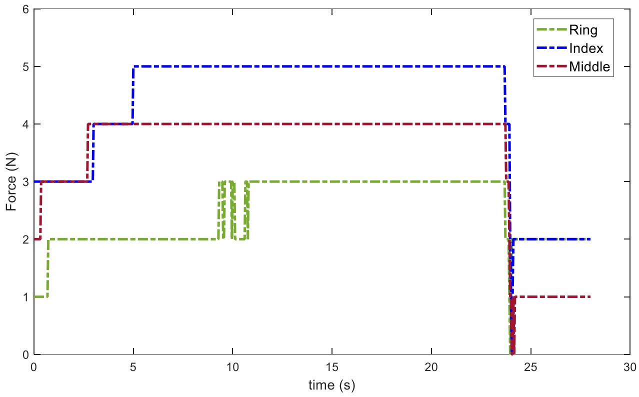
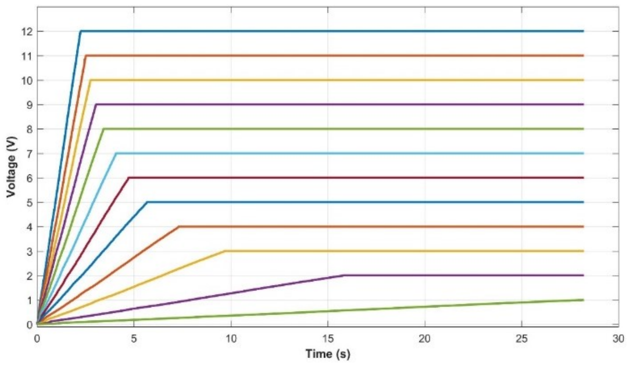
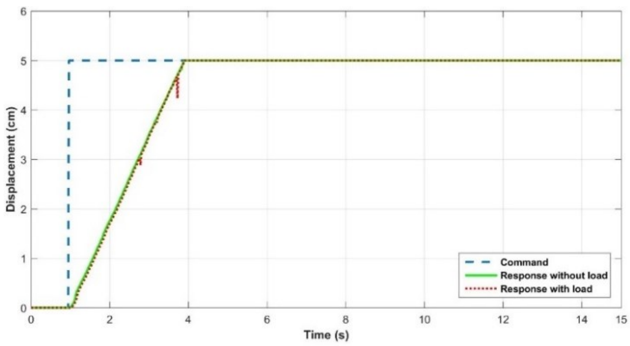


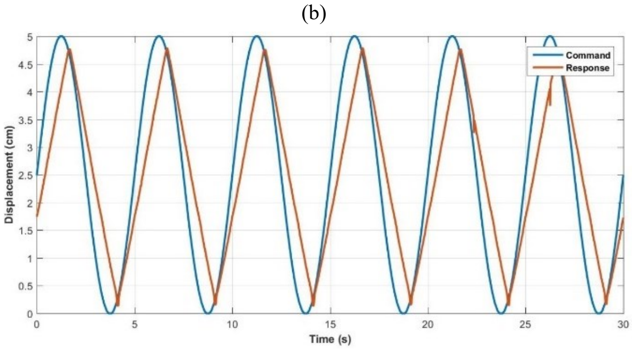
Fig. 8. Grasp force on each finger



(a)



(b)



(c)

Fig. 9. Open-loop and closed-loop responses from the soft glove. (a) Voltage input signal variations to drive the linear actuator from 0 cm to 5 cm (full extension). (b) Response of the soft glove from the step input command. (c) Soft exoskeleton glove response to the sinusoidal commanded signal.

For the performance of the feedback control commanded with the EEG signal, a user was commanded the soft glove to assist the finger flexion and extension. The linear actuator displacement stroke followed the input signal command from the EEG attention signal as shown in Fig. 10. The modified on-off control with the error dead-zone of $\pm$ 0.05 cm successfully reduced the linear actuator stroke displacement oscillation. The feedback control generated a steady state error of around 0.1 cm. A user was tasked to grasp a bottle of drinking water and lift the bottle using the user attention signal measured by single-channel EEG. Based on the test result, the user successfully commanded the soft glove to assist the finger flexion in grasping and lifting the bottle without falling to the ground, as depicted in Fig. 11. These results confirm that by implementing single-channel EEG, the soft glove can be driven and integrate easily with simple processing and control algorithms compared to multichannel EEG [52], [66], [68], [69], [74]. This study applies simple processing for EEG with simple tasks (open/closed) and also utilizes a fixed length of tendon. In the future, designing the glove with adjustable tendon length will be conducted and augmented with multi-channel EEG for more complex tasks.

Involving humans as study participants in EEG research raises ethical considerations. Therefore, carefully considering the ethical and safety aspects of EEG research, researchers can ensure the responsible and safe use of EEG technology for advancing scientific knowledge and developing new applications, especially in soft wearable robotic technology.

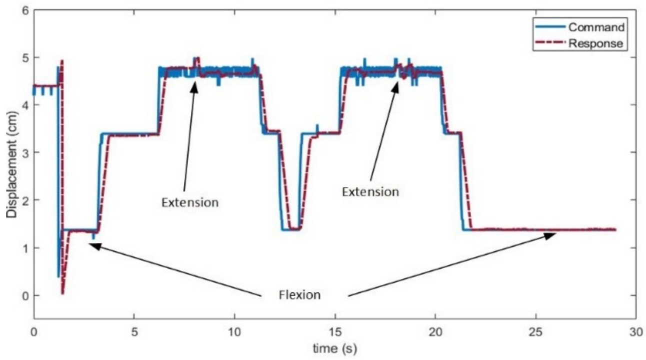


Fig. 10. Soft exoskeleton glove response to the commanded input signal from EEG

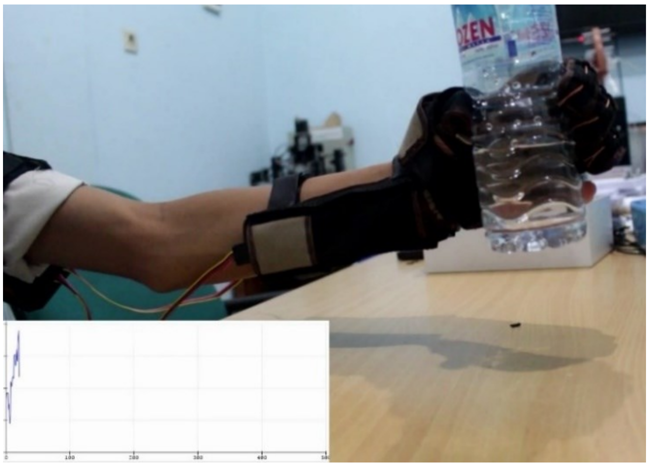


Fig. 11. Soft exoskeleton glove commanded using EEG signal

IV. CONCLUSIONS

In this research, the soft exoskeleton glove has been developed using fabric material to make it comfortable for the user to wear and attach. The exoskeleton glove is intended to provide mechanical assistance through flexion and extension movements on the user's hand. We have successfully integrated single-channel EEG with a soft exoskeleton glove. The user can move the soft glove for flexion or extension by using his mind as an attention signal. The attention signal generated from single-channel EEG is susceptible to being influenced by the environment and the user's body conditions. Based on our research results, a tired body condition from a workout can reduce the attention signal. Listening to music also influences the generated attention signal. It will increase if someone listens to music he/she likes, and vice versa. Our findings indicate that noise and fatigue can significantly weaken the attention signals used to control the soft exoskeleton glove. To optimize performance, it is recommended to use the glove system in a quiet environment and when the user is well-rested.

The position of finger flexion and extension movements can be controlled using on-off feedback control with a steady state of around 0.1 cm. The maximum grasping forces produced to provide mechanical assistance on the index, ring, and middle fingers are 5 N, 4 N, and 3 N, respectively. The proposed soft exoskeleton glove can be a potential assistive and rehabilitation devices for people with hand impairment. Using an attention signal measured by the single channel EEG, a user can easily control the soft glove motion for flexion and extension mechanical assistance to grasp and lift an object.

The developed soft exoskeleton augmented with single-channel EEG technology is still under development, and its effectiveness can vary depending on the specific condition and individual needs. However, there are potential benefits for improving independence and quality of life for stroke survivors or those with spinal cord injuries, making it an affordable device for rehabilitation and assistive technology. Soft exoskeleton gloves offer advantages but they also pose potential limitations such as strength, heat, and sweat. In future study, multi-channel EEG with deep learning will be augmented in the soft glove for more complex grasping tasks. More advanced nonlinear control will be developed to control the motion of linear actuator.

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