A Robot for Brain–Controlled Grasping

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ABSTRACT

In this paper we present a system that allows patients with motor disabilities to grasp everyday objects. A closed-loop Brain–Machine Interface (BMI) instantiates a connection between the human central nervous system and an industry robot designed to execute the grasping task.

Two central problems were addressed in this paper, namely I) the implementation of a BMI to translate a subject's voluntary modulation of brain activation patterns into commands for target selection and grasp execution and II) the development of a robot that autonomously grasps natural objects. Our approach in the work was to implement as much intelligence as possible into an industry standard robotic system to claim a minimum of information flow from the patient to the system. The final system demonstrates the feasibility of brain controlled grasping of natural objects with a robotic arm which is an important step towards the development of intelligent prostheses for paralyzed patients.

Categories and Subject Descriptors

C.3 [**Computer Systems Organization**] Special-Purpose and Application-Based Systems – *Signal processing systems*

I.2.9, I.2.10 [**Computing Methodologies**] Artificial Intelligence – *Robotics, Vision and Scene Understanding*

General Terms

Human Factors, Measurement, Reliability, Experimentation

Keywords

Virtual Reality, Grasping, Thought, Brain, MEG

1. INTRODUCTION

A majority of the fifteen million people who suffer from stroke every year [20] suffer from paralysis at various degrees and remain paralyzed even after a rehabilitation therapy. Furthermore, neurodegenerative diseases deprive others of their ability to communicate with their environment after a relatively brief period. The extensive research in the field of Brain Machine Interfaces (BMI) development renders the vision of controlling robots by thoughts more likely. A brain controlled prosthesis could assist people with severe physical disabilities to interact with their environments [29, 40].

Severely paralyzed patients would greatly benefit from a device that allows them to autonomously perform everyday-tasks like picking up food or drinks, operating a telephone handset, or picking up a book. However, standard industry user interfaces and grasping strategies are not suitable for brain-controlled anthropomorphic prostheses. Even combinations of multiple human–machine interfaces e.g. tactile skin [31], speech recognition or computer vision [14, 16, 33], do not furnish the functionality required to provide services to people with disabilities. Moreover, the information flow available from brain activity decoding with non-invasive methods such as electroencephalography (EEG) or magnetoencephalography (MEG) is too low for a continuous online control of many degrees of freedom in the robot [36, 37].

In this paper we address these fundamental issues and show solutions for user control with non-invasive methods and grasping in natural situations. For this purpose we make the robot as autonomous as possible in order to keep the information flow from the human required to control the robot as low as possible. Our non-invasive approach complements the work of Hochberg et al. [15], Kubánek et al. [18], Acharya et al. [1] and others who are decoding brain signals for continuous control and thus highly depend on invasive brain data recordings.

2. MATERIAL AND METHODS

2.1 System Overview

The system we developed consists of an industry robot (Mitsubishi RV E2) equipped with a servo-electric three finger gripper (Schunk Dexterous Hand SDH) with tactile sensors on the fingertips [24], both connected to a PC via RS232, and a stereoscopic camera (see Figure 2, Figure 3). The camera provides 3D representations of graspable objects and their orientation. The objects are presented via a Virtual Reality application (Microsoft Windows XP, Java3D/OpenGL) to subjects who were instructed to select one of them for grasping by voluntarily modulating their brain activity by directing their attention to the target. After the target object is decoded from brain activity (MEG system: BTi Magnes 3600 WH, 4D Neuroimaging, 248 magnetometers), the grasp is executed autonomously by the robot.

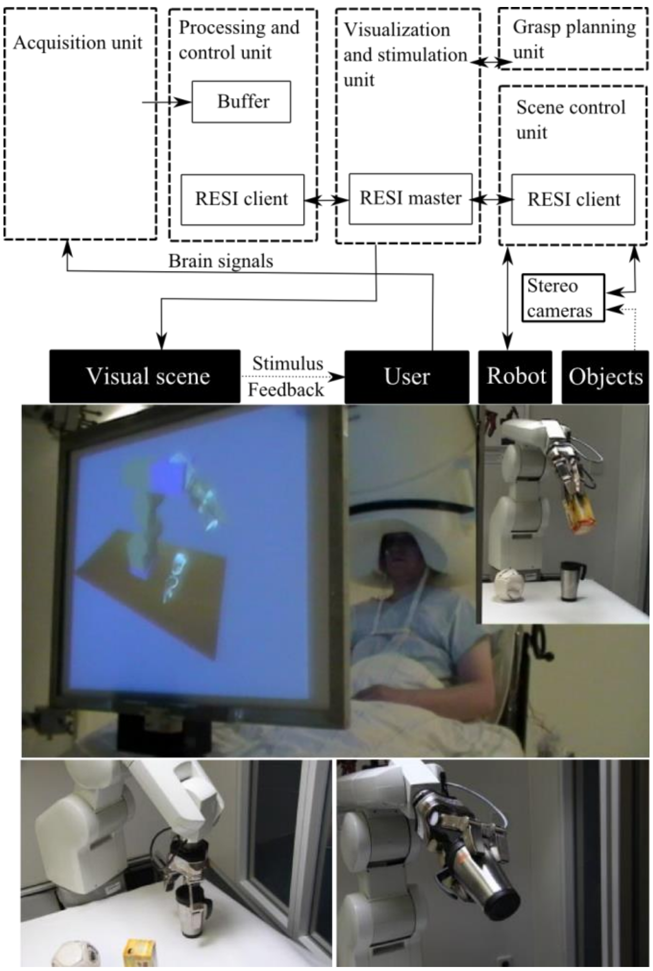

Figure 1: Top: System overview and outputs. Bottom: The subject in the MEG selects an object for grasping by voluntary modulation of brain activity. The other insets show the gripper grasping different objects.

In our BMI setup we make use of five software systems distributed over different computers in the internet. These modules include a data acquisition unit, a processing and control unit, one visualisation and stimulation unit, the grasp planning unit and a scene control unit (see Figure 1). From the data acquisition computer custom client software sends the raw brain data to a buffer running inside the processing and control unit. This unit includes custom BMI software implemented in MATLAB which controls the experiment, processes the data and sends control commands to the visualisation and stimulation unit using our real-time service interface RESI[1]. The visualisation and stimulation unit renders the virtual scene, including the robot, table and grasp targets, in 3D, appends coloured faces and rings for user stimulation and presents the scenario to the user. In order to do this, this module requires the grasp trajectory generated by the grasp planning unit as well as the physical grasp targets recognized by a stereo camera system and transmitted by the scene control unit. In addition, the scene control unit interfaces the physical robot in order to move the virtual robot synchronously.

2.2 Object Recognition

A stereo-vision based object recognition system brings along one major challenge: Only parts of the object surface visible to the cameras can be recognized. Two strategies we considered to solve this problem: I) Recording images from different points of view and merging all the images to one complete 3D model or II) accepting the default point of view and use the tactile sensors at the fingertip of the gripper to complete the placement of the grasp the object.

In respect to our aim to develop an intelligent prosthesis it is neither acceptable for a patient to carry a set of cameras on a huge construction nor to scan the environment by moving the camera attached to the robot to different target positions in the user's vicinity. Therefore, we decided to apply strategy II). Our system consists of only two Allied Vision Technologies Marlin IEEE1394 grayscale cameras (resolution: 1280x1024) and a dimmable "efpe-design" 2x55W light source placed on the top of the scene.

Figure 2: Object Recognition System

The cameras were positioned 120cm over the table at a distance of 45cm. The camera system mainly detects the upper part of the object. The upper silhouette is therefore the most prominent feature of the target and will allow a coarse prepositioning of the gripper with our grasp planning algorithm. This is a drawback as for grasping the fingers need to come close to the lateral parts of the target. However, VR-based grasp planning can only serve as

[1] http://www.iff.fraunhofer.de/en/business-units/virtual-engineering/real-time-interface.html

pre-positioning the gripper. Irrespective of the algorithm we implement in VR, in physical reality the force-based physical interaction between gripper and object which can be detected by joint actuator encoders and contact sensors at the fingertips is required to control the final grasp.

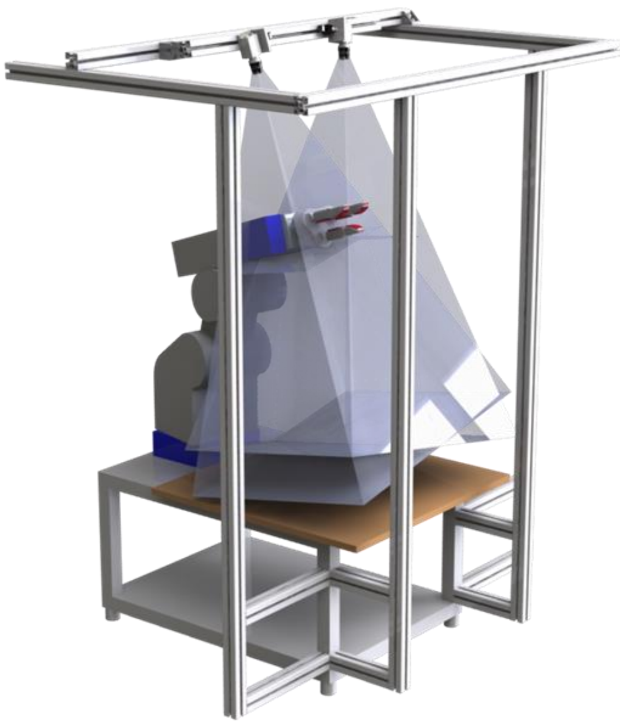

Figure 3: Robotic manipulator attached to an aluminium framework with a table for the grasp targets and the camera system for object recognition. The field of view of the cameras is shown semi-transparent.

The calibration is performed with the help of a calibration board. Calibration includes compensation of lens distortion and specification of the epipolar lines and has to be performed only once.

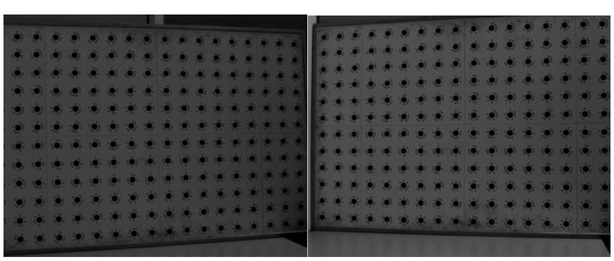

Figure 4: Stereoscopic images of the calibration board

After calibration, matching pixels in the left and right camera images can be used to calculate their spatial depth. Algorithms published in [32] were used to perform the stereo matching (epipolar line length: 150 pixel; correlation window size: 17x17 pixel). To this end, all resulting 3D points are defined in the camera coordinate system. The transformation to robot coordinates is calculated by using the same calibration markers in the robot framework, a construction made of aluminium profiles the robot is firmly attached to.

Figure 5: Stereoscopic images of the robot framework. In the left image the eight markers are highlighted.

Each marker consists of a big dot specifying the location and a set of small dots making the marker distinguishable from others by assigning a binary coded number to it. Figure 6 shows some example markers and their numeric representation.

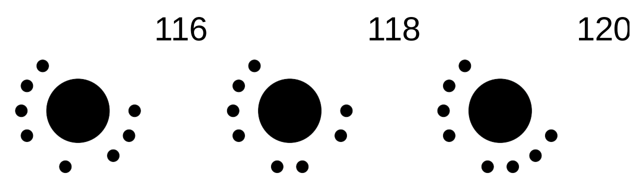

Figure 6: Used markers

Although stereo-vision systems are already widely spread and numerous publications present the 3D reconstruction algorithms [32] and applications [31], two principle problems still had to be solved for the system: I) Segmentation of the result data and II) Artefact removal.

Since 3D segmentation was error-prone due to soft shadows and limited surface information, the segmentation of the objects was already done in 2D image space. Therefore, by applying a binary threshold filter, a region-growing filter and contour-extracting filter, each foreground pixel in both images is tagged with the identifier of the object it belongs to. Our system depends on a specific known background colour which can be well separated from the foreground. In our demonstrator we put a white sheet of paper under the grasp targets.

Irrespective of the object illumination quality, the correlation analysis on the epipolar lines [32] reveals artefacts, especially when we capture the entire surface of the grasp target. For artefact detection we implemented a region check based on the number of other surface points in the vicinity of one 3D point to decide if it is an artefact or not. An object accepted for grasping is required to consist of 1.500 3D points minimum where each point must have a neighbour point in the distance of 10 mm.

2.3 Grasp Planning

A grasp planning algorithm for autonomous robots is expected to fulfil certain requirements in a BMI setting:

a) Applicable for complex grippers with anthropomorphic structures (robotic hands).
b) Robust in natural environments with complex grasp targets.

c) Aware of the restrictions and kinematic limits of the manipulator.
d) Able to deal with obstacles and stereo-vision recognized incomplete objects.
e) Execute fast and/or parallelize well.

A study of the literature about grasp planning clearly showed that none of the published algorithms fulfils all these requirements [2, 4, 5, 7–10, 13, 25, 30, 38, 39]. Therefore, a new algorithm for grasp planning was developed for this system. The algorithm generates point poles on the surface of the grasp target. Between these poles and the ones placed on the manipulator a virtual force field is instantiated. The impact of the forces on the manipulator is simulated in consecutive time frames. The innovation of this algorithm is the involvement of exponentially scaled force magnitudes that allowed us to integrate even collision detection and collision avoidance. Forces driving intruded poles out of the target are calculated the same way as those moving the gripper close to the target. The mathematical details of the grasp planning algorithm can be found in [28].

The grasp planning algorithm sums up all the torques resulting from the distances of the pole pairs. Therefore, the calculation of the actuating torques can be performed in parallel on a multi-core CPU.

The performance and result of the grasp planner highly depends on the distribution and number of point poles used for calculation. For CAD designed virtual objects we placed the poles on each triangle of the grasp target [17, 27, 28]. Stereo-vision itself does not generate surface triangles. Furthermore, the tessellation of point clouds resulting from object recognition only produces good results if the points are well distributed over the entire relevant surface. As our system cannot meet this condition we approximate the grasp targets with virtual bounding ellipsoids. To avoid underestimation of invisible lower parts of the grasp target we increase the size of the ellipsoid by the point cloud orthogonally projected to the floor plane. Additionally, the length of both semi-axes was increased statically by a fixed amount. Figure 7 shows the resulting ellipsoid for virtual and 3D-captured objects.

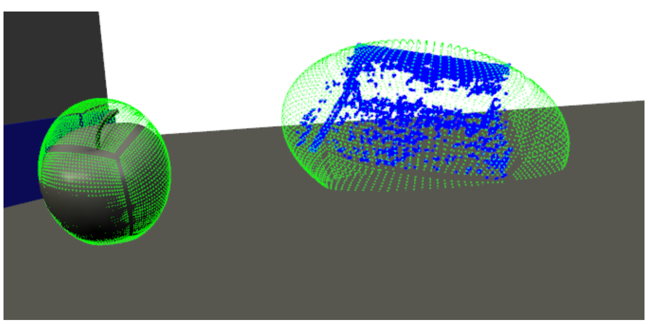

Figure 7: A bounding ellipsoid is placed around each grasp target to guide grasp placement. The algorithm works for virtual (left) and 3D-captured objects (right).

The point poles are equidistantly placed over the surface of the ellipsoid. On the basis of a collision analysis we decide which frame has to be relayed to the robot. Timeframes with a deeper intrusion of gripper contact points into the ellipsoid are dismissed. The increased size of the ellipsoid makes small intrusions tolerable. When the stability test responds a positive force-closure condition [6, 11, 41], the grasper is commanded to close the hand. In this case, the gripper uses the tactile sensors to come close to the physical object which is always smaller than the bounding ellipsoid. Hereby, the sensors serve as trigger for gripper–object contact, influence the desired speed of a gripper finger, dependent on the degree of target contact and allow analysing whether the object is firmly attached to the robot or not.

2.4 Brain Decoding – Grasp Target Selection

We performed two experiments to test two different approaches to select objects for grasping by voluntary changes of brain activity. In both experiments subjects performed 2–4 training runs to provide the classifier with training data. In most runs the target object to be selected was cued in order to be able to determine the correctness of the selection. However, we also applied runs with free selection to demonstrate the independence of the system. Here, subjects signalled an erroneous detection by saying “no” to provide the possibility of evaluating the accuracy.

One characteristic brain signal potentially useful for triggering a grasp is the steady state visual evoked potential (SSVEP, for a review see: [35]). Visual flicker stimulation causes neural activity changes at the same frequency in the brain which can then be decoded from the MEG to determine the focussed target. In order to stimulate subjects with flickering targets, we developed a VR application that can be controlled by our real-time service interface.

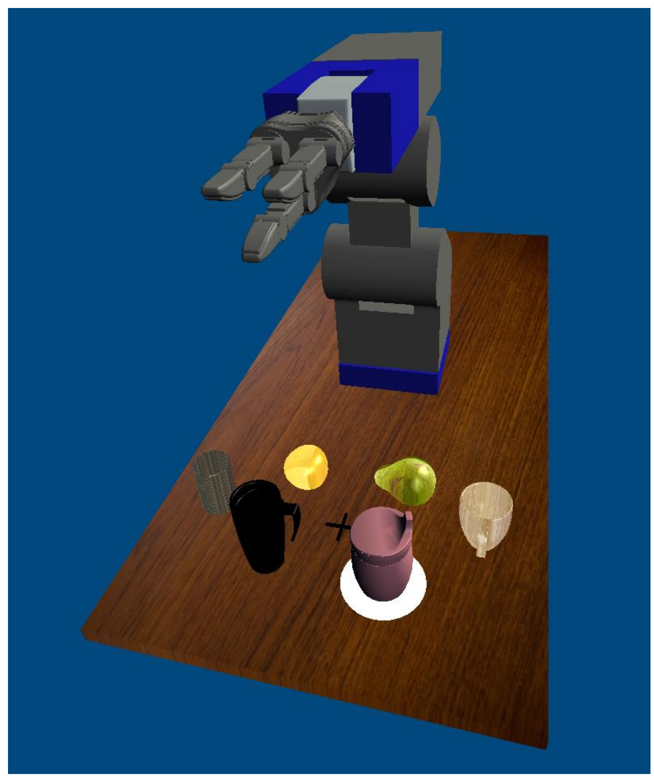

Figure 8: Objects selectable for grasping are presented in a VR scenario to the subject. Object backgrounds were flashed to create identifiable object tags in the user’s brain activity.

In the experiment we flicker the background of four selectable objects at different frequencies (6.67Hz, 8.57Hz, 10Hz, 15 Hz), which elicits brainwaves at the same frequencies measured with the MEG. Directing attention towards a flickering object enhances the amplitude of the brain oscillations at the specific frequency. This increase can be detected and used to select the target object. Additionally, coloured circles were displayed to provide feedback which object was selected. We detected the SSVEPs by determining spectral features, based on a Fourier transform, for each stimulated frequency from a 4.5s signal interval at 59 MEG sensors that we expected to capture early visual processing activity. A classifier based on penalized logistic regression decoded the potential target frequency from this feature space. Using this paradigm, we performed a study with 22 subjects. On average, 74.4% of the trials were correctly decoded in the online closed-loop BMI (25% chance level). Improvements on the decoding performance to 93.8% in an additional offline analysis of the same MEG-data indicated that the accuracy of the online decoder can be considerably improved. The detailed methods and results of the experiment are reported in [26].

The second paradigm we implemented for grasp target selection is based on the oddball paradigm [12]. In our variant of this paradigm the occurrence of an infrequent target stimulus which is a short flash of the object's background, is decoded from MEG measurements. The detection is based on the fact that the perception of a rare stimulus in a series of irrelevant stimuli elicits increased electrical activity in the brain approximately 300 ms after the stimulus, also known as the P300 potential. We flashed the object backgrounds in random sequences 5 times each within ten seconds, avoiding successive flashes at the same object. In addition, we increased the number of selectable objects to six (see Figure 8). We detected the P300 potential by support vector machine (SVM) classification [34]. The feature space was represented by discrete MEG time series values sampled at 32 Hz, lasting 1 second from the start of a flash stimulation and involving 152 hypothetically preselected sensors. We reduced the number of features by selecting 64 sensors after an initial classifier training and subsequently ranking the weight values of the SVM's decision function. The SVM was then retrained in the smaller feature space and updated after a run was finished. We performed the experiment with 17 subjects and found even better performance than with the SSVEP paradigm. The P300 paradigm allowed for 77.7% correct detections of the target object from brain activity (16.7% chance level) when we instructed the target object in each trial. We observed an increase of decoding accuracy during the course of the experiment, indicating that training improved performance. Furthermore, accuracy was higher when targets were freely chosen compared to when targets were cued. Importantly, object selection was very accurate (91.2%) when the grasp of the robotic gripper was shown in the VR-environment as feedback. This suggests that a sense of agency is an important human factor in the control of the system. A more detailed description of this experiment can be found in [28].

Finally, we tested brain controlled grasping of stereoscopically recognized objects in two subjects using the P300 oddball paradigm with three objects and online classification. The decoded intention was forwarded to the grasp planner and consequently to the virtual and real robot. The first subject performed 18 selection trials without grasp initiation and 6 selection trials with grasp initiation. In both cases 100% selection accuracy was achieved. The second subject performed 36 selection-only trials with 91.7% accuracy and six trials followed by a grasp with 100% accuracy. The guessing level was 33.3%.

3. RESULTS AND DISCUSSION

3.1 Object Recognition

We tested our system with a couple of natural camera-recognized objects (telephone headset, cup, tea box, ball, see Figure 1, Figure 9) which are relatively good-natured (no transparencies, no big specular reflective areas on top) but representative of relevant objects. Although there are big gaps in the surface reconstruction, no problematic artefacts could be observed that prevented the successful grasp of the tested objects when the object was standing upright.

The camera system, as presented in this paper, has a limited 3D-scanning volume of about 500mm/500mm/200mm (width/length/height). Compared to the human field of vision and workspace of a human limb this is quite restrictive. Nevertheless, the accuracy of a recognized object point is in the sub-millimetre range and no noise on the captured 3D-data could be observed. This was one reason to prefer this system over Microsoft Kinect which provides lower resolved and noisy recognition results [22].

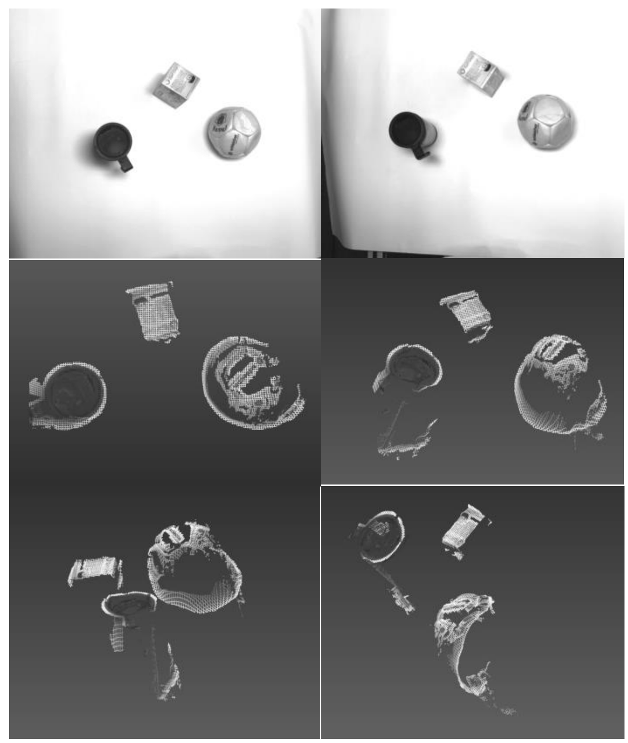

Figure 9: Sample results of the object recognition algorithm.

Up to now we strongly depend on well textured surfaces of the grasp targets. A light projection system could significantly improve our grasp planning. The choice of a suitable type of light projection for future applications is an open issue.

3.2 Grasp Planning

The presented algorithm for grasp planning satisfies all mentioned requirements of a brain-controlled grasping robot. There is no prior knowledge about a specific robot and its structure embedded in the algorithm. Thus, the algorithm has the potential to work with any robotic gripper. The grasp planner only requires the kinematic CAD-data of the robot and the specification of the contact regions (point poles on surface parts of the gripper) in the XWS-format [3]. With this information it is able to grasp objects represented by a point cloud (set of 3D-coordinates). New grasp targets can be transferred to the grasp planner when available. The result of the grasp planning process is both, the grasp pose and the robot trajectory to reach it, avoiding obstacles like the table or other grasp targets.

Both Figure 9 and Figure 10 show big gaps in the reconstructed surface of the grasp target. Nevertheless, our ellipsoid-based approach is able to deal with these problems, although the targets are not elliptic. Therefore, our algorithm can be expected to be robust in natural environments.

The selected start pose of the robot highly influences the calculated grasp. Therefore, modification of the start pose can be considered an intuitive way to adapt the grasp to the purpose the user has with the target. This will be an important feature in the further development because the system presented here has no information about the semantic context of a point cloud.

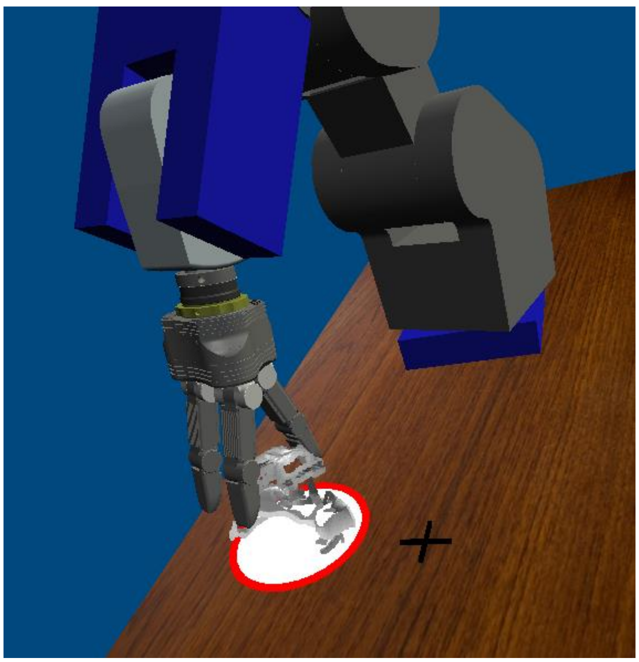

Figure 10: Grasp planning for stereo-vision recognized objects

The manipulation of the robot on the basis of a virtual force field can theoretically run into local situations where the algorithm cannot converge. This happens if an obstacle is between the gripper and the grasp target. The propulsive collision forces prevent the manipulator from intruding into the obstacle but the attractive forces antagonise, thus the manipulator stops. In the moment we have no strategy to avoid this problem in general. Nevertheless, if the grasp targets were not placed too close to each other, this problem could not be observed in our setting.

Small objects are still challenging for the grasper because the grippers' fingers cannot surround small and only partially captured objects if the obstacle "table" is too close.

3.3 Brain Decoding – Grasp Target Selection

We demonstrated that the control of a robotic device including a complex gripper with 14 degrees of freedom (two of them are mechanically coupled) is possible by decoding conscious brain wave modulations of the user. We implemented user-friendly communication paradigms into our demonstrator which rely on visual stimulation. The initiation of a grasp requires low mental effort and is highly accurate compared to continuous imagination of limb movement aiming to control the ongoing movement using non-invasive modalities [19, 21, 23].

Our results show that both the P300 and the SSVEP paradigm allowed for reliable object detection. Importantly, all subjects were able to gain control over the system after only a few minutes of training and the performance improved considerably in short training periods.

The influence of human factors on BCI control has been rarely considered in BCI design. Our results suggest that the degree of agency in the task and the type of feedback can improve accuracy of user control of the BCI system. We speculate that these factors help the subject to keep the level of attention in the task high. This was unexpected because the robot grasp feedback increased the time interval between two time intervals and thus could have made the task more boring for the subject.

4. CONCLUSION

The paper I) shows that a subject's voluntary modulation of brain activation patterns can be decoded and translated into commands that initiate a grasp to a selected object and II) describes a robot that autonomously grasps natural objects and thus completes the loop of a BMI. We successfully showed that a grasp of one of up to six objects can be initiated by brain waves and a robot with a complex manipulator can execute a grasp to a target object only by analysing the point cloud of the target. Importantly, the core algorithms of the system do not require any prior knowledge of the robot. We conclude that we achieved an important step towards our goal of constructing an intelligent assistive device or prosthetic limb for completely paralyzed patients.

Our autonomous grasper is set up to deal with specific problems of brain-robot control. Nevertheless, the grasp planning algorithm does not contain specifics of the grasper and therefore can be adapted to new and even much more complex kinematic structures (e.g. Shadow Dexterous Hand[2]).

Certainly, MEG signal acquisition and the control of an industry robot are not suitable for daily use and particularly not for use as a prosthetic device. Rather, we consider our study basic research and an important milestone to the development of an EEG controlled lightweight robotic arm attachable to a patient.

We developed communication strategies to transfer data and control commands to the different components that are involved in our BMI based grasping system. Since we performed experiments with subjects sitting in a magnetically shielded room we developed a VR-based real-time interfaced application. However, also for EEG based BMIs this application can serve as presentation unit to control the system. Using MEG signals, we investigated the ability of users to initiate grasp commands by focusing steady state stimulations and shifting attention to short object background flashes.

[2] http://www.shadowrobot.com/products/dexterous-hand/

5. ACKNOWLEDGMENTS

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