Cerebro

Motor Imagery based Prosthetic arm control with Haptic feedback

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Abstract

A 6-DOF arm that can be controlled using Motor Imagery EEG signals and a haptic feed back system is implemented to materialize the exerted pressure.

1 Introduction

The project proposes an approach towards EEG-driven position control of a robot arm by utilizing motor imagery, P300 waveform and Visually evoked Potential to align the robot arm with desired target position.
The user produces motor imagery signals to control the motion of the arm. The P300 waveforms gives us sufficient data to detect whether we are performing any motion or even imagining doing so. This becomes even more accurate with C3, C4, PZ, FZ signals coming into picture. Taking these signals as features gives us appropriate information on the motion imagined by the user. This information can be used to control different parameters that are necessary for controlling the arm.

This Project has a lot of Applications. This will facilitate the living of individuals with upper extremity impairment. The Brain-computer interface can act as a medium for them to use robotic arm for the activities of their daily life. Haptic feedback will give them the sense of touch. This can be achieved by giving neuro-feed back to the brain. The haptic feedback can be very helpful when it comes to invasive surgery using robotic arms.

2 Methodology

2.1 Building a 6DOF arm

A 6DOF humanoid arm is built by 3d printing the CAD model open sourced by Poppy Project, a humanoid robotic startup. The final arm will be capable of traversing any x,y,z coordinates within the range, along with rolling, rotating of the arm. Six servos are attached on the elbow, wrist and shoulder, each two respectively. Extra servos will be needed for the finger movements. The movement of the arm is achieved with inverse kinematics.

Figure 1: The CAD model.

2.2 Inverse Kinematics

Inverse kinematics problem of a robot is finding the angles of the robot by having the end position. It allows us to traverse our gripper to specific coordinate mentioned and grab a particular object. Higher degrees of freedom will have a more complicated solution. The length of each edge is considered to get the final joint angles.

2.3 Control with Flex sensors

The flex sensor uses flexible conductive ink printed on flexible base forming a resistor. It works when bent with the ink on the outside of the curve. When bent, the outside layer is stretched and thus extends, resulting in reduced cross section. This reduced cross section and increased length results in an increased resistance, which can be measured.
This variable resistance of the flex sensor can be mapped to different positions of the finger. Different fingers of the robotic arm will have different flex sensors attached to it. The position of each finger, calculated from the EEG Signal, will be the required value. The flex sensors' resistance will give us actual positions of the fingers. A suitable linear control algorithm will be framed to bring the actual position close to or exactly same as the calculated position using servo motors.
The resistance of the flex sensor can be obtained by combining the flex sensor with a static resistor to create a voltage divider, which can produce a variable voltage that can be read by analog-to-digital converter of a micro controller.

2.4 Haptic feedback

Force sensors are placed at the fingers of the robotic arm. The data is serially transmitted to the controller.Glove has PDMS membrane embedded in it. PDMS is viscoelastic material.Balloon actuation is achieved by the pressure dependent swelling and saturation phenomena of 2 flexible PDMS diaphragms.Top diaphragm layer has horizontal channels where the air can be pumped from an external compressor which is controlled using PWM in accordance with the data obtained from force sensor.

2.5 Electrode Placements

The signals we will be needing for motor imagery are C3, C4, PZ, FZ region. These regions are present in the central region of our head. EEG electrodes are placed in the respective positions along with the reference electrode which is placed over any of the ear lobe. The reference electrode is given as The reference electrode is given to shorted negative terminals of the channels, while the other four electrodes are given to positive terminal of the respective channels.

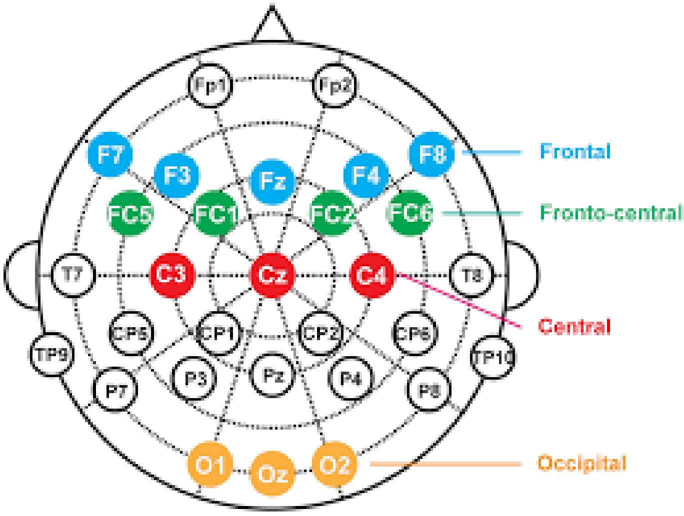

Figure 2: Electrode placement.

2.6 EEG signal Acquisition

ADS1299 is a device by Texas Instruments. It has 8 channels, that is, 8 differential amplifiers. The negative terminal of the amplifiers can be shorted and reference voltage is applied, which will be the same across all negative terminals. The common mode noise is significantly reduced on giving input signals through the differential amplifier. The dc noise is reduced by adding a High pass filter with sufficient cutoff voltage. The 50hz live-line voltage interference can be reduced in a similar way by adding a low pass filter with a cutoff frequency of 40hz. A better way to reduce 50hz noise is to implement second order butter worth filter ,the roll off doubles up reducing the noise even more.
The output signal from ADS1299 is sent to Arduino using serial Peripheral interface.This is further transferred to PC serially. Python receives the serial data and feeds the data to classification algorithm.

Figure 3: The acquisition board.

2.7 Motor Imagery Data Classification

The data is saved in a data buffer of length 5 seconds. The number of samples will be the baudrate * 5. This data is fed either to SVM Classifier or CNN or RNN. The model is chosen based on the validation accuracy. SVM is currently the popular algorithm used for EEG signal classification. The classic, one vs rest classification can be used to classify the signals from one another. But using Recurrent Neural Networks may improve the accuracy significantly since EEG signal is a time series. The data is fed into Recurrent neural networks with applicable hyper parameters to get the final output.

2.8 Control using Classification output

We have to control the up/down, right/left, top/bottom, yaw, pitch, roll of the arm. Since the only varying parameters in the inverse kinematics equation of 6dof arm are X, Y, Z coordinates, roll, pitch, yaw, we can easily control the arm using few parameters. An additional parameter is needed for the grasping of fists. The output from the classification algorithm can be used to control these parameters thereby controlling the arm. The two step process includes moving the arm in the horizontal plane right above the target object. The moving the arm vertically down until we reach the object. Then we use the grasp parameter to grab the object and again use the two step process to place the object somewhere else. The two step process is preferred because it requires comparatively lesser parameters and is easier to control.

3 Further Improvements

The Arm control can be further improved with visual feedback. The video camera may be placed in back of the hand or we can use the aerial view. Then we can use the error in visual feed back for better control. Reinforcement learning algorithm can be used to train the arm from its mistakes. The model will allow the arm to overcome its previous mistakes, finally ending up doing the required action.

4 Requirements

4.1 Hardware Requirements

1. Acquisition device
2. 3d Printed STLs
3. EEG electrodes
4. Electrode paste
5. Servo Motors
6. Flex sensors
7. Air Pump
8. Rubber Gloves
9. Vibration sensors

4.2 Software Requirements

1. Python
2. ROS
3. Tensorflow or Pytorch
4. Arduino IDE

5 References

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- Poppy Project github repository "https://github.com/poppy-project/Poppy-basic-arms"