P300 based brain-robot interface prototype to enable multi-modal interaction for patients with limited mobility

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Abstract— **Patients who lost their ability to move and talk are often socially deprived. To assist them, we present a prototype of a telepresence humanoid robotic system that aims to extend the social sphere and autonomy of the patients via an EEG based brain-computer interface. The system enables a multi-modal and bidirectional communication. It empowers the patient to interact with the robot and command it using a high level P300 BCI that interprets the patient's answers to questions asked by the robot. Additionally, the system allows interaction with other people. By forwarding some of the robot's sensations to the patient, the patient's senses and action space are extended and a telepresence of the patient is created. A use-case validation of the system shows success in achieving bidirectional communication between an able-bodied test subject and the robotic system as well as in interactions with other people.**

I. INTRODUCTION

Patients with severe motor disabilities, such as the ones caused by stroke or amyotrophic lateral sclerosis have often lost their ability to both communicate and move independently. These patients require a high amount of attendance but it is often not possible to give them all the care they deserve. According to the Bureau of Labor Statistics of the United states, the country will need an estimate of 1.09 million nurses by 2024 [26]. The situation worldwide is similar [22] making it necessary to think about how to best assist patients demanding a high amount of time.

A. Human-robot interaction

People in social deprivation, such as the patients we attempt to assist, have a lower life expectancy than those with a wider social sphere [5] and have a bigger risk of cognitive decline in old age [33]. Robots that produce positive emotions in humans and engage in social interaction have been shown to be beneficial for people in social deprivation [33]. Not only are these systems helpful to perform tasks that improve the quality of the life of the patients, such as supporting them to take their medicines or cleaning, but also can help them to enhance their physical and mental health [4].
Therefore, we propose the use of a humanoid robot capable of producing positive emotions in humans, as a strategy to help these patients in social deprivation and keeping them healthy through a system that engages social interaction. Previous works on telepresence interfaces has shown a positive impact by reducing workload in health care [19] and helping the caretakers to check the health of the patients in real time. These telepresence systems can also be useful for patients with reduced mobility to explore the world [27] and thereby regaining some autonomy.

B. BCI Systems suitable for care-taking service robots

In cases of severe motor disabilities patients cannot vocally communicate. Therefore, we propose to use a brain-computer interface (BCI) as a communication channel. BCIs have been shown to greatly help patients with spinal chord injury by controlling robotic arms [16], [30] or other external devices. With motor imagery BCIs, a reliable cursor movement on a screen has been achieved. This cursor movement induced by motor imagery can be used for typing on a virtual keyboard [23] with on average 28 characters per minute or even for using a commercially available tablet computer [21] in order to communicate with the outside world. Electro-encephalography (EEG) offers a non-invasive way to record cortical signals and a paradigm based on the P300 response is frequently used to enable communication though virtual typing on a computer screen. Recent studies with healthy patients achieved communication rates of up to 12 characters per minutes [29].
As McFarland and Wolpaw expressed in [17], "BCIs [can be used] for communication and control" . However, not many BCIs have tried to combine communication and control. We therefore propose a BCI through which the patient can communicate with a robot through high level commands in order to control it. Kuhner et al. [14], for example, developed a motor imagery based high level goal selection BCI in combination with a service robot. The user interaction happened through a computer screen and the commands were sent to a static industrial KUKA robotic arm. Although their user interface used very simple high level commands, the communication with the robot was far from a human-like conversation.

C. Proposed system

To assist these patients and enhance their quality of life, we developed a prototype of a humanoid robotic system with which they can communicate via a non-invasive BCI

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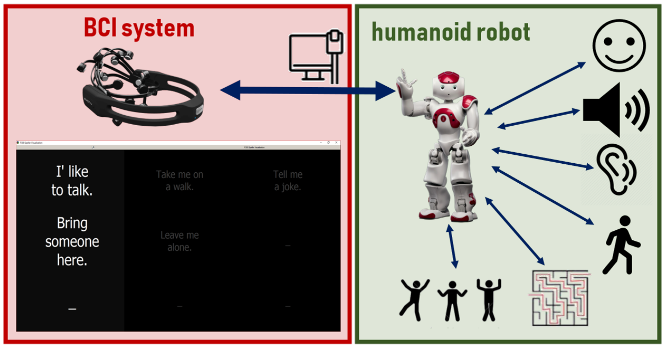

Fig. 1. System overview: P300 BCI lets user select answers on a screen by focusing on them (left). These selection are transmitted to a humanoid robotic system. The robot is capable of (clockwise on the right) face recognition, talking, hearing and natural language processing, walking, navigation, arm and head movement. Thereby the robot is able to verbally communicate with both the patient and other people. By forwarding some of its senses to the patient, the robot creates a telepresence of the patient.

and which can execute simple tasks for them. We use a humanoid robot able to engage in verbal and nonverbal communication with the patient to make interaction more natural as compared to just a computer screen. Besides communicating directly with the patient, the robotic system is able to interact with the outside world including other people. In the meantime, the robot's senses, for example the camera view, is shared with the patient in order to extend the patient's senses. This engages interaction between patient and other people by using the robotic platform as an extension of the patient's body to create a telepresence of the patient. The novelty of this system lies in the combination of communication via a high level BCI and a humanoid robotic system which can act both as a telepresence and as somebody to communicate with.

II. Methods

A. Communication channels

The communication scenario consists of interactions between three main actors: the patient, the robotic system and people around the patient. Figure 1 shows an interaction diagram of the system including all robot functionalities that allow the robot to accomplish an effective communication with the patient, environment and people around the patient.

The robot-patient communication is performed through four communication channels, the first one is the communication between the robot and the BCI. Through this channel, the BCI transmits the patient's answers to the robot's verbal questions and the robot transmits back confirmation upon execution. The second communication channel is the auditory channel through which the robot asks questions and gives feedback that informs the patient directly about the command understood by the robot and the execution of the next action. The third communication channel is the shared senses channel, namely the video streaming feature, that allows the patient to explore the environment through the robot's eyes. Finally, the fourth communication channel is the non-verbal communication channel. This channel intends to engage a pleasant communication with the patient by imitating human non-verbal communication.

The communication between the robotic platform and the people around the patient is verbal. The robot verbally conveys the patient's needs and waits for a reply that it can understand through its natural language processing module. In order to identify the person requested by the patient, the robot has a face recognition module.

B. Interaction design

Multiple different interactions between patient and robot are possible (see figure 2). Besides engaging in direct communication, the robot can bring other people to the patient, can tell jokes and take the patient on a virtual walk by streaming the ego view to the patient's camera. After finalisation of a task, the robot asks the patient when it should get back to them in order to provide a means of control when to start talking again[1].

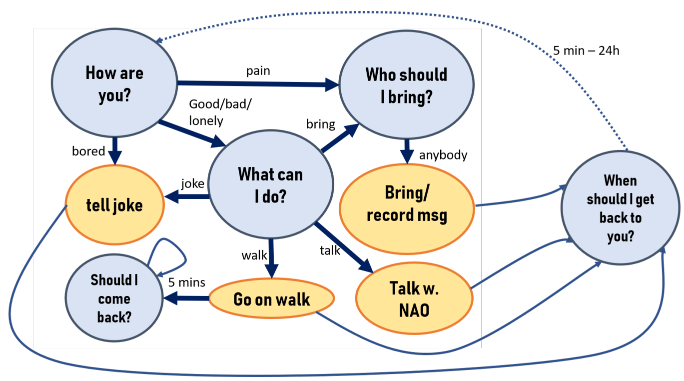

Fig. 2. Patient-robot interaction currently implemented in the prototype. Blue bubbles symbolise BCI interfaces with fixed set of answers. Text on arrows signify possible answers.

C. Brain computer interface

1) Experimental paradigm: In order to decode the patient's answers to the robot's questions, a P300 BCI was implemented using OpenViBE [25] and Python. The classification of P300 responses to letters flashing up on a screen has previously been used to enable communication through a noninvasive BCI [9]. Standard P300 spellers consist of a 6x6 grid of characters, where rows and columns sequentially, but randomly, flash up. The patient has to focus on one particular character in order to select it. If the target letter is flashed up, a positive deflection in EEG activity after around 300 ms (P300) can be observed mostly over the parietal cortex [20]. A binary classifier can be trained to discriminate between target signal and non-target signal. In order to allow the selection of higher level answers like "I am feeling good." instead of just single characters, a new interface was designed. It contains a 3x3 grid, where each of the 9 boxes contains a word or short sentence (see bottom left of figure 1). The visual stimulation consists of an alternation of one

[1]An example of such an interaction is shown in a video: `tiny.cc/telepresence_bci_robot2`

row or column flashing (0.2s) and no flashing (0.3s). After every row and column has flashed up once, the stimulation is repeated for up to twelve times to constitute a trial. Between repetitions, a 1.0s waiting time and between trials a 3.0s waiting time is introduced to make sure that responses are not overlapping. For offline recording, sessions with ten trials and twelve repetitions each have been recorded, which leads to 720 stimulations per session for a 3x3 matrix.

2) Signal acquisition: The EEG signal was acquired at 128 Hz using a 14 channel Emotive Epoc+ headset [11] (see rop left of figure(see left of figure **??**)). The Emotive headset has the advantage of being a contextual EEG device, which means that its appearance is less disturbing than standard medical EEG systems. More importantly, it is easy to set-up and as such suitable for home applications. This comes at the price of less channels and slightly lower decodability of P300 responses [8].

3) Signal processing and feature selection: The signal was bandpassed between 1 and 20 Hz with a 4th order Butterworth filter. After selecting the six channels closest to the parietal region and epoching from 0 to 600ms after stimulation, the signal was averaged across 6 repetitions (similar to OpenViBE example P300 paradigm [1]). This decreases the number of repetitions available for classification, but strongly increases the signal to noise ratio based on the assumption of uncorrelated noise [28]. It therefore improved the classification of individual binary classifications measured as cross-validations score by 0.1. Features were calculated by decimating the signal by a factor of 8. This creates features that are more invariant to slight time shifts. Having 120 trials for classifier training ($720/6$ because of averaging), this is quite a high number of features and is prone to overfitting [31]. However, reducing the number of features, e.g. by Fisher ranking or PCA, did not show improvements in cross validation (cv) scores. Therefore, the simpler approach, i.e. without additional dimensionality reduction, was chosen. Figure 3 shows an example of the signals observed.

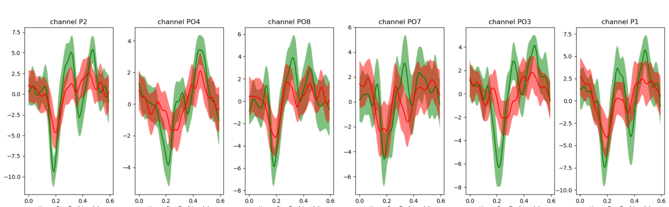

Fig. 3. Signal average and standard deviation for target (green) and no-target (red) response within first 600ms after stimulation for session with best classification performance. N=40 target and N=80 no-target.

4) Offline classification: Krusienski et al. compared different classifiers for P300 and found that linear discriminant analysis (LDA) classifiers yielded the best performance [13]. Therefore, an LDA classifier was chosen as well. Adding shrinkage is frequently implemented reduce over-fitting and yielded an improvement in cv score of 0.08. Support vector machines (SVM) often perform well with little training trials, because only a few support vectors are required to define the decision surface. Therefore, they were tested as well, both with radial basis functions (RBF) and linear kernel, but did not show any improvement. LDA with shrinkage was chosen, because it yielded the highest performance in 10-fold cross-validation across multiple sessions.

5) Online classification: Before every online experiment, an offline calibration has to be performed for around nine minutes in order to train the classifier. Doing so right before an online experiment accounts for the influence of slightly different electrode positions. This classifier was used to predict target/no-target labels in online trials for features calculated in the same way as offline. Instead of the maximum likely class label, the classifier was used to return the *probability* of a certain row or column being the target. Applied on all rows and columns flashing up in an online trial, this yields target probabilities for each row and column being flashed up. In order to get from multiple classifications to one decision about the target focused on, Bayesian updating was performed. Consider a classification of flashing in a single row which returns a target probability of 0.7 and no-target probability of 0.3. This means, that both other rows together have a probability of 0.3 of being the target. Following this approach the probability distribution across row/column has been calculated for every row/column flashing up, i.e. 3 times per direction. These distributions are multiplied with each other and a uniform prior and are normalised to yield a valid posterior probability density function $P(i|D)$:

$$P(i|D) = \frac{P(D_1|i) * P(D_2|i) * P(D_3|i) * P(i)}{P(D)}, \qquad (1)$$

where i is the row/column index, $P(D_x|i)$ stands for the likelihood of data D_x obtained from stimulating row/column x and $P(i)$ is the prior. If the posterior probability of a single row/column exceeds a threshold of 0.9, the result was accepted. Otherwise, another trial was initialised to accumulate additional evidence.

6) Online communication system: The BCI system waits for a command from the robot to initialise an online trial. Upon receipt of the message, the recording and visual stimulation is started. Upon finishing the recording of that trial, the data is passed on to the classifier and once the probabilities of a single row and column each exceed 0.9, the result is returned to the robot. If this is not the case, the trial is repeated. The recording of one trial with six repetitions takes $30s$ with the computational time being negligible. Therefore, the time to select an answer takes at least $30s$, but multiples of it, if the certainty was too low.

III. Robotic platform

In this use-case validation of a service robot for patients unable to talk and move, we use the robotic platform Nao. This robotic platform developed by Aldebaran robotics is a versatile humanoid robot commercially available at considerable low price, which makes it suitable for usage both in hospitals and at home. This robot easily evokes positive emotions in humans. Evoking positive emotions in humans is an important aspect for robots performing social tasks because they make the human-robot interaction easier by helping the users develop interest in learning to use the system [27].

The robot acts as an extension of the patient's body to interact with the world. The modules that integrate the robot architecture transmit the robot's senses to the patient to give the highest possible amount of feedback. To design the robots' interaction with other people in the most natural way, its movements need to be fluent and engage interaction [32]. Additionally, it is necessary to recognise different people as well as their reactions. To do so, a face recognition module and a natural language processing module were implemented. These modules help the robot not only to better give feedback to the patient but also to interact in a natural way with other people.

1) Robot-public communication: The talk, face recognition and natural language processing modules offer an interface between other people and the patient. These modules allow the patient to interact with other people by telling their needs to an specific person. Afterwards they identify a reply from this person and record the person's answer and thereby emulate a direct conversation.

The first step in order to recognise a face is to detect the face position. Therefore, the face recognition module implements a haar-cascade classifier. This returns the position of the faces in the robot camera image to the face recognition module in order to identify the target person.

The face recognition was implemented using the eigenfaces and a multiclass support vector machine that returns a classification score to recognise the face of the person in the image. The natural language processing node was developed using the NAOqi speech recognition tool.

2) Movement design: Engaging attention by looking directly to the face is a core skill for non-verbal communication and a crucial aspect for joint attention communication [15] as an example of non-verbal communication [18]. By adding movements and expressions, it is possible to perform clearer and more effective communication between humans [12]. Thus, movements were integrated into the robot execution in order to engage communication with the patient and with other people.

An average human changes their posture around four times per minute within a conversation with a movement velocity of around hundred degrees per second [10]. Based on that, a natural head movement was implemented. In the same way, greeting movements and movements to look directly at people's faces were implemented in order to improve engagement into conversations.

3) Sharing senses: One of the central goals of this telepresence BCI guided service robot is to offer a body extension to the patient. To accomplish this goal, the robot shares visual and auditory cues with the patient. The robot is able to share its camera images with the patient through a video streaming service. The video streaming service can be turned on or off according to the actions the patient selected. For instance, it will be turned on when the patient wants to go for a walk and turned off when the patient wants to be alone.

The implemented feature of directly recording a message for the patient is another way to share senses with the patient. Through this functionality, the patient can listen to a recorded voice message. As a consequence the patient could feel more socially involved because it seems as if the second person would be close at the moment.

IV. Results

A. BCI evaluation

All tests were performed with a single healthy subject in sessions spanning multiple days. Informed oral consent was collected prior to every experiment. In three different sessions, the shrinkage LDA classifier yielded an accuracy of $93.3 + -3.4\%$ (10 fold cross-validated) on individual target/no target classifications.

1) Offline calibration:

a) Boxes with text or digits: : Previous P300 spellers used boxes with characters instead of boxes with whole words or even short sentences. In order to exclude the possibility that adding information reduces classification accuracy, a test with a screen with digits from 1 to 9 was conducted. However, this resulted in a reduction of cv score (-0.13) and therefore, it was excluded that it limits performance and the multiple word high-level commands were kept to provide a conversation-like interaction.

2) Online classification: The BCI system was tested online in combination with the robot system. In order to ensure high comparability and to speed up the evaluation, the online classification accuracy was quantified in a pseudo-online fashion in experiments involving only the BCI system. Two offline sessions were recorded directly after each other. Then, the second session was split into individual trials where each trial was classified by a classifier trained on the first session in the same way it would have been classified in an online session. In two separate sessions, the classifier trained on the first session was able to predict 7 and 9 out of 10 trials of the second session.

B. System evaluation

1) Communication rate: The BCI system takes at minimum 30s to return an answer to the robot's question, multiples of it, if the accuracy is low. Depending on the length of the answer (shortest answer is "no", longest possible currently is "Bring someone here" with 16 characters), the rate of characters per minute varies between 4 and 32. However, this is not the best measure of accuracy for a P300 BCI with high level selections. The time per selection could be reduced by decreasing the time between flashes or reducing the averaging factor, but this would reduce classification accuracy.

C. Example interaction

In order to show the performance of our BCI guided service robot we share a link to a demo video showing one of the use cases performed by our implemented system [2]. In this demo video we show how a patient wants to tell a specific person to come and visit him. To do so, the robot starts a conversation with the patient to inquire his needs. Once it is aware of the patient's needs, it navigates through the room in order to find the the target person. While doing so, the robot streams its camera video to the patient to share its observations. Upon arrival to the position where the target person should be, it searches for the person and recognises their face in order to tell them to come and visit the patient. In the conversation with the target person, the robot waits for the person's answer. In case the person cannot come to visit the patient, the robot will ask for a voice message in order to inform the patient about the reason why the requested person is prevented. Otherwise, the robot will ask the person to walk along with it to visit the patient.

V. Discussion

A. BCI performance

a) Classification accuracy: : A reliable BCI system is more likely to be adopted by users [6]. Therefore, it is crucial to optimise classification performance and section IV-A showed how it was done for this system. Duvinage et al. used a similar OpenViBE paradigm and classifier with a 2x2 P300 speller matrix in order to compare the Emotive headset's performance with a medical EEG device. Their offline classification accuracy for Emotive was around 80% using averaging across two repetitions [8]. We yield offline accuracies of over 90% in the final system layout. This is most likely due to using 6x averaging and optimising the electrode location. The paper of Krusienski et al. compared different classifiers for P300 and also showed a strong dependence of classification accuracy on the number of repetitions. Classifying a second session with a classifier trained on the first session, they reached accuracies of up to 95% when averaging 15 times, but below 80% when averaging five times (N subjects = 8) [13]. Our pseudo-online results with six fold averaging of $7/10$ and $9/10$ are in the range of what is to be expected based on Krusienski et al..

b) Interface layout: : Most previous P300 BCIs relied on speller matrices, where one character at a time can be selected. P300 BCIs purely based on higher level commands are rare to find in the literature. We decided for a 3x3 matrix with higher level commands, because most basic interactions follow structured patterns and therefore replies or decisions can be made with a single BCI selection, which requires less ongoing concentration by the patient. A schema previously adopted are word suggestions similar to an auto-complete function while typing on a phone. In 2014, Akram et al. were able to double the amount of characters per minute from 2 to 4 with a word suggestion scheme [2]. Recently, participants in a study by Speier at al. were able to spell on average 12.7 characters per minute (N subjects = 12) [29]. This was an improvement by around 15% compared to not using a probabilistic language model. Their character selection is much faster than in our system (max 2/minute), but one selection in our system can contain even a short sentence. Our approach is very modular, leaving the possibility to add any number of interfaces with 9 options, therefore allowing extension to any structured conversation. One could also include the option to select a P300 speller in case none of the options presented are of interest. Interestingly, our system performance was higher for an interface with words than for the same interface, but with numbers (0.92 vs. 0.79 cv accuracy). While this is not statistically significant due to the low sample size, it is an effect that should be further investigated.

[2] tiny.cc/telepresence_bci_robot2

B. Switching on

An important point of discussion for every BCI is the problem of switching on the system. In most BCI systems, the user does not have control over switching it on, but instead it has to be switched on externally. The current system is switched on by the robot initialising the interaction. The user does not have active control to switch the system on. However, upon finishing the interaction, the patient has the option to specify when they want the robot to get back to them to re-start interaction. Therefore, the patient has predictive control on when to initialise interaction. Pfurtscheller at al. propose to use hybrid BCIs as a possible solution by adding a second modality as a "brain switch". They suggest using for example heart rate or a steady state visual evoked potential paradigm to switch on the system [24]. In this scenario the Emotive headset limits the number of methods used as brain switch but a feasible option would be a single steady-state visual evoked potential (SSVEP) based switch. It is easy to classify with a low false positive rate because it is spatially distinct.

C. Engaging interaction

Non-verbal communication plays an important role in coordinating teammates in collaborative tasks. The same non-verbal communication strategies applied in human to human collaborative tasks can be applied in human-robot collaborative tasks to improve the performance of robot systems [7]. In this BCI guided service robot implementation, the robotic platform needs to cooperate with people around the patient to help the patient in their needs and with the patient to get to know their needs.

In order to achieve that, different non-verbal communication gestures were implemented in the the execution of the robot's actions. Before every interaction to a human, the robot will perform a greeting routine in order to engage a conversation, after that the robot will look directly at the human face and tell its message. Whether the answer to the robot message comes from the patient through the BCI system or verbally in the case of a person around, the robot will wait attentively for a human response in order to perform the next action. The robotic platform will always look direct at the person it is interacting with in order to motivate clear communication with the subject and give verbal feedback of the next action to be done. This intends to inform the patient or the people around about the robot's current status and the next commands to be executed.

D. Patients' needs

In order to develop BCIs that enhance the quality of life for the patients, it is of major importance to research on the needs of the communities that the BCIs are developed for. While there is not much literature on the the needs of locked in and stroke patients, multiple studies analyse the needs of spinal cord injured patients [6], [3]. Blabe et al. [6] systematically analysed responses of around 150 patients with spinal cord injury in the cervical region. They found that the greatest improvement of the quality of life would be rehabilitation of hand function. 60-70% responded that they would be interested in fast typing, showing that there is strong interest in communication even though these patients still possess the ability to talk. 35-60% of their patients would use a system where they control a robot with a camera, which has similarity to parts of this system. Interestingly, this percentage was increasing, the more severe the injury (SCI on higher level) was. Our system combines multiple of the features that have been surveyed to be of interest to patients, i.e. communication and extension of the patient's senses through streaming senses from the robot to the patient. This suggests that patients would have interest in such a system. Our system provides a platform which can be extended in multiple different ways. We validated a simple prototype with constrained interactions in a healthy individual. Useful extensions or improvements of the system will require involvement of patients to optimally address their needs.

VI. Conclusions

We presented a use-case of a P300 based BCI system for a patient to communicate with and through a humanoid service robot. Both offline and online classification accuracies of the BCI are in the range of previously published methods. The robotic platform offers the possibility to share senses and thereby becomes a body extension tool and a telepresence of the patient. Furthermore it enables the patient to interact indirectly with other people using person recognition tools and fluid verbal and non-verbal communication. The novelty of this system lies in the combination of communication via a high level BCI and a humanoid robotic system which can act both as a telepresence and as somebody to communicate with. The system is designed in a modular way such that extensions to other predefined communication structures are possible and giving the robot additional abilities can be integrated within the current system.

The code for this project is available at `https://github.com/germandival/BCI_guided_service_robot`

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