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Brain-Computer Interface controlled humanoid pre-trained for interaction with people

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People with the disabilities are in need to have an assistive technology that will alleviate their life through improving its social aspects. This article presents a Brain-Computer Interface (BCI) based remote presence system for humanoid NAO robot. The system would be useful for partially or fully paralyzed patients to interact with people and live active social life. A P300 based BCI is used to control high-level desires of the humanoid and visual stimulus presentation is implemented to control a humanoid robot. "Programming by Demonstration (PbD)" methods are used to train the robot to perform human interactive actions and NAO robot native speller is used to talk with people. In general, the proposed solution combines two major techniques: Programming by demonstration and BCI. An experiment is designed and conducted on 5 different healthy subjects to perform a handshake, waving, walking and etc., verifying the applicability of the proposed approach.

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1 INTRODUCTION

Partially or fully paralyzed people are restricted in many aspects. For them performing the Activities of Daily Living (ADLs), as eating or cleaning up, require an additional assistance[2]. Previous research was mainly focused on developing the system for the ADLs purposes [1, 2]. However, for a sophisticated living, human-beings require a social interaction between each other. This also happens to be challenging for people with disabilities. Due to this fact, we propose to use the an efficient telepresence system for robot-human social interaction, where the robot is an action performing tool. Since the interaction is social, besides the technological functions, the physical representation (appearance) is of equal importance for human-robot interaction (HRI) [6]. To establish the proper interaction, we used NAO robot, as it is widely used in social assistive technology (SAR) [3]. Another important aspect is to model the system that will require the least amount of effort from the patient side. Our proposed solution allows users to make only high-level decisions. A humanoid robot is

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pre-trained using PbD. This allows performing several tasks which are chosen by patient preference to interact with people. Firstly, it is a convenient way of action mechanism in terms of natural human behavior. People consciously making only high-level decisions and perform actions by their body in an unconscious manner. In other words, people are pre-trained to perform several tasks such as a hand-shaking beforehand and consciously decides to execute those tasks when needed [5]. The proposed model is of the same kind, where the robot is pre-trained for tasks beforehand and controlled consciously through BCI system. Secondly, this kind of system is less complex in terms of realization and easier to use in comparison to other human assistive technologies such as exoskeletons or highly skilled service robots.

2 MATERIALS AND METHODS

2.1 System architecture

To establish the connection between NAO robot, BCI, and programming environment, the FieldTrip buffer is utilized as a server. The interaction between the user and the system happens through the P300 paradigm based GUI and Audio-Video(AV) feedback. The subject, based on the input from the AV of NAO robot, mentally selects the command from the screen, such as "Greetings". The continuous acquisition BCI system captures the EEG signals, performs signal processing and model selection. A BCI trained model is based on L2 regularized logistic regression algorithm. NAO end-effector (both hands) trajectories were trained by Gaussian-Mixture Regression algorithm and controlled by P300 events maintained by FieldTrip Buffer. The training of the NAO robot can be done at any time, since NAO script is independent client of the buffer. However, NAO training should be done by healthy subject beforehand. Due to technical characteristics, the robot is suitable to be remotely present, sending audio/video feedback to controller/subject. It has 25 degrees of freedom, a height of 59 cm, 2 high resolutions cameras that allows to mimic complex and natural humanoid movements. Aldebaran robot interacts with the environment due to numerous sensors, located throughout the body, 4 directional microphones and loudspeakers provide a required oral communication. Moreover, the presence of 2 IP connection kinds such as LAN and WiFi facilitates makes this robot able to be remotely present. In general advantages of NAO robot are well-suited for needs of developing effective social avatar to talk to and interact with people in general.

2.2 Brain-Computer Interface

2.2.1 Electroencephalography. The subjects' EEG data was captured using a 16-channel, active Ag/AgCl electrodes (g.USBamp, g.LADYbird, Guger Technologies OG, Schiedlberg, Austria). Sampling frequency was taken as 256 Hz. The layout of the electrodes followed the International 10-20 system standard and was situated mainly in the centroparietal lobe of the cortex.

2.2.2 Experimental setup. P300 interface contained a 4×4 grid of characters Fig.1 with the correspondent commands, through which robot is controlled. The experiment involved five subsequent participants seated in front of the LCD monitor that had a P300 GUI and video stream from the robot's cameras. The experiment required only a single session from the subjects. Firstly, the training phase was performed. The target symbol, one from the grid, was shown on the screen. Then the columns and rows of the grid start to flash and the participants needed then to induce any kind of mental attention when the target symbol flashed. The induced signal generates an increase in the voltage of the signal after

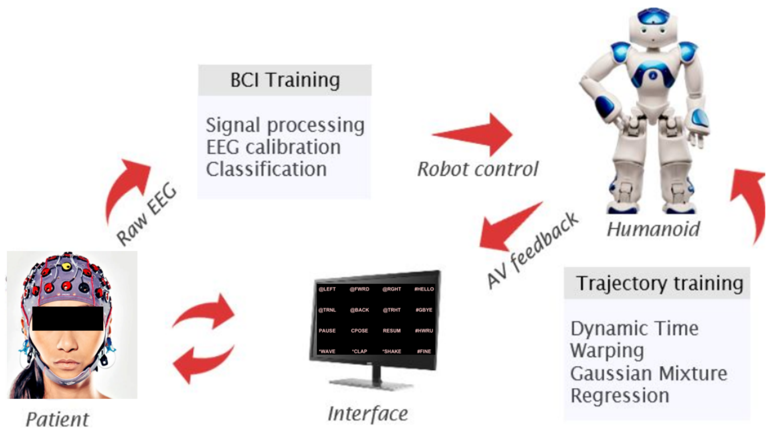

Fig. 1. System architecture overview

approximately 300ms. In overall, the training was done on 5 symbols, with three complete row and column stimulus repetitions. The time between flashing of target events was set to 600 msec. The inter-stimulus time length was 100 msec. The feedback took 3000 msec, while the time for inter-sequence duration took 2 seconds. Inter-sequence duration was set to 2 seconds while feedback duration was equal to 3 seconds.

2.3 Programming by demonstration

2.3.1 Training algorithm. PbD considers the training of robots by showing them the way to perform. The biggest advantage of PbD is that users do not need to have programming/robotics background knowledge and basically, robots can be trained by anybody, dramatically decreasing the costs and increasing flexibility of robots. Various methods and algorithms are used in PbD and the current approach is based on reinforcement teaching realized using Gaussian Mixture Models algorithm. Gaussian states parameters are initialized by K-means clustering, then GMM model is learned. Afterwards, GM Regression is applied to the model and new end-effector trajectory is generated [4].

2.3.2 Robot tasks training session. Task demonstration requires NAO end-effector to be in gravity compensation mode in order to be flexible enough to be moved around. Several tasks are trained/tested including "Right hand waving", "Handshake" and "Clapping". Each task requires several demonstrations depending on the complexity, and in general, 3 demos were used for each action. One time step vector consists of 7 variables: time variable, 3 position, and 3 orientation values. The data was preprocessed using Dynamic Time Warping algorithm to align demonstrations of different lengths to each other. A GMM model is learned for such 7D space and stored in a memory for each task. The number of Gaussian states was chosen empirically as 5, but in general increasing this number leads to better regression trajectory. At reproduction stage, GMR algorithm is exploited, given time vector as an input and retrieving values for position and orientation of NAO hands.

3 CONCLUSION

This paper represents a BCI and PbD based system for improving interaction with environment process of disabled people. The resulting accuracy of real-time BCI performance was

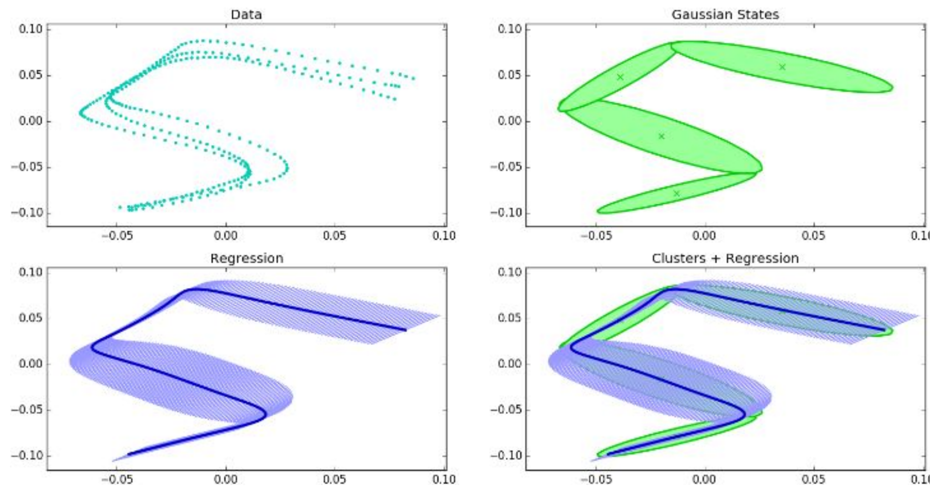

Fig. 2. Trajectory training from raw data to regression

within the range of 65-91% and in average BCI accuracy was about 78%. The subjects were able to communicate seven commands per minute to interact with the NAO-robot using the designed BCI system. In future, Asynchronous BCI system could be used for improving accuracy of BCI model and more advanced PbD techniques for performing more complex tasks.

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