Design and implementation of a behavioral sequence framework for human-robot interaction utilizing brain-computer interface and haptic feedback

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ABSTRACT

In assistive robotics, research in Brain Computer Interface aims to understand human intent to enhance Human-Robot Interaction and augment human performance. In this research, a framework to enable a person with an upper limb disability to use an assistive system towards maintaining self-reliance is introduced and its implementation and evaluation are discussed. The framework interlinks functional components and establishes a behavioral sequence to operate the assistive system in three stages; action classification, verification, and execution. An action is classified based on identified human intent and verified through haptic and/or visual feedback before execution. The human intent is conveyed through facial expressions and verified through head movements. The interlinked functional components are an EEG sensing device, a head movement recorder, a dual-purpose glove, a visual feedback

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environment, and a robotic arm. Five volunteers are used to evaluate the ability of the system to recognize a facial expression, the time required to respond using head movements, convey information through vibrotactile feedback effects, and the ability to follow the established behavioral sequence. Based on the evaluation, a personalized training data set should be used to calibrate facial expression recognition and define the time required to respond during verification. Custom vibrotactile effects were effective in conveying system information to the user. The volunteers were able to follow the behavioral sequence and control the system with a success rate of 80.00%*, thus providing confidence to recruit more volunteers to identify and address improvements and expand the operational capability of the framework.*

Keywords: Human Robot Interaction, Brain Computer Interface, Vibrotactile Haptic Feedback, Virtual Environment, Assistive Robotics, Interaction Framework

1 INTRODUCTION

Brain Computer Interface (BCI) and Human Robot Interaction (HRI) belong in a multidisciplinary field that provides the ability to interlink multiple functional components associated with an assistive system while providing an interaction interface. Using this interface, a person can interact with the system to express their intent, receive feedback and control a robot to perform a physical interaction. For the functional components to follow a behavioral sequence and operate in unison, a framework is required. A behavioral sequence can be established using this framework to simulate an autonomous behavior of a system while confirming approved interactions for a certain scenario, task or action.

In a daily routine, a person accomplishes various tasks by performing motion actions related to grasping and moving objects, coordinating motion sequences, and sensing object properties using the hand and utilizing human haptics during physical exploration. These actions are generally not overwhelming for an able-bodied person whereas, they can pose a challenge to perform without additional human assistance for an individual with limited upper limb motion or a disability. In such scenarios, the integration of an assistive system in the daily life of a person to perform a desired action can help them maintain self-dependence. An assistive system incorporating machinery such as a robot capable of interaction with the physical environment refers to a system that can maintain or improve the functional capability of a person with a disability [1].

Assistive systems for social interactions consider various factors and interaction methods [2]. The system needs to understand when humans want to engage and be able to communicate with the user through verbal and non-verbal modalities. The proposed interaction approach would allow a user to interact with the assistive system using non-verbal forms of communication (facial expressions, head movements, and hand gestures) and in addition sense robot responses through haptic interaction.

Various ailments such as spinal cord injuries, strokes, muscular dystrophy, or limb amputation can lead to an upper limb disability. In the majority of cases, the person retains the ability to generate brain signals for various physical actions even after loosing motor control. In the United States alone approximately 5,400,000 people have some form of paralysis [3], and almost 185,000 people undergo some form of amputation every year [4]. The field of HRI and BCI could consider such limitations towards identifying and investigating ways to enable the interaction of humans with custom developed assistive systems.

In this research, we propose a framework to interlink multiple functional components and establish a behavioral sequence for an assistive system including a robotic arm for physical interaction. The framework is implemented in LabVIEW™due to its ability to communicate bidirectionally with diverse hardware components, ease of graphical programming, and development of customized graphical user interfaces. The assistive system utilizes the framework to communicate with various functional components; an EEG sensing device (Emotiv™Insight headset), a head movement recorder (gyroscope module), a dual-purpose glove for user input and haptic feedback, a visual robot simulator (Webots) and a robot for physical interaction (Braccio robot). This system could enable a person with an upper limb disability to control it using non-verbal user inputs (facial expressions, head movements, and hand gestures) to perform a physical interaction by verifying or rejecting the originally understood action to be performed by the machine.

2 RELATED WORK

The growing market of commercially available electroencephalogram (EEG) based devices has enabled research in the field of BCI to expand over the last few years. Headsets by Emotiv such as EPOC+, EPOC X, and Insight are some of the many available EEG sensing devices frequently used in academic research. Several studies have utilized the Emotiv headsets to extract either raw EEG data or classified data to control some form of robotic hardware [5–12].

Chowdhury et al. [5] investigated the use of four mental commands to control the motion of a mobile robot in four directions and an untrained facial expression to stop an ongoing motion. They presented an accuracy of 72.65% for motion control by able-bodied people and 82% by individuals with a disability. They also reported that the training success rates for all mental commands varied by large margins which could lead to a false interpretation. Ouyang et al. [10] investigated the implementation of mapping four mental commands to move a robotic end effector. A majority of the subjects were able to only perform control using one to two mental commands with low accuracy, and also had difficulty triggering more than two (2) commands. Aguiar et al. [8] and Zamora et al. [11] presented the usage of facial expressions and gyroscope data captured using Emotiv EEG headsets to control a simple robotic arm. A robotic arm was controlled in both studies with an accuracy of over 80%. While these studies were able to achieve reasonably high accuracy, there were still opportunities for false positives, resulting in the robot performing an unintended action. These false positives reinforce the need that the understood or classified action must be verified before robot execution to avoid unintended motions or worse injuring a person.

Virtual simulations can be an effective medium to verify robot actions to avoid undesirable behavior. According to Choi et. al. [13], virtual simulation provides the ability to simulate a selected operation based on the user decision. This is beneficial in the field of HRI since it provides a safe environment for verification of the selected action before robot execution. Webots is such a virtual simulation package commonly used in investigations with BCI to simulate robot actions [14–18].

Haptic feedback provided in the form of vibrations or vibrotactile feedback can be used to guide a person by providing a perception that could be interpreted in reference to the direction a movement should follow [19], aid in proprioceptive rehabilitation [20] or generate a tactile sensation [21, 22]. Vibrotactile feedback provided on the fingertips allowed a person to sense vibration variations due to the presence of a high concentration of mechanoreceptors under the glabrous skin [23]. This ability to sense could allow a person to understand non-visual information provided in the form of tactons. Tactons are vibrotactile feedback effects that vary in amplitude, frequency, duration, and rhythm [24]. Chan et al. [25] reported that these vibrotactile feedback effects can be identified by a person even when a person is engaged in a different task.

In general, HRI frameworks capture and interpret BCI inputs and generate control commands to operate an assistive system. Upon receiving a BCI input, the EEG signals are interpreted by a controller which extracts recognizable and classifiable features. Then, the controller will generate control commands based on these features [26–29]. After receiving the control commands, the robotic systems perform the intended task while informing the user of the task status using sensory stimuli which could be visual, auditory, or tactile. These frameworks focus on using signal processing methodologies to interpret EEG signals provided by the user in an attempt to reduce false positives. In such scenarios, once the framework receives the EEG signals, the user is not part of the decision making process and needs to visually monitor the assistive hardware to understand what the robot is doing and appropriately react if the action being performed is correct or not. In these systems, the user is not provided a priori information of the classified and interpreted action to be performed (through visual simulation or vibrotactile feedback) neither the means to approve or reject the understood action before execution.

Research in our laboratory investigates methodologies to integrate multiple functional components of BCI and HRI and approaches to provide vibrotactile haptic feedback to the user, thus providing an interface to communicate between multiple functional components and a library of distinguishable haptic feedback effects. The interface to communicate between multiple functional components utilizes Node-RED to transfer information from the Emotiv BCI program to Webots and LabVIEW. This information corresponds to classified mental commands, facial expressions, and head movements to control the operation of a Braccio robot [30]. A procedure is developed to generate and provide distinguishable vibrotactile feedback. A set of vibrotactile feedback effects is developed and evaluated to determine the ability of a person to distinguish and identify these effects [31].

This investigation further extends our research in the field of BCI and HRI and presents a framework that can be used by individuals with upper limb disabilities. The framework will establish a behavioral sequence to govern the behavior of the system and interlink multiple functional components to safely perform an action utilizing a BCI input. The proposed framework is intended to increase the involvement of the user in the decision making process before sending the control commands to an assistive device in an effort to reduce the number of false positives and provide the user the ability to act before the action is performed instead of reacting while the action is being performed.

3 FRAMEWORK

The behavioral sequence established by the proposed framework allows a person (user) to operate the system using a non-verbal form of communication (facial expressions, head movements, and hand gestures) and receive system responses in the form of haptic and/or visual feedback to verify the interpreted action before executing. The framework is implemented using a Master Control Environment to link the functional components to the user, and executing physical actions that an assistive system could perform. The functional components associated with the system are an EEG sensing device (Emotiv Insight headset), a head movement recorder (gyroscope module), a dual-purpose glove for user input and haptic feedback, a visual robot simulator (Webots), and a machine for physical interaction (Braccio robot). A set of requirements are defined to apply the framework to an assistive system. The framework should have the ability to:

- Map a desired action and a system response to a user input.
- Acquire and interpret user input for action classification.
- Allow a user to verify (accept or reject) a classified action before its execution.
- Execute a classified action.

Table 1 presents the current list of facial expressions and head movements, mapped associated robot actions, and vibrotactile feedback effects predefined in the framework. The relationships presented in this table could easily be modified in the framework and customized based on the capabilities of the user.

Table 1: Mapped commands, corresponding actions, and vibrotactile feedback effects

Input command	Robot action	Vibrotactile feedback effect	Action description
Facial expression: ***Clench***	Pick object	WVF-1	Initiate robot motion to move the end effector at the object pick up location while ensuring the gripper is open while approaching the target location.
Facial expression: ***Raised Eyebrow***	Place object	WVF-2	Initiate robot motion for object pickup by closing the gripper to grasp the object, then moving the robot to the target location while maintaining a closed gripper, and then opening the gripper to place the object at the target location.
Facial expression: ***Frown***	Maneuver object	WVF-3	Initiate user control over robot's motion to perform a non-preprogrammed action using input in the form of head movement and hand gestures.
Head movement: ***Nod Type 1***	Task confirmation: ***Accept***		Capture the user intent to confirm if the classified task is correct during the verification phase.
Head movement: ***Nod Type 2***	Task confirmation: ***Reject***		Capture the user intent to confirm if the classified task is incorrect during the verification phase.
	Notification for action execution completion	WVF-4	Indicate at the system level the actuation command signal for the robot action has been sent to the controller and executed.

The framework follows a behavioral sequence established through three stages of operation to classify an action based on user input, verify the classification, and execute or reject the classified action. During each stage of operation and based on its purpose, various modules are invoked to accomplish the objective of each stage. The functional components are associated and linked to these modules depending on their functionality. The modules are as follows:

• Module 1: Read and classify user inputs

Module 1 is responsible for understanding the user intent. The associated functional components are an Emotiv Insight headset, a gyroscope module, and a dual-function glove for user input and haptic feedback. Using this module, user input in the form of facial expressions, head movements, and hand gestures can be acquired and interpreted in the assistive system. To use module 1 effectively, the user should be trained on the type of user inputs recognized by the system using instructional cues on the operation of the framework and system capabilities.

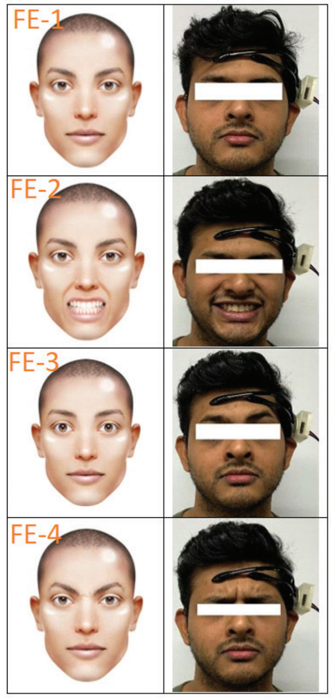
A training dataset must be generated and used to recognize and interpret a facial expression effectively. The four facial expressions FE-1, FE-2, FE-3, and FE-4 (figure 1a) are interpreted in the system as neutral, clench, raised eyebrows, and frown respectively. Two head movements HMM-0-A and HMM-0-B (figure 1b) are interpreted by the system as Nod type 1 to accept and Nod type 2 to reject a classified action. For HMM-0-A, the user head is tilted both forward and backward starting and ending at a neutral position. For HMM-0-B, the user head is turned both left and right starting and ending at a neutral position. The head neutral position is defined as the state where the head is not tilted or turned in any direction.

On selection of action 'Maneuver object', the user is able to control the robot motion in real-time to translate the end effector of the Braccio robot (see figure 2) along the global $X-$ and $Y-$axes using head movements HMM-1-A, HMM-1-B, HMM-2-A, and HMM-2-B, and rotate the robot about the global $Y-$axis at the base joint $(J0)$ using the head movements HMM-3-A and HMM-3-B as presented in figure 1b. The opening and closing of the end effector is mapped to the motion of the ring finger. The safety switch is mapped to the thumb position on the dual-purpose glove which is required to be engaged in order for the robot to translate or rotate. Otherwise, the robot will not move and maintain its current pose irrespective of user inputs being provided. The safety switch can be engaged by the hand gesture of moving the thumb towards the palm and must maintain this position for the robot to move.

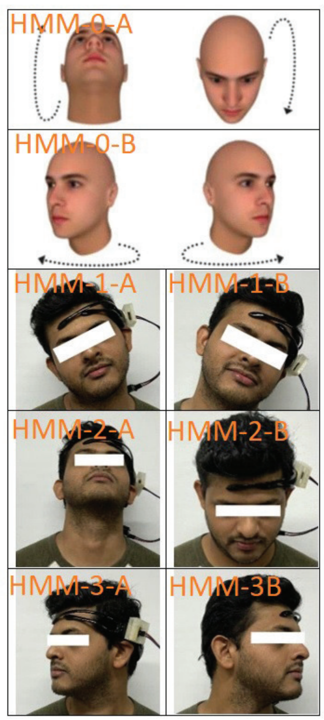
HMM-1-A and HMM-1-B translate the robot end effector backward and forward along the global $Y-$axis and require the head to be tilted to the right and left respectively and hold its position. HMM-2-A and HMM-2-B translate the robot end effector backward and forward along the global $X-$axis and require the head to be tilted forward and backward respectively and then hold its position. HMM-3-A and HMM-3-B rotate the robot clockwise and counterclockwise and require the head to be turned to the right and left respectively and hold its position. These inputs are currently mapped to the workspace and operation of a Braccio robot discussed in section 4.6 but can be easily mapped to any other action or task that can be performed by a machine in the assistive system following the proposed framework.

• Module 2: Signal verification using haptic feedback

Module 2 is responsible for conveying system responses to the user for verification using haptic feedback for a classified action based on the user input. The associated functional component is the dual-function glove. In this module, the system uses a unique vibrotactile feedback effect mapped to an action to inform the user of the action classified by



(a) Mapped facial expressions



(b) Mapped head movements

Fig. 1: User inputs: facial expressions and head movements

the system. Vibrotactile feedback is also provided to inform the user when an action execution has been completed by the system. The current vibrotactile feedback effects mapped in the system are presented in figure 3, and they differ from each other based on the vibration intensity variations over a time period. To effectively use Module 2, the user

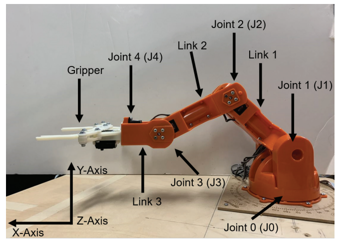


Fig. 2: Braccio robot

should be trained on the sensation induced by the vibrotactile feedback device for each effect and the associated action. The training will allow the user to correctly recognize and interpret the vibrotactile feedback for signal verification and improve system operational fidelity.

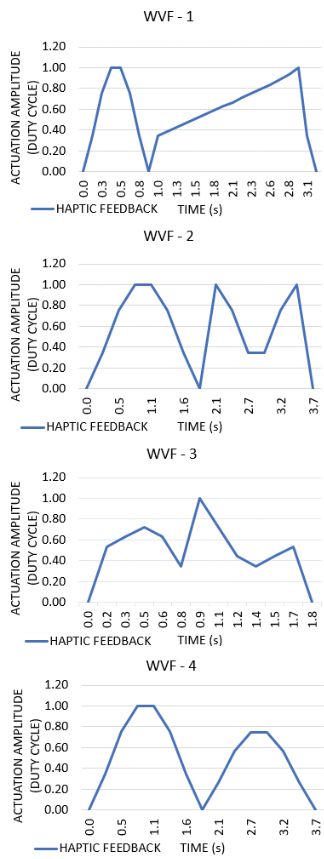


Fig. 3: Robot action/system response output mapping for vibrotactile feedback effects: WVF-1 Pick object, WVF-2 Place object, WVF-3 Manual control mode, WVF-4 Confirm action completed

• Module 3: Signal verification using virtual simulation

Module 3 is responsible for conveying system responses to the user for verification using visual feedback for a classified action based on the user input. The associated functional component is Webots, a robotic simulator for visual feedback, training, and evaluation platform. Using this module, the system presents a visual simulation of the robot motion to inform the user of the action classified by the system. The simulated robot motions in Webots for two actions, 'Pick object' and 'Place object' are presented in figure 4. Webots could also be used for training the user and evaluating the robotic arm motion in a simulated environment before executing the interpreted action on hardware. Even though the simulation to be performed by the robot is currently programmed for 'Pick object' and 'Place object' actions, other actions could easily be added to the system.

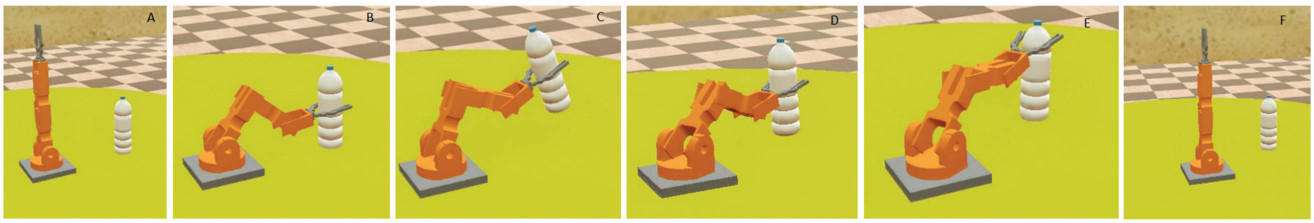


Fig. 4: Webots virtual simulation of robot performing the classified actions of Pick (approach) object and Place (grasp, place, and release) object

• Module 4: Action execution

Module 4 is responsible for executing a classified action using the machine attached to the system to perform physical interactions. The associated functional component is the Braccio robotic arm. The three actions to be performed by the robotic arm currently defined in the system are 'Pick object', 'Place object', and 'Maneuver object'. The 'Pick object' and 'Place object' are preprogrammed, whereas 'Maneuver object' allows the user to perform a non-preprogrammed action by generating the motion commands based on the non-verbal user input in the form of head movements and hand gestures. A time-lapsed sequence of motions performed by the Braccio robot for the 'Pick object' and 'Place object' actions after being classified and verified is presented in figure 5.

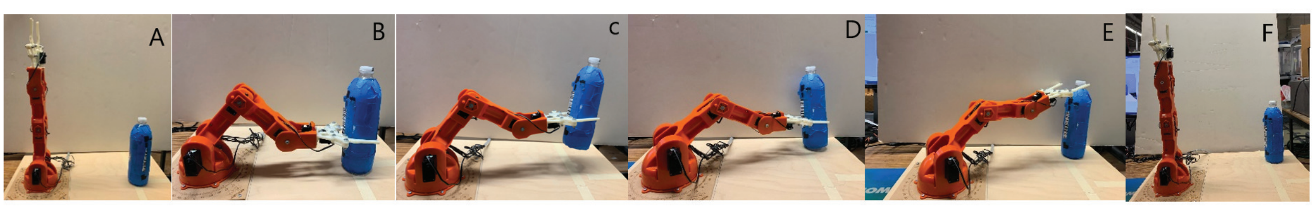


Fig. 5: Actual robot performing the classified actions of Pick (approach) object and Place (grasp, move, place, and release) object

The model of the proposed framework for an assistive system linking all four modules is presented in figure 6. These modules are linked according to the framework forming an interactive system that can execute actions based on the classification of user inputs specified in Module 1. These user inputs are a form of unique and personal human-human non-verbal communication [32] and allow for the system inputs to be customized and personalized. Utilizing these user inputs, the framework is intended to operate in three stages invoking the appropriate modules as needed. The stages of operation of the framework are as follows:

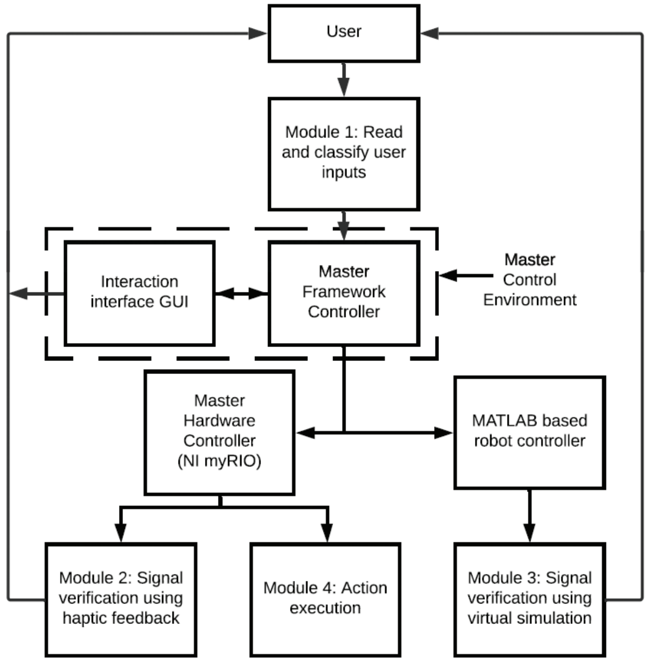


Fig. 6: Framework model for an assistive system

• Stage 1: Action classification

In this stage, Module 1 is invoked. The user facial expressions are captured and recognized based on the available user training data. This recognition allows the framework to interpret the user intent and then classify the action to be performed based on mapped expressions and actions. Action classification can only be successful if the recognized facial expression has an action associated to it. If the facial expression is not classified, then the framework will wait for another user input. Based on the action classified, the commands for the robot motion and the corresponding haptic feedback effects are retrieved. After successful classification of the user input, the framework will proceed to Stage 2 or else it will maintain the current state of all interlinked modules and associated functional components and wait for the next user input.

• Stage 2: Action verification

In this stage, Modules 1, 2, and 3 are invoked. The action classified in the framework is verified using haptic and visual feedback. Visual feedback is only provided after the user accepts the classified action conveyed using haptic feedback. Visual feedback is only provided for the 'Pick object' and 'Place object' actions and not the 'Maneuver object'. After every verification feedback, the user must respond using either Nod type 1 or Nod type 2 within a response period of 5 seconds. If the classified action is accepted by the user, the framework will proceed to Stage 3 or else reinitialize all system inputs and return to Stage 1. The simulated robot motion for two actions, 'Pick object' and 'Place object', in Webots is shown in figure 4.

• Stage 3: Action execution

In this stage, Modules 1, 2, and 4 are invoked. On successful verification of the classified action, the action is performed using either the robot motion commands retrieved for preprogrammed actions during Stage 1 or by generating robot motion commands based on user input using Module 1. After completion of the intended action, the user is notified using haptic feedback. On completion of the action, the framework will reinitialize the system inputs to accept new commands and return to Stage 1. A sequence performed by the Braccio robot for the 'Pick object' and 'Place object' actions, after being classified and verified is shown in figure 5.

The detailed behavioral sequence established by the framework is presented in figure 7.

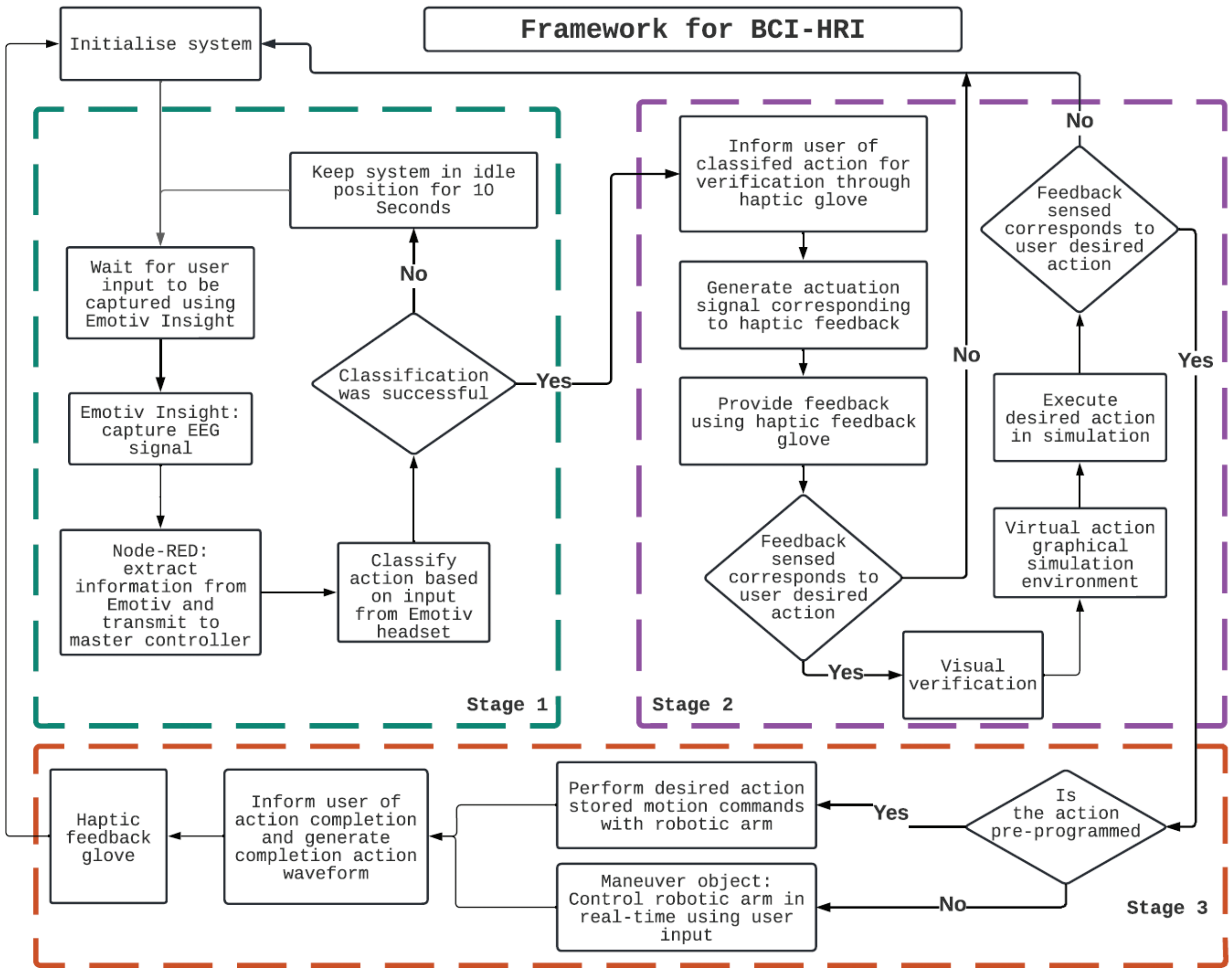


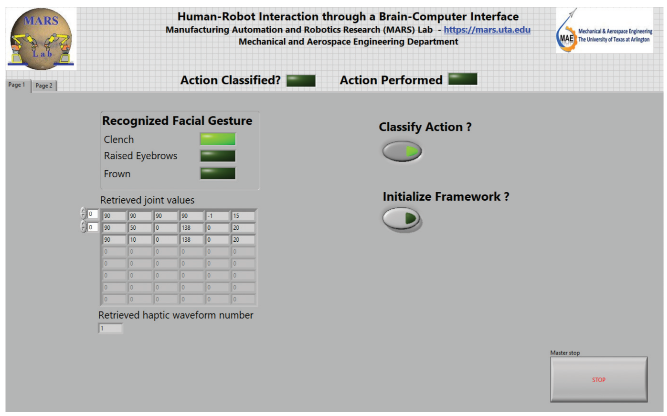
Fig. 7: Behavioral sequence due to the proposed framework

4 MASTER CONTROL ENVIRONMENT AND FUNCTIONAL COMPONENTS

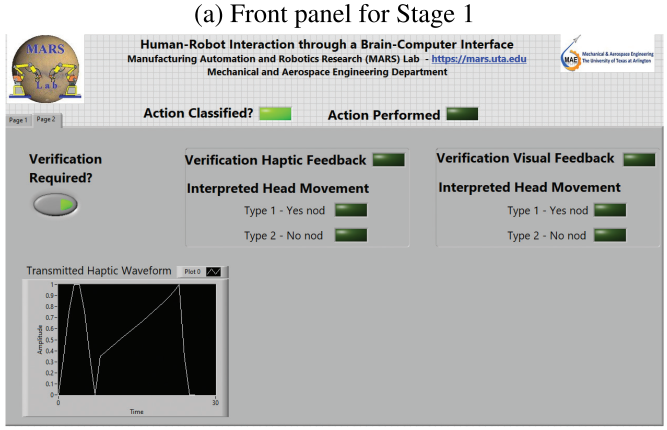
The assistive system consists of various functional components working in unison according to the operational stages defined by the framework. The functional components include an Emotiv Insight headset, gyroscope module, a dual-function glove, Webots, and a Braccio robot. The Master Control Environment (MCE) is implemented using LabVIEW to communicate with the functional components and execute the behavioral sequence defined by the framework.

4.1 MASTER CONTROL ENVIRONMENT

LabVIEW is a system design platform and development environment used to program the MCE for the assistive system. The MCE consists of a GUI and a Master Framework Controller (MFC) to enforce the behavioral sequence defined by the framework, interpret sensor data and generate actuation signals. The MFC interfaces with Master Hardware Controller, an NI myRIO microcontroller, to acquire and analyze sensor data and process actuation commands. The MFC also interfaces with a MATLAB based robot controller which generates control commands for the visual simulation in Webots. The GUI of the MCE allows for the continuous monitoring of any desired signal and the different stages of operation. Figures 8a and b present the front panel for the MCE's interactive interface for monitoring the operation of Stage 1 and the operations of Stages 2 and 3 respectively.



(a) Front panel for Stage 1



(b) Front panel for Stage 2 and Stage 3

Fig. 8: MCE (interactive interface) - front panel

4.2 EEG SENSING DEVICE - EMOTIV INSIGHT

The Emotiv Insight headset is a non-invasive 5-channel EEG sensing headset paired with the EmotivBCI program. The information collected using the Emotiv Insight headset is extracted using Emotiv-BCI Node-RED toolbox available in Node-RED, a browser-based programming language. This toolbox extracts information associated with facial expression recognition and then the information is sent to the MCE for action classification. The Emotiv-BCI Node-RED toolbox could interface directly with the EEG sensing headset after it has been trained using the EmotivBCI program. The EmotivBCI program can recognize facial expressions based on the sensed EEG signals and user training, and allows for the visualization of the EEG signals. Then, following the manufacturer software guidelines, the user trains facial expressions using on-screen avatars as shown in the left column in figure 1 [33, 34]. Using Node-RED allowed us to define the accuracy threshold for facial expression recognition and the ability to customize the system to the individual user since accuracy threshold feature is available in the EmotivBCI software. In our work, this threshold was defined at 90 out of 100.

4.3 GYROSCOPE MODULE

Even though the Emotiv headset has a built-in gyroscope to capture head movements, we implemented a third-party gyroscope (PmodGYRO sensor based on an ST-L3G4200D MEMS gyroscope) considering future expansion towards defining new types of user inputs based on sensor fusion. The gyroscope data (angular velocity) is acquired and processed by the Master Hardware Controller to compute the angular displacement. The angular displacement is used by the MCE to identify the type/direction of head movement by comparing it to experimentally defined user-specific displacement thresholds. Independently acquired sample gyroscope data sets as a function of time corresponding to Nod type 1 and Nod type 2 are superimposed and presented in figure 9.

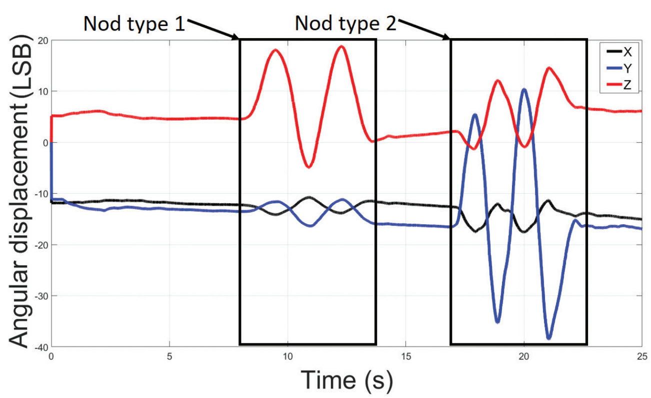


Fig. 9: Independent gyroscope signals for Nod type 1 and Nod type 2 superimposed as function of time

4.4 DUAL-FUNCTION GLOVE

The custom dual-function glove for user input and haptic feedback developed at our research laboratory is presented in figure 10. The device can sense hand gestures performed by the ring finger and the thumb using resistive flex sensors. The vibrotactile feedback at each fingertip is generated by an eccentric rotating mass (ERM) actuator of $10mm$ diameter operating at a frequency of $220Hz$. The actuators are driven using a DRV2605L actuator driver board powered by a $3.3V$ power supply provided through the Master Hardware Controller. The controller records sensor output at a rate of $200Hz$ and operates at a frequency of $1kHz$ to generate a PWM signal based on the desired input vibrotactile feedback effect to drive the ERM actuators.

Fig. 10: Dual-purpose glove: glove inner side (left) and glove outer side (right)

4.5 WEBOTS

Webots is one of many available open-source graphical 3D robot simulators. It is used in this work to provide visual feedback in the form of simulating the robot motion based on the preprogrammed actions in the system. Webots uses a MATLAB based robot controller which interfaces with the MFC to receive motion commands corresponding to the action to be performed. The simulation for the 'Pick object' and 'Place object' actions are presented in figure 4.

4.6 BRACCIO ROBOT

In this research, the robot selected to perform a user desired action is a Braccio tabletop robot shown in figure 5 [35]. This robot is selected considering user safety during the development and evaluation of the new framework and its operational simplicity. The robot motion is controlled using PWM signals from the Master Hardware Controller for each joint servo actuator. If 'Maneuver object' action is selected, the robot motion can be controlled using head movements to translate the gripper (end effector) along the global $X-$ and $Y-$axes and rotate the robot about the global $Y-$axis at joint $J0$ and hand gestures to open and close the gripper. The inverse kinematics of the robot are programmed and performed in real-time. The limits for translation of the end effector and rotation of the robot are governed by the joint limits of the robot.

5 FRAMEWORK EVALUATION AND DISCUSSION

For the initial evaluation, a volunteer-based study is performed to determine the effectiveness and identify aspects crucial to the development of the proposed framework. Using the MCE, the proposed framework is implemented to interlink the functional components of the assistive system and to define the behavioral sequence.

5.1 EVALUATION PROTOCOL

Five volunteers (able-bodied male students in the age range of 25-35) participated in this evaluation on their own accord without any form of compensation. These volunteers were provided instructional cues about the operation of the assistive system based on the proposed framework using a demonstration to pick, move and place an object from and to a known location. During the demonstration, the volunteers were explained the system operational stages, associated functional components, and the types of inputs and outputs expected. After receiving the instructional cues, the volunteers were introduced to the EmotivBCI program, head movements, and hand gestures to control the robot motion, and sense the distinguishable vibrotactile feedback effects to be able to communicate with the assistive system.

The volunteers were asked to wear the headset (after being cleaned) according to the manufacturer guidelines such that the EEG signal strength reaches a minimum of 95% and then take part in the training process available through the EmotivBCI program for recognition of the facial expressions of neutral, clench, raised eyebrows and frown. Motion corresponding to the head movements and hand gestures is demonstrated to the volunteers, and then replicated by them to understand how to provide an input recognizable by the system. The volunteers also use the dual purpose glove and explained that feedback would only be provided on the tip of the index finger. The volunteers were trained by introducing the sensation due to feedback effects mapped in the system while viewing the graphical representation of the vibrotactile feedback effects and memorizing the associated robot action/system response.

The volunteers participated in the framework evaluation after receiving the instructional cues and completing the training. The evaluation was performed using the assistive system to verify the ability to follow the behavioral sequence established by the framework.

5.2 FRAMEWORK EVALUATION

The procedure to evaluate the framework and the results obtained are discussed. The framework evaluation includes verifying the ability to follow a behavioral sequence to execute a desired action or task and handle unintended facial expressions or false positives. Along with the framework evaluation, the ability of the system to properly recognize a facial expression, the time required to perform a head movement, and the ability of the volunteers to recall a robot action/system response by sensing vibrotactile feedback is evaluated.

- Evaluation of facial expression recognition

  A training data set of the facial expressions of the researcher was prepared and used. The evaluation was performed using the EmotivBCI program for the five volunteers. The average recognition success rate for each volunteer for three facial expressions over three repetitions is presented in figure 11.

  The average recognition success rate for the researcher was 88.88% whereas the average recognition across the five volunteers was found to be 64.44%. In addition, the EEG quality for each sensor was observed to fluctuate between $0\% - 100\%$ when a facial expression was performed or changed by the volunteers. Therefore, a custom training data set for each user should be developed and used. The EmotivBCI software does not provide the user the ability or the tools to define an accuracy threshold for facial expression recognition.

- Evaluation of time period required for head movement

  The response period, the time needed for a person to provide input for Stage 2, was determined based on the time required for the five volunteers to perform Nod type 1 and Nod type 2. The variations in the time period required by the

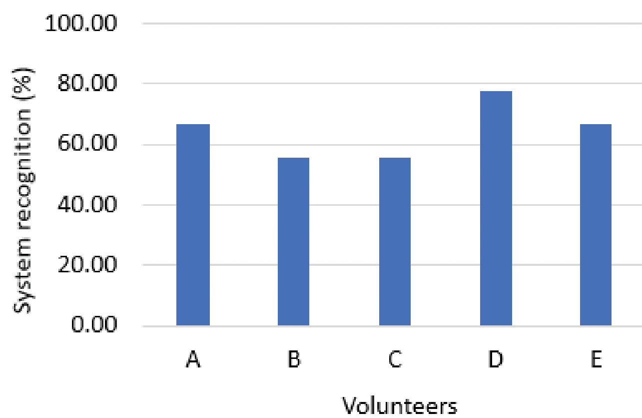


Fig. 11: Average facial expression recognition for each volunteer based on an a priori training data set provided by the researcher

volunteers to perform the head movements to either accept or reject a classified action were recorded over 3 repetitions and presented in figure 12.

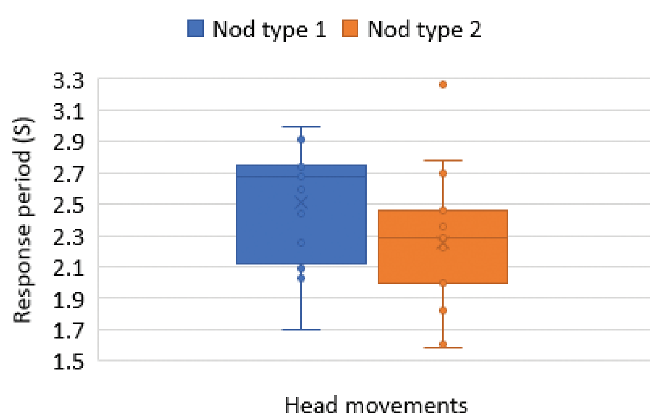


Fig. 12: Average response time to perform a head movement by all volunteers

The maximum response periods were found experimentally not to exceed 3 seconds for either head movement but did vary for each volunteer. Therefore, a default time period of 5 seconds including 2 seconds of buffer period to perform the head movement might be adequate. The ability, though, to define a custom time period is provided to the user to allow the system to be personalized and customized for each user.

• Ability to recognize vibrotactile feedback effects

The ability to recognize vibrotactile feedback effects was evaluated to understand if a person is able to recall an associated robot action or system response. The vibrotactile feedback effects utilized for evaluation are presented in figure 3 and the associated robot actions and system responses are presented in table 1. An overall recognition success rate of 80.00% was observed in the ability of a person to recall the correct robot action/system response over three repetitions per volunteer. Figure 13 presents the average successful recall rate for each robot action/system response when the corresponding vibrotactile feedback is provided in random order on the index finger. Therefore, vibrotactile feedback effects can be used to convey information from the robot to the user.

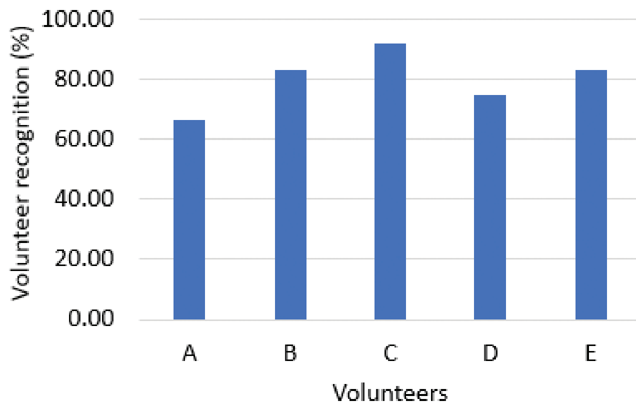


Fig. 13: Ability of a volunteer to recognize vibrotactile feedback effects and recall a robot action or system response

Before evaluating the ability to follow the behavioral sequence based on the proposed framework, the volunteers were informed of the actions and the order in which these actions are to be performed (to move a plastic bottle from and to known locations).

A customized facial expression training data set generated for each volunteer is used and a threshold on facial expression accuracy was set at a score of 90 out of 100 through the Emotiv-BCI Node-RED toolbox. The thresholds to recognize the head movements were experimentally defined and set for each volunteer for the evaluation of two cases as follows:

• Case 1: Ability to execute a desired action.

The volunteers used facial expressions to first pick the object and then place it. The average success rate for each volunteer to perform the pick and place actions over three repetitions is presented in figure 14. An overall success rate of 80.00% was observed in the ability of the volunteers to operate the system and follow the framework to perform the desired action. Three volunteers (B, C, E) had a success rate of 66.67% due to incorrect recognition of facial expressions while the remaining two volunteers (A, D) had a success rate of 100%.

The volunteers were able to identify the action corresponding to haptic and visual feedback. They were able to verify (accept or reject) an action before executing it depending on whether the feedback matches the user intended action. A time period of 5 seconds was allotted for each volunteer for providing a response to verify or reject a classified action. This time period was found to be adequate for all volunteers. Overall, the volunteers were able to perform the desired action and were observed to successfully follow the specified behavioral sequence.

• Case 2: Ability to handle unintended facial expressions or false positive user inputs.

During this evaluation phase, the volunteers were asked to provide either a clench or raised eyebrow or frown facial expression as input but directed to provide a response in the form of a head movement to reject the classified action during the verification process in order to treat it as an unintended input and prevent the system from executing the action using the robot. All five volunteers over 3 repetitions each were able to successfully prevent the system from

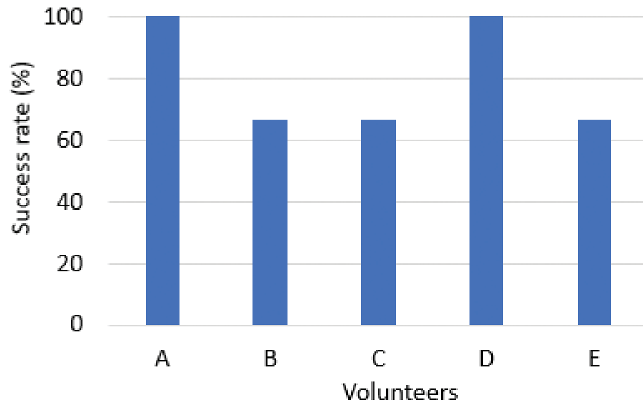


Fig. 14: Volunteer success in operating the developed system

executing the action and the system automatically reinitialized to accept new inputs.

Based on the evaluation, it was observed that the training data set used to classify a facial expression needed to be personalized for every user as the system average recognition rate for facial expressions dropped to 64.44%. The time required to perform a head movement by each volunteer varied indicating that every user might need to set their own response periods. The system response communicated to the volunteers in the form of vibrotactile feedback was found to be an effective method to convey system response with a success rate of 80.00%. The volunteers demonstrated the ability to operate the system to perform an action with a success rate of 80.00% and were able to follow the behavioral sequence established by the framework.

According to these results, it is recommended that a calibration stage be added to the framework to allow a user to customize and personalize the system and define threshold values corresponding to the expected user inputs. This study provides confidence to recruit additional test subjects both able-bodied and persons with assistive needs for a more comprehensive evaluation of the utility of the framework to identify limitations and/or areas of improvement.

CONCLUSIONS

In this research on BCI and HRI, we presented the development and evaluation of a proposed framework that interlinks multiple functional components associated with an assistive system and establishes a behavioral sequence to operate the system. The system is operated in stages to classify, verify and execute an action. The action is classified by interpreting facial expressions performed by the user (BCI input) and verified by providing haptic and/or visual feedback to the user.

The user inputs (facial expressions and head movements), system responses (vibrotactile feedback), and the actions to be performed are mapped in the system. The functional components are a non-invasive EEG sensing device (Emotiv Insight), a head movement recorder (gyroscope module), a dual-purpose glove for user input and haptic feedback, a visual feedback environment (Webots), and a robotic arm (Braccio robot). These components belong to the different modules invoked based on the stage of operation.

Experiments were performed using five volunteers. The average facial recognition using a non-personalized data set was at $\sim 65.00\%$. It was found that a personalized training data set should be used to improve the recognition of facial expressions. The experiments also indicate that a personalized time to perform head movements might need be defined. The ability of the volunteers to identify and distinguish haptic feedback had an average recognition rate of 80.00% indicating that haptic feedback is an effective modality through which the system could convey information to the user. The volunteers were observed to follow the established behavioral sequence to control the system and perform a set of actions with an average success rate of 80.00%. These results demonstrate the utility of the framework for application in assistive environments operated by people with upper limb disabilities towards maintaining self-reliance. This initial successful evaluation validates the proposed approach and provides confidence to further evaluate the framework with more volunteers with different capabilities to identify possible limitations and improvements and initiate research in system autonomy.

FUNDING DATA

This research was not funded by any agency.

ACKNOWLEDGMENTS

The authors would like to thank the anonymous volunteers who, on their own accord and without any kind of compensation, participated in the initial evaluation of the developed framework. The authors also thank the reviewers for their constructive comments that helped improve the manuscript from its original form.

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