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# Concept of an intrabody networked brain-computer interface controlled assistive robotic system

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**Abstract.** In this paper we present a concept of an assistive robotic system for the people with disabilities. Since the target users most likely have difficulties using standard user interfaces, e.g. keyboard and mouse as input devices for a graphical user interface, we propose brain-computer interface (BCI) to be used for controlling the system. Novelty of our approach lays in the integration of the entire system using an intrabody communication (IBC) network. Using the IBC network reduces the need of superfluous wiring and reduces the time needed to setup the system for use, i.e. it greatly simplifies the use of the system from the user perspective.

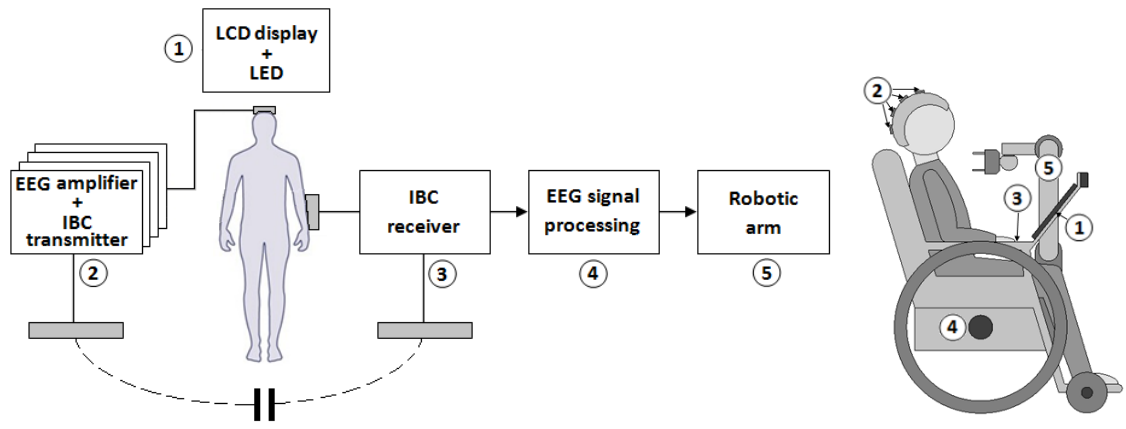
**Keywords.** Brain Computer Interface (BCI), Intrabody Communication (IBC), Assistive Robotics

## 1. Introduction

A brain-computer interface (BCI) is an alternative way of communication and control that is independent of normal neuromuscular pathways (Wolpaw et al., 2002). This technology has many possible applications, like hands-free gaming, rehabilitation, detection of cognitive load or alertness in specific professions, etc. One of the most challenging applications of BCIs is the restoration of communication and control for disabled people, that is, people suffering from paralysis due to different neuromuscular diseases (e.g. amyotrophic lateral sclerosis) or due to a brain or a spinal cord injury.

Although latest development in BCI systems has demonstrated that high-performance neuroprosthetic control is possible using intracortical microelectrodes (Collinger et al., 2012), and that somewhat similar results can be obtained by less invasive methods like electroencephalography (EEG) as shown by McFarland et al. (2010), there is a trend of coupling simple BCIs with *intelligent* systems (shared control) to achieve more complex behavior (Carlson et al., 2012) without the need for a complex BCI which implies longer training, increased user workload, etc. Therefore, we have envisioned an BCI object manipulation system where a user would use different mental strategies to communicate his/her intentions on objects in his/her surroundings, and a robotic system which can execute the intended actions autonomously.

Novelty of our proposed system is in the use of intrabody communication in order to connect the individual system components, namely the brain-computer interface and the robotic manipulator into a complete assistive robotic system. Intrabody communication (IBC) is relatively new type of communication, first described by Zimmerman (1995), in which the human body represents a signal transmission medium. The body itself is used to connect different electronic devices (such as sensor nodes) placed on, inside or near the human body, that become a part of the same Body Area Network (BAN). The most important advantages of IBC technology over conventional RF communication systems are the reduction of electromagnetic interference, low power consumption, high data rate, and health safety.




(a) Block diagram of the proposed system

(b) Proposed system overview

Fig. 1. Proposed system

## 2. System arhitecture

In the envisioned assistive robotic system, after the acquisition, each measured EEG signal is digitized, modulated and transmitted via the user's body, using intrabody communication. The overall number of the channels depends on the number of EEG electrodes. The received signal is demodulated and delivered to the central control unit, where the signal processing is performed. After the extraction of useful information from EEG signal (this depends on the BCI paradigm used), a decision is made and the appropriate action is undertaken by the robotic system.

The block diagram of the proposed system is shown in Fig. 1a, and the overview of the proposed system is given in Fig. 1b. The numbers in these figures refer to the following parts of the system: 1 to the LCD display with LED, 2 to sensor nodes consisting of EEG amplifier and IBC transmitter, 3 to IBC receiver, 4 to EEG signal processing unit, and 5 to robotic arm. Individual parts of the system are described in greater detail in the following subsections (2.1, 2.2 and 2.3)

### 2.1. BCI

The goal of a BCI is to detect specific patterns in brain electrical activity, e.g. in EEG, and use them as a control signal for computers and other devices. There are different brain patterns that can be used for this purpose and among the most popular ones are steady-state visual evoked potentials (SSVEPs), the P300 wave and changes in neural oscillations during mental tasks, e.g. motor imagery as shown in Fig. 2.

SSVEPs emerge in EEG when a person is presented with a fast train of visual stimuli, occurring with a frequency greater than 4 Hz. Neurons in the visual cortex synchronize their firing with the frequency of the stimuli, and we can detect a prominent peak in a frequency spectrum of EEG at the stimulation frequency and its harmonics. SSVEPs are among the most robust signals used for BCIs, but there is a great performance variability between different users. To compensate for this variability, careful selection of stimulation parameters for each user is critical (Wang et al., 2006; Byczuk et al., 2012). These parameters are numerous, but the most important ones are the frequency of stimulation and the channel location.

There are many ways of generating SSVEP stimuli (Zhu et al., 2010). Very often used SSVEP stimuli are alternating checkerboards, stimuli taken from clinical practice. When presenting stimuli on a computer monitor, reliable presentation depends on the refresh rate of the monitor, so only frequencies with periods that are multiples of the monitor's refresh period can be considered (Cecotti et al., 2010). We use E-Prime software (Psychology software tools) for obtaining reliable stimuli. A disadvantage of using the monitor to present stimuli is the limited number of frequencies that can be reliably implemented. Therefore we developed an SSVEP stimulator that can control flickering of LEDs in a wide range of frequencies. Before the online usage of the SSVEP BCI, we are performing a detailed scanning for each user where we present a user with a range of frequencies between 5 and 35 Hz in order to detect frequencies that are more suitable for a particular user. Another purpose of the scanning session is to detect optimal channels for the SSVEP detection. There are many methods for choosing a relevant subset of electrodes (Friman et al., 2007; Prueckl and Guger, 2010), and one of the most popular is using a single bipolar channel. Using only two active electrode sites has an explanation in the effort of using the smallest number of electrodes possible for the detection of reliable control signals. This reduces a discomfort caused by placing a large amount of EEG electrodes on a user's head and applying electrode gel on many head sites.

The other popular choice of the control signal –

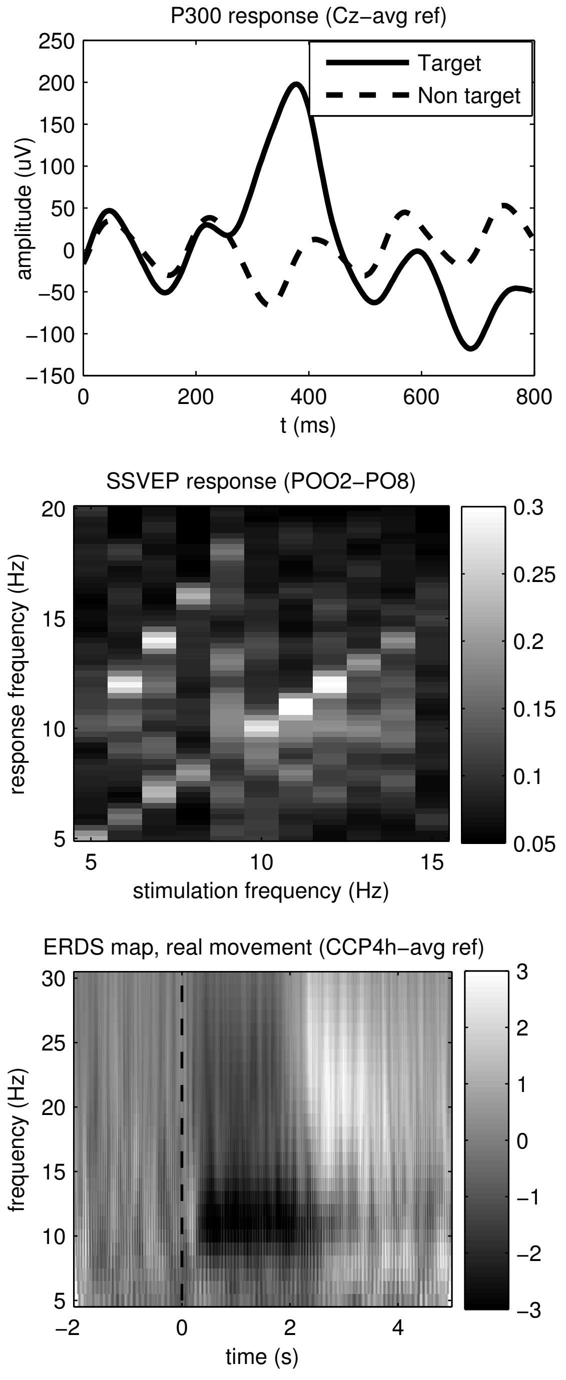



Fig. 2. Examples of signals used in BCIs, in all cases signals are the result of averaging over several trials; P300 response shows a positive ERP component emerging around 300 ms after target stimuli; SSVEP response shows a peak at the frequency of stimulation and its first harmonic; ERDS map shows ERD in mu frequency band first and ERS in beta band afterwards

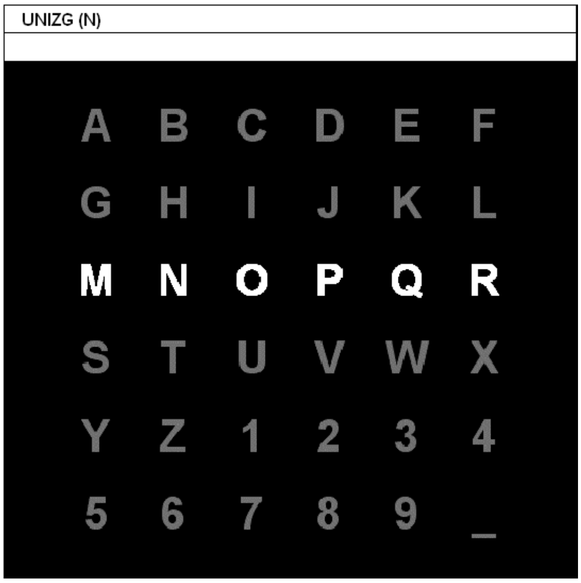



Fig. 3. P300 speller matrix

the P300 wave – is a component of a cognitive event related potential (ERP). It manifests as a positive deflection in the EEG that peaks around 300 ms after the presentation of a rare and task-relevant stimulus. This neural mechanism is usually triggered in an "oddball" paradigm: the user is presented with two types of stimuli – infrequent target stimuli and frequent non-target stimuli. The P300 response is more prominent with more distinct and rare target stimuli (Polich, 2007).

The most commonly used paradigm that utilizes the P300 for BCI control is the P300 matrix speller by Farwell and Donchin (1988). In this paradigm the user is presented with 36 symbols arranged in a 6 by 6 matrix (Fig. 3). The user is instructed to focus his attention on the desired symbol. Next, the rows and columns are flashed one by one, with target row/column flashes eliciting P300 responses in the user's EEG. The sequence of 12 distinct stimuli (6 for rows and 6 for columns) is repeated several times because robust detection of P300 usually requires averaging of multiple responses. Sequences of 12 stimuli are randomly permuted between repetitions. The symbol that is contained both in the predicted row and predicted column is output by the system.

In the preliminary studies we have focused on offline analyses of publicly available data collected according to the described P300 matrix paradigm, namely the data set IIb from the BCI Competition 2003 (Blankertz et al., 2004). The BCI algorithm that we have implemented gives results that are better than those of the contestants, even though it uses simpler methods as shown in (Melinščak et al., 2013). We intend to continue this line of inquiry by using bigger data sets and implementing online analysis.

When a person is performing a movement, this changes the amplitude of certain neural oscillations, namely mu rhythm, in brain regions associated with movement planning and execution (Pfurtscheller and Lopes da Silva, 1999). These changes occur even before a movement starts, in a form of event-related desynchronization (amplitude attenuation) in a frequency range of about 8-12 Hz. After movement execution event-related synchronization (amplitude enhancement) in a higher frequency range of about 20-30 Hz occurs. These changes are movement specific, which means that different areas of the brain are affected during different movements. Therefore we can distinguish movements of a left or a right hand, or feet. For BCI applications an interesting fact is that these brain patterns can be obtained even with motor imagery and therefore can be used as control signals for the paralyzed (Pfurtscheller et al., 1997, 2005).

### 2.2. IBC

There are two main methods of signal transmission through the body: galvanic and capacitive (Lučev et al., 2010b). In the galvanic coupling method the transmission of electrical signal is obtained by injecting the alternating electric current into the human body (Pun et al., 2011; Chen et al., 2012). On the contrary, in the capacitive coupling method the induced electrical signal is controlled by an electric potential (Lučev et al., 2010a, 2012). In the intrabody communication at least two pairs of electrodes are used, namely transmitter (TX) and receiver (RX) electrode pairs, which both consist of a signal and a ground electrode. Both signal electrodes are placed on the surface of the body. Unlike the galvanic coupling, in the capacitive coupling approach transmitter (TX-G) and receiver (RX-G) ground electrodes do not have to be in contact with the body – they are placed either on the body or above the associated signal electrodes. The gain of the received signal depends on the electrode arrangement, and is the highest if the transmitter and receiver ground electrodes are placed above the signal electrodes and remain disconnected from the body (Lučev et al., 2012), as in Fig. 4. The signal forward path is closed through the body between transmitter (TX-S) and receiver (RX-S) signal electrodes. The signal return path between receiver and transmitter ground electrodes is closed through the surrounding environment. Thus, the electric properties of the environment, as well as dielectric properties of the human body, dimensions and position of electrode pairs, have significant effect on the quality of signal transmission.

### 2.3. Robotic Manipulator

For the autonomous robotic system, we decided to leverage existing approach that is agnostic to the specific robotic platform used, and has been successfully demonstrated on Willow Garage's PR2 robot and Fraunhofer IPA's Care-o-Bot (Chitta et al., 2012). The

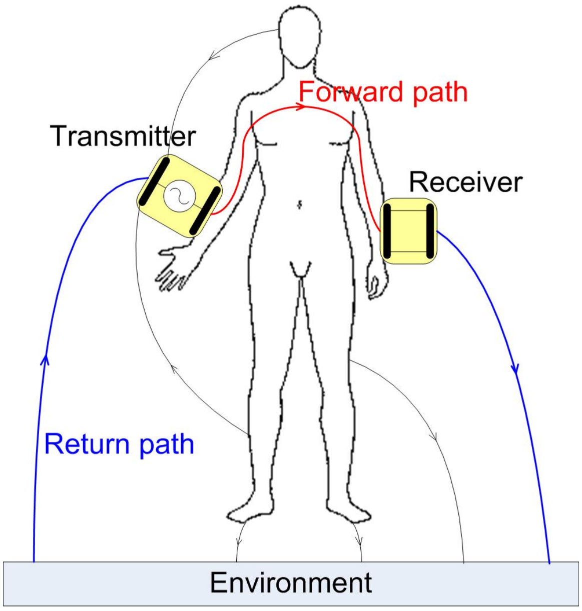



Fig. 4. Schematic diagram of an intrabody communication system utilizing capacitive coupling

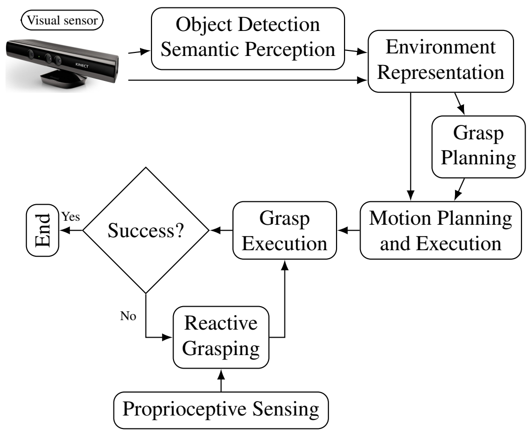



Fig. 5. High-level system diagram for executing pick and place tasks implemented in (Chitta et al., 2012)

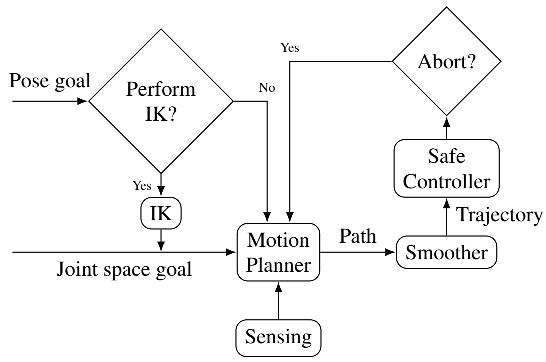



Fig. 6. System architecture of the motion planning and execution component

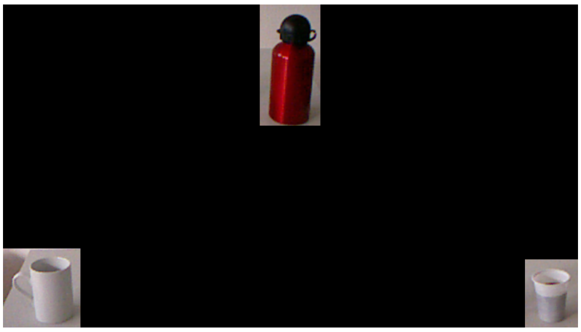


Fig. 7. BCI user interface

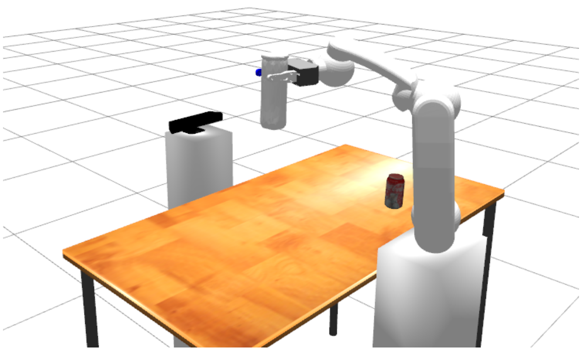


Fig. 8. Object pickup demonstration in Gazebo

high level diagram of the system is shown in Fig. 5. Aforementioned system also leverages many other existing approaches for different subtasks. E.g. for the grasp planning, the system can augment a cluster based grasp planner with *GraspIt!* grasp simulator and a database (Ciocarlie et al., 2011).

Furthermore, the motion planning and execution component, depicted in Fig. 6, uses Kinematics and Dynamics Library (Smits, 2013) to provide numeric inverse kinematics calculations for a general robotic arm. Motion Planner itself is not much more than an interface to the Open Motion Planning Library (Şucan et al., 2012) which includes many randomized motion planners.

To this end, our system consists of a Kinect sensor, Schunk PowerBall 6-DOF robotic arm, a WSG-50 1-DOF gripper and an SSVEP based BCI system utilizing LEDs for visual stimuli generation.

User interface of the BCI system is a combination of the LCD display and visual stimuli generating LEDs. LEDs are placed at the bottom corners and top center of the display, where the objects segmented by the perception system are presented, as shown in Fig. 7. This amounts to three simultaneous stimuli, and may require using one of those places as a listing element, e.g. a *Next* button utilized in other typical user interfaces, to enable selection among more than three segmented objects. Once the desired object is picked up by the robotic system, the same BCI system can be used for inputting the desired action. Actions can be represented using pictograms.

System uses Kinect sensor for scene understanding, e.g. to segment objects on a tabletop. To this end, depth camera data is used exclusively. On the other hand, when presenting segmentation results to the user, color camera is used.

After segmentation, BCI system is invoked for the user to select the desired object. When the user makes the selection, system starts object pickup planning and execution procedures.

Firstly, grasp poses are calculated and tested for the selected object. Although we have modeled WSG-50 gripper for the *GraspIt!* simulator, we have decided to use the simpler point cluster based grasp planner from (Chitta et al., 2012). While *GraspIt!* is much more advanced, one has to have extensive object mesh database optionally complemented with an extensive object—gripper grasp database. In the end the performance of such a system depends on the object recognition performance, which has a lot of room for improvement.

After potential grasp poses have been obtained, they are tested by an inverse kinematics (IK) module, to see if the arm can position the gripper in the desired pose. We used (Smits, 2013) for solving the IK problem, but one can simply plug in a symbolic IK solver module for the arm in question when available. Grasp poses that pass this test, are checked for collisions using the model of the arm, gripper and the environment. First found grasp that is collision free is planned using (Şucan et al., 2012), filtered and executed.

Finally, after the gripper has been placed in a grasp pose, grasp execution can commence. Our WSG-50 gripper is equipped with a force sensor in one of it's fingers, making it suitable for implementation of the reactive grasp execution.

System was simulated using Gazebo, and the result of picking up object is shown in Fig. 8.

## 3. Conclusion and Future Work

Of our conceptual system, we have implemented its individual parts to a certain extent. E.g. we have implemented an LED based SSVEP BCI, capacitive coupling IBC and a semi autonomous robotic arm. Apart from integrating all these parts into a complete system, we have some ideas on improving those individual parts for future work.

Each kind of BCI suffers in a certain extent from the BCI illiteracy (Allison and Neuper, 2010). Also, performance of a user on different tasks can vary in time. Therefore, it is very appealing to have a system that integrates different mental strategies and adapts to the current user and user's current mental state. Our goal is to use aforementioned mental strategies to obtain signals for controlling robotic manipulator (robotic arm can be mounted on a mobile platform, e.g. an autonomous wheelchair) in different scenarios. For example, the P300 speller can be adapted for a robot control in a way that the matrix shows pictograms of different high level commands that a robot can perform, instead of letters and numbers in the original P300 matrix. Since both proposed (SSVEP and P300 based) BCI user interfaces assume a display/monitor is used, the same could be employed for mobile platform teleoperation. That way, instead of overseeing the environment, the user could be laying in bed in another room.

Connecting other physiological sensors (like ECG, breathing or blood pressure sensors) to IBC transmitters would allow continuous monitoring of the user's health status. Also, the whole user experience could be further improved by strategically placing more IBC receivers in other commonly used equipment (like wheelchair or bed) or embedding them in the clothes (smart textiles), thus increasing user's mobility while keeping full functionality of a developed intrabody networked BCI-controlled assistive robotic system.

We intend to pursue these suggestions as to achieve the final goal of obtaining a BCI controlled assistive robotic system which is adaptable, mobile and user friendly.

## 4. Acknowledgments

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