Trained by Demonstration Humanoid Robot Controlled via a BCI system for Telepresence

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***Abstract*—Onerous life of paralyzed people is a substantial problem of the world society and improving their life quality would be a great achievement. This paper proposes a solution in this regard based on telepresence, where a patient perceives and interacts with a world through an embodiment of a robot controlled by a Brain-Computer Interface (BCI) system. The proposed approach brings together two leading techniques: Programming by Demonstration and BCI. Several tasks could be learned by the robot observing someone performing the function. The end user would issue commands to the robot, using a BCI system, concerning its movement and the tasks to be performed. An experiment is designed and conducted, verifying the applicability of the proposed approach.**

I. Introduction

Human action mechanism consists of two parts: decision making and performing. Decision to ride a bike comes first and then, if person is trained enough, he/she performs a riding process by applying low-level mechanical techniques such as rotating pedals with legs, holding balance by body, control helm using arms and etc. The key point is that people do not decode each low-level mechanical motion consciously, and such processes are realized autonomously [1]. Some research has already addressed the issues of disabled people self-assistance by directly controlling various kinds of robots with BCI systems. Chae et al. demonstrate the use of humanoids in telepresence and their ability to accomplish complex tasks [3]. Although for some scenarios using robotic manipulators would be more convenient (specially where mo mobility is required), humanoids are logically more suitable for telepresence, as they are psychologically more accepted by humans [4] in an interaction.

Asynchronous BCI system is one of the candidate BCI systems where timing is controlled by an operator [3], [5], [6] [2]. However, such systems are usually limited to 2-3 task choices, require intensive attention of the patients and have long training time, making their usage troublesome for paralyzed people. Synchronous BCI systems are also used in telepresence frequently. BCI system based on Steady State Visual Evoked Potentials (SSVEP) could have high accuracy results operating with short or even no training session [7], [8], [9]. SSVEP does not require a training algorithm for each individual and is respectively fast. On the other hand, effective frequency range restricts the number of choices in the interface, but the biggest disadvantage of SSVEP is the intensive eye strains caused by flickering.

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Electromyographic signals were also used in BCI telepresence systems. Li et al. used muscular signals of two arms of a subject, left and right arms to turn the robot left and right respectively, and both arms to walk forward [5]. However, this is not a feasible solution for disabled people, since they may have problems with controlling their arm muscles. There were several attempts of creating systems to solve the problem of low information transfer speed of BCI systems. One solution is the usage of hierarchical BCI (HBCI), where several subtasks are combined into one task and called as one event next time [8]. Another solution is the usage of an overtrained robot, to perform complex tasks, but have very specific choices, such as going and picking up a specific ball from an exact place [10]. Both these approaches are perspectives for future telepresence models, however now, they are problematic in terms of general usage, since they are restricted in workspaces or have very specific tasks. Chae et al. have proposed a control system for humanoid locomotion with low - level Cartesian event functions such as walking forward or turning left/right [3]. Though, those functions are not low - level from mechanics perspectives, since humanoid walking is a complex dynamical problem, and the robot is already pre-trained to walk in a factory. The aim of this work is to extend such design style, by creating a framework where robots can be easily trained and controlled by BCI to perform those skills. Robot training is done using programming by demonstration technique based on Gaussian Mixture Models and Regression. Such framework satisfies the principle of unconscious human learning and cognitive decision making model [1]. We present an architecture based on synchronous P300 BCI system that is more reliable/accurate than the other similar systems and has respectively short training time which is crucial for paralyzed people.

II. Materials and methods

A. System Architecture Overview

Overall system flow is managed by Fieldtrip Buffer which regulates BCI and NAO robot control systems, handles and

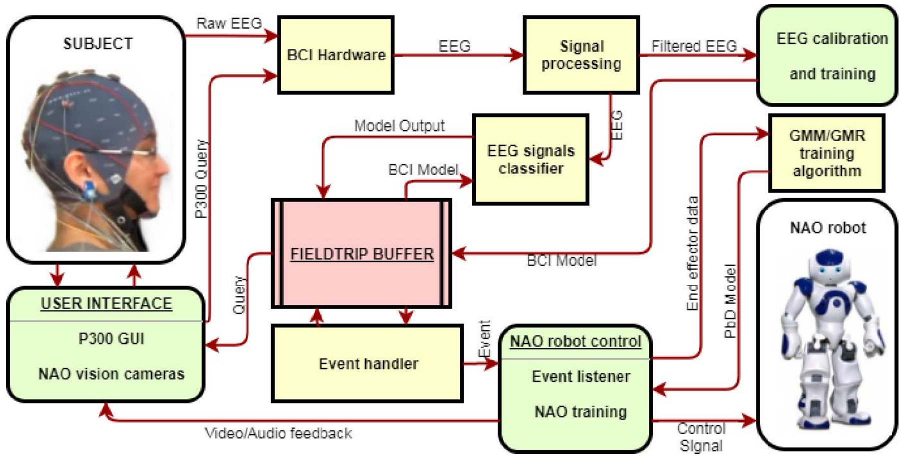

Fig. 1: Overall system pipeline controlled by a Fieldtrip Buffer

sends events. Subject interacts with P300 graphical user interface and gets feedback from NAO robot in the form of video and audio stream. Calibration is requested by BCI system at the beginning, signal processing is performed on raw EEG, the model is trained and stored in the buffer for current session. At testing stage BCI model classifies processed EEG data and the buffer handles events on a real-time basis. Events are continuously listened by NAO control script implemented on Python. The script avoids events stacking to improve real-time response of the system, i.e. in case 2 events came one after another, script will execute only first event and will ignore any other events till NAO finishes current task. Moreover, we do not need to train the NAO before BCI session, since BCI and PbD models are independent of each other. NAO can be retrained anytime, even while BCI session holds on. In such case, at the next call of that event, NAO will perform retrained new action. Training is done using Gaussian Mixture Models technique from PbD field, where Gaussian Mixture Regression for end-effector motion is retrieved from demonstrations and performed by the robot. Finally, NAO robot used for telepresence, since it has several advantages such as: convenient psychological perception of humanoid, various sensors on whole body, 2 cameras, 4 directional microphones and WiFi.

B. BCI Experimental setup

1) Electroencephalography: Scalp EEG was recorded using a 16-channel, active Ag/AgCl electrodes (g.USBamp, g.LADYbird, Guger Technologies OG, Schiedlberg, Austria) with a sampling frequency = 256 Hz, resolution = 16-bit, dynamic range = $\pm$ 3:2768 mV, and bandwidth = 0-1000Hz. The EEG electrodes were positioned according to the International 10-20 system and covered centroparietal lobe of the cortex. The right earlobe of participant's were used for a ground electrode, whereas the FCz location were used for a reference electrode.

2) Calibration session: We implemented a visual stimulus presentation to control a humanoid robot using a 4×4 grid of characters presented via an LCD monitor. The commands correspond to different controls as depicted in Fig.2. Each

Fig. 2: A visual cue used to evoke P300 and provide direct control commands to the NAO robot

participant performed a single session during which their EEG signals were measured. Total number of sequenced to acquire training data was fixed at five. Each sequence consisted of three complete row/col stimulus repetition. Inter stimulus duration and the duration of a row/col intensification was equal to 100 msec. The minimum time between the same target letter highlights were set to 600 msec. Inter sequence duration was set to 2 seconds while feedback duration was equal to 3 seconds.

3) Signal Processing and Classification: Continuous EEG data were segmented into a target and non-target trials with 600 ms duration after the cue onset. Any arbitrary offsets in data were removed by subtracting the total mean from each channel. Further, data were artifact edited for bad trials and channels, i.e., any trial or channel with values greater than three standard deviations over the median trial and/or channel were excluded. In the next step, a spatial whitening filter was applied to minimize the source mixing and volume conduction effects. Finally, EEG data were band-pass filtered between 0.5-12 Hz range by a Fourier filter. This was achieved by 1) applying a weight in Fourier domain to suppress unwanted frequencies outside the frequency of interest, and 2) performing inverse Fourier transform to obtain filtered EEG data.

Given n-trials of EEG data by $\{(x_i, y_i)_{i=1}^n\}, x_i \in X^{\{m,n\}}$, an observation $y \in \{\pm 1\}^n$ and a prediction $f(x_i)$ denoted by a triplet $(x, y, f(x)) \in X \times Y \times Y$. We use a supervised learning algorithm to estimate $f : X \to \{\pm 1\}$ or $f : X \to R$ which predicts outputs as a target P300 or non-target P300 events for a new observation $x \in X$. Specifically, we adopt a $l2$-norm regularized logistic regression to learn optimal $f^* : X \to \{\pm 1\}$ by minimizing cross-entropy error $E(f) = \ln\big(1 + \exp(-y(f))\big) + \lambda f$ using a stochastic gradient descent technique. A tenfold cross validation was performed for a model selection where optimal hyper/parameters of classifier were estimated.

C. Programming by Demonstration

Robot programming by demonstration (PbD) provides a user-friendly way of transferring skills from humans to the robots, not requiring specific programming/robotics skills, and this makes the robots more applicable in many areas, such as homes, hospitals, or factories [12]. There are several approaches available for PbD, and in this work the one based on Gaussian mixture models (GMM) is employed [11]. GMM parameters are initialized using K-means clustering. After the parameters of the GMM are learned, it could be used to reproduce a new trajectory, using the Gaussian mixture regression (GMR). Demonstration data are collected by performing a task for several times. Each demonstration $m \in 1, ..., M$ contains T datapoints of D dimension $\{\boldsymbol{\xi}\} \in \mathbb{R}^{D \times T}$. To deal with demonstrations of different length, dynamic time warping (DTW) is applied on the trajectory data to make them of the same size. The GMM model parameters are defined by $\{\pi_i, \boldsymbol{\mu}_i, \boldsymbol{\Sigma}_i\}_{i=1}^K$, where π_i are the priors/mixing coefficients, $\boldsymbol{\mu}_i$ and $\boldsymbol{\Sigma}_i$ are the center and covariance matrix of the i-th Gaussian component. These GMM parameters are estimated using the EM algorithm. In the reproduction phase, Gaussian Mixture Regression (GMR) algorithm is used to estimate the trajectory. GMR relies on the joint probability density function $\mathscr{P}(\boldsymbol{\xi}^{\mathscr{I}}, \boldsymbol{\xi}^{\mathscr{O}}) \sim \sum_{i=1}^K \pi_i \mathscr{N}(\boldsymbol{\mu}_i, \boldsymbol{\Sigma}_i)$ of the dataset $\boldsymbol{\xi}$. At each time step t, the datapoint $\boldsymbol{\xi}_t$ is decomposed into $\boldsymbol{\xi}_t^{\mathscr{I}}$ and $\boldsymbol{\xi}_t^{\mathscr{O}}$ where the superscripts $\mathscr{I}$ and $\mathscr{O}$ denote dimensions spanned by the input and output variables, respectively. Similarly, $\boldsymbol{\xi}_t$, $\boldsymbol{\mu}_i$ and $\boldsymbol{\Sigma}_i$ can be written as:

$$\boldsymbol{\xi}_t = \begin{bmatrix} \boldsymbol{\xi}_t^{\mathscr{I}} \\ \boldsymbol{\xi}_t^{\mathscr{O}} \end{bmatrix}, \boldsymbol{\mu}_i = \begin{bmatrix} \boldsymbol{\mu}_i^{\mathscr{I}} \\ \boldsymbol{\mu}_i^{\mathscr{O}} \end{bmatrix}, \boldsymbol{\Sigma}_i = \begin{bmatrix} \boldsymbol{\Sigma}_i^{\mathscr{I}} & \boldsymbol{\Sigma}_i^{\mathscr{I}\mathscr{O}} \\ \boldsymbol{\Sigma}_i^{\mathscr{O}\mathscr{I}} & \boldsymbol{\Sigma}_i^{\mathscr{O}}. \end{bmatrix} \quad (1)$$

$\mathscr{P}(\boldsymbol{\xi}_t^{\mathscr{I}} | \boldsymbol{\xi}_t^{\mathscr{O}})$ is calculated as the conditional distribution at each reproduction step t and the evaluated $\hat{\boldsymbol{\xi}}_t^{\mathscr{O}}$ is used as the position of the end-effector of the robot for that time step t [11].

III. Results

1) Real-time operation: Following the calibration task, a classifier model was optimized on the acquired training data without taking off the EEG cap, which took less than a minute duration. Once the optimal model was obtained, subjects were instructed to voluntarily control the humanoid robot without any time constraint predefined. NAO robot is placed at specific location on the floor. The sequence of tasks should be as follows: go forward, turn right, go forward, turn left, say

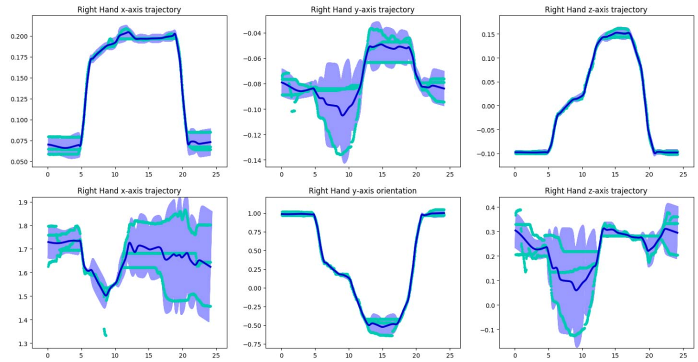

Fig. 3: Right hand ”Handshake” trajectory demonstration data (in green) and reproduction by GMR (in dark blue): a) x - axis position b) y - axis position c) z - axis position d) x -axis orientation e) y-axis orientation f) z-axis orientation. The highlighted area shows the estimated covariance for the trajectory.

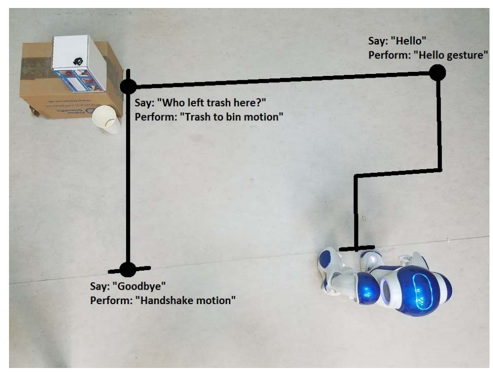

Fig. 4: Top view of the experimental setup of Nao robot and sequence of his tasks to perform

”hello” and perform ”hello gesture”, turn left and go forward several times until reaching a box with a trash on top of it, say ”who left trash here?” and perform ”knock down a trash” motion, turn left and go forward several times, say ”Goodbye” and perform ”handshake motion”. The top view of the experimental scenario is depicted in Fig. 4. As an example of reproduced trajectories, the demonstrations and reproduction data for the ”Handshake” motion of the right arm of the robot are illustrated in Fig. 3. The reproduced trajectory is denoted by the dark solid line, and the highlighted area depicts the estimated covariance.

2) BCI performance: Data from five subjects were analyzed in total to perform specific sequence of tasks. Fig. 5 show an example of a typical grand averaged P300-waveforms obtained after pre-processing and data cleaning (first column) and the topographic distribution of P300 potential across different subjects both for target and non-target events. These inputs were used to model a classifier to further control the humanoid NAO robot. One can notice a highly variable topographic distribution of P300 waveforms in Fig. 5 across subjects. This kind of variation was also observed within trials, that

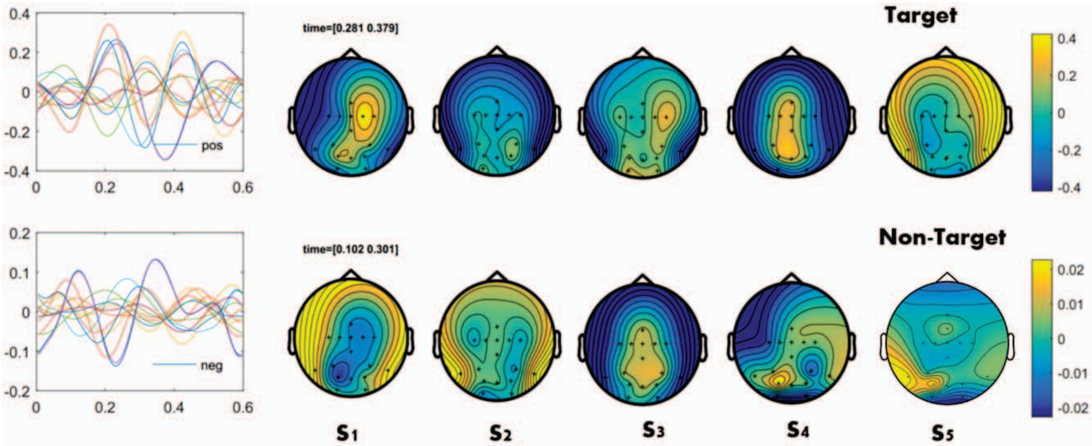

Fig. 5: Grand averaged P300 potentials and its topographic distributions across five subjects {S1... S5}. *Top-row*: target P300 and *Bottom-row*: non-Target P300 waveforms.

potentially affected the classifier performances. Figure 6 shows variable results of a classier modeling step from tenfold cross-validation and the performance of a BCI step from a real-time operation session.

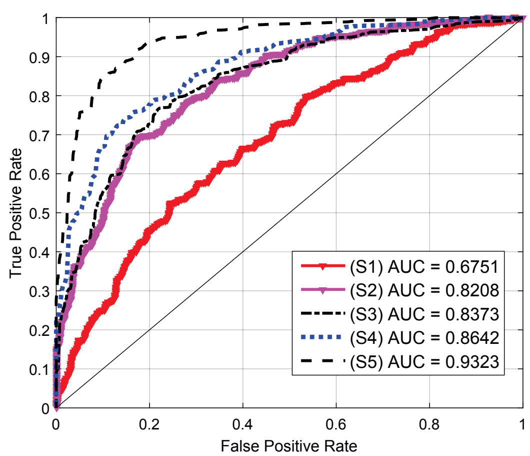

Fig. 6: Overall accuracy of BCI system from real-time experiments in terms of area under the ROC curve for all five subjects (S1, S2, S3, S4, S5) .

IV. Conclusions

This paper presents a framework for P300-BCI based telepresence robot to facilitate the life of severely disabled people for being socially active thus improve their quality of life. One particular feature of study is that the robot is trained using a programming by demonstration approach which adds extra flexibility to the conventional BCI-based telepresence paradigms. The real-time accuracy of P300-BCI was above 78% on average. Improving the BCI accuracy including devising motor imagery based approaches, and integrating more advanced PbD approaches (such as task-parameterized GMM and its various derivatives as [13]) into the current system, to increase the range and type of the tasks that could be done by the robot, would be considered in the future work.

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