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Controlling a Robotic Arm Through Neural Activity⋆⋆⋆

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Abstract. Researchers are eager to explore Brain-Computer Interface (BCI) systems in terms of their potential clinical applications. These systems, often integrated with Electroencephalography (EEG), have been developed to assist individuals with disabilities in their daily activities. EEG can detect auditory Steady-State Evoked Potentials (SSEPs); entrained neural responses produced by auditory stimulation, that are typically strongest for amplitude modulations around 40Hz. This research explored whether neural activity could control a UR-5 robotic arm. During the initial phase, participants attended to auditory stimuli (35Hz & 40Hz) presented separately to each ear, whilst a dry electrode EEG system recorded brain signals. This data was used to train a classifier for the main experiment. In this experiment, participants attended to either their left or right ear whilst wearing a dry EEG, prompting a binary response to command the UR-5 robotic arm to move either left or right. Further development of BCI systems in conjunction with EEG systems is necessary to facilitate the execution of more intricate movements of the UR-5 robotic arm, with potential applications in clinical contexts.

Keywords: EEG · UR-5 Robotic Arm · Brain-Computer Interface.

1 Introduction

Numerous studies have explored the applications of Brain-Computer Interface (BCI) systems within clinical contexts to assist individuals with disabilities. BCI systems have been extensively researched in conjunction with electroencephalography (EEG) systems to establish connections with neural activity. EEG captures the collective electrical activity of populations of cortical neurons using scalp sensors. Integration of online EEG systems with machine learning techniques has been useful in enabling human control of robots or wheelchairs [1]. Using BCI systems to control robots through neural activity could aid those with disabilities to perform daily tasks more independently.

BCI systems rely on evoked or spontaneous neural activity for control [2]. Spontaneous brain activity occurs naturally, without external stimuli, whereas evoked activity responds to sensory input. Both types of brain activity can be

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used to discern user intention, typically by training a classifier algorithm to distinguish different brain states.

A useful phenomenon in this context is the auditory Steady-State Evoked Potential (SSEP), which is an entrained neural response elicited by periodic auditory stimuli, with optimal sensitivity typically observed at frequencies around 40Hz [12]. Since this frequency is much lower than the human ear can detect, it is typical to modulate the amplitude of a higher frequency carrier waveform. Auditory SSEPs are well-isolated in the Fourier spectrum of EEG signals from frontocentrally located electrodes. By presenting stimuli at two different frequencies simultaneously, attention can manipulate evoked potentials in the brain depending on which frequency is being attended to [3] [4]. Synthesising these insights, this project tested whether SSEPs could be used to control the movement of a robotic arm, by way of decoding through multivariate pattern analysis. Hence, this project used auditory stimuli at 35Hz and 40Hz to manipulate evoked potentials measured through EEG, to direct a robotic arm to move in a specific direction that corresponded with the frequency the participants attended to.

2 Related Work

Similar experiments have been conducted in the field of robotics by attempting to control a robot through neural signals. Some related work includes animal studies where electrodes are implanted into their brain to retrieve neural information to control a robotic arm [5] [6] [7]. However, such studies usually obtain better spatial and temporal resolution due to their invasive properties, which cannot typically be achieved with humans. Experiments conducted with humans instead use non-invasive techniques like EEG in conjunction with BCI systems [8], as used in the present project. For instance, EEG has been used in humans to execute grasping and reaching of a robotic arm [9]. In [11], the authors used data from 4 people to train a support vector machine (SVM) classifier to identify left and right brain signals in order to control a robot arm, reaching an accuracy of 85%. Higashi et al. [13] extracted binary signal from Auditory Steady State Responses (ASSR) in order to train different classifiers (PCA, LDA and linear SVM) on brain signals recorded from 10 subjects (all males, aged between 22 and 30 years old) using an amplifier MEG-6116 (NIHON KOHDEN). The present project adopts a similar approach, by demonstrating a successful experiment with 12 people (6 males and 6 females, aged between 21 and 42 years old) using a dry electrode G.tec USBamp amplifier EEG system. Our approach differs from the work in [13] in that they ran a one-stage experiment where they recorded brain signals and trained different classifiers to see how well they performed. In contrast, we developed a two-stage protocol composed of a first pilot study to record brain signals from 12 subjects in order to train an SVM classifier and a second step where 4 subjects were asked to move a robotic arm in real-time using their brain signals. Additionally, our approach also performs better than [13], more detail is given in the results section.

3 Methods

A pilot study was conducted where 12 participants (6 males and 6 females, aged between 21 and 42 years old) attended to auditory stimuli (35Hz & 40Hz modulations of a 1kHz pure tone carrier) in separate ears, whilst a dry electrode G.tec USBamp amplifier EEG system recorded brain signals from 8 scalp locations. Each participant completed 20 trials of 30 seconds duration attending to the left ear's signal, and 20 trials attending to the right ear's signal. The data were segmented into 1 second epochs and used to train an SVM classifier for the main experiment. After training, the classifier produced a global accuracy score, along with individual accuracy scores for each participant.

Once the classifier was trained, the main experiment was carried out with 4 people (including some from the pilot study). During this experiment, participants attended to either their left or right ear whilst the dry electrode EEG system collected their neural responses. These were decoded in real time using the trained SVM classifier to generate a binary response instructing the robot to either move left or right (see Fig. 1). Thus as neural signals were received, the UR-5 robotic arm would move either left or right in real-time – depending on the neural responses the classifier received. See Fig. 2 for a schematic illustrating the setup of the main experiment.

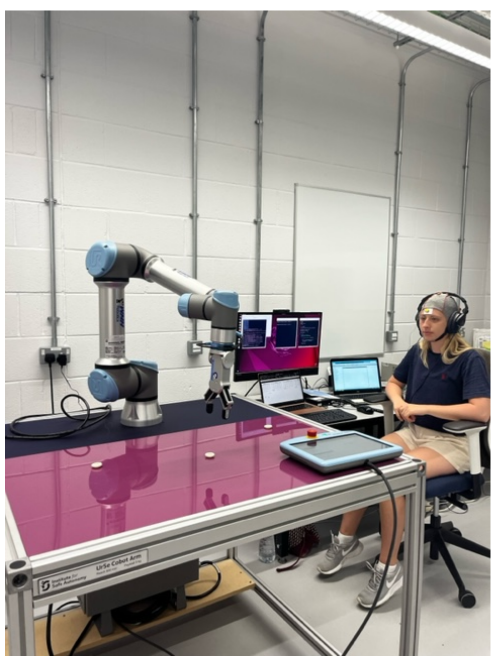

Fig. 1. Photograph of a participant during the experiment.

Several software programs were used for the execution of the main experiment. Matlab 2015a was used to train the EEG data from the pilot study, and was also used in the main experiment to collect the EEG data so the trained classifier could make a binary response. The binary response was communicated through an Ethernet cable to a PC which was receiving signals in Python using TCP client-server communication. This Python script would then communicate through TCP with the UR-5 robotic arm to execute the correct movement (either left or right) depending on the signal received from the EEG computer, using Python URX library[1]. Ethical approval was sought from and approved by the Department of Psychology at the University of York.

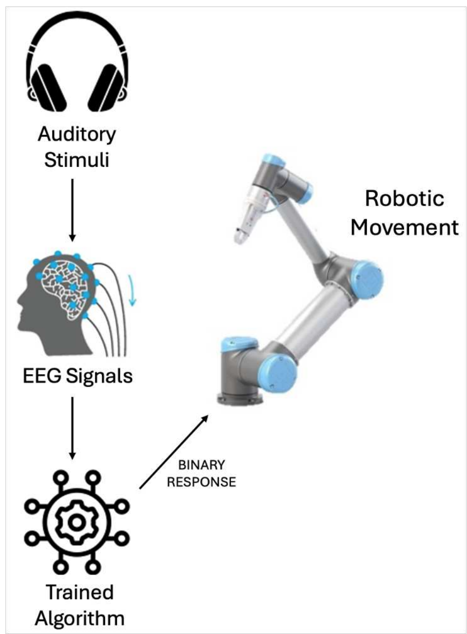

Fig. 2. Schematic showing how EEG signals were used to control the UR-5 robot arm.

4 Results

The trained classifier was 81.71% accurate for making binary responses of left or right, a similar level of accuracy was found in [11], although the robot movements and brain signals are different. Our results are better than the similar work in [13] which had its classifiers with around 72%-75% accuracy. This could be due to differences in the hardware setup that we used and the diversity of our subject group.

[1] `https://github.com/jkur/python-urx/tree/SW3.5`

In the main experiment, the 4 participants were able to move successfully the UR-5 robotic arm in real time based on the received EEG signals, with an accuracy of 73.75% for left responses and 65% for right responses. These accuracy percentages are lower than the accuracy percentage of the classifier due to the small sample size in the main experiment. However, all participant accuracy scores for the trained classifier scored over 50%, thus not occurring by chance (see Fig 3). A video of the experiment can be found in this link: `https://drive.google.com/file/d/1SRTC3IM4yzu2SIkbGKZ8xcuiXzPjjjir/view?usp=sharing`.

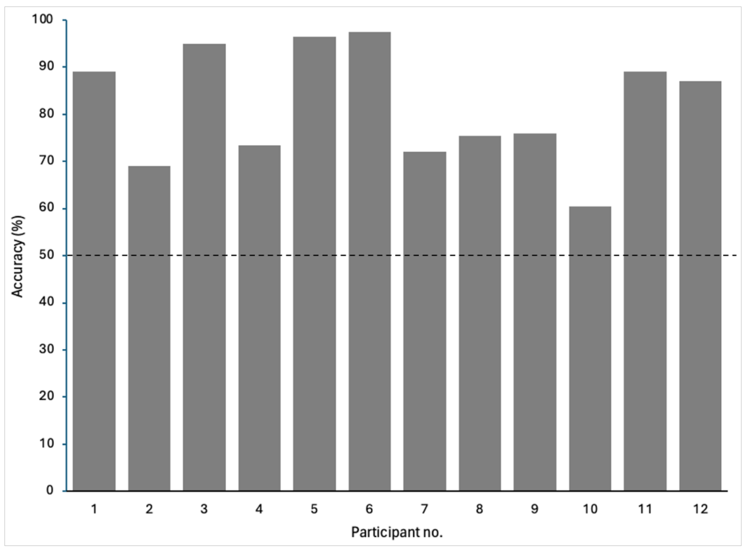

Fig. 3. Each participant's accuracy scores from the trained model for making binary decisions of left or right. Black dashed line represents chance level (50%).

5 Conclusion

This study offers support for the extension of BCI systems into clinical environments, where they could aid individuals with disabilities in accomplishing daily activities [10]. Clinicians may want to consider promoting these non-invasive BCI systems over invasive alternatives due to their advantages. Non-invasive systems are notably more practical and lack the significant side effects associated with invasive procedures, such as surgery.

Subsequent research on BCI systems in this domain could explore improving classifier accuracy by increasing participant numbers and conducting more trials to provide more data for training the classifier. Additionally, the framework of this experiment could be adapted to incorporate alternative stimuli, such as varying frequencies of skin vibrations, or prompting the robot to perform more intricate actions, like vertical movements or object manipulation. Future work could also look at different kinds of machine learned feature extractors and the adaptation of classifier for individual subjects. In essence, this project establishes a basis for future experiments aimed at refining non-invasive BCI systems combined with EEG for potential application in clinical contexts.

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