Continuous Control of the DLR Light-Weight Robot III by a human with tetraplegia using the BrainGate2 Neural Interface System

J. Vogel, S. Haddadin, J.D. Simeral, S.D. Stavisky, D.Bacher, L.R. Hochberg, J.P. Donoghue, P. van der Smagt

Abstract We have investigated control of the DLR Light-Weight Robot III with DLR Five-Finger Hand by a person with tetraplegia using the BrainGate2 Neural Interface System. The goal of this research is to develop assistive technologies for people with severe physical disabilities. This shall allow them to regain some independence in the handling of objects, e.g. to drink a glass of water. First results of the developed control loop are very encouraging and allow the participant to perform simple interaction tasks with her environment, e.g., pick up a bottle and move it around. To this end, only a few minutes of system training is required, after which the system can be used.

Joern Vogel, Sami Haddadin and Patrick van der Smagt
Institute of Robotics and Mechatronics, German Aerospace Center / DLR Oberpfaffenhofen, Germany, e-mail: {joern.vogel,sami.haddadin,smagt}@dlr.de

John Simeral, Sergey Stavisky, Daniel Bacher and Leigh Hochberg
School of Engineering, Brown University, Providence, RI,
e-mail: {john_simeral,sergey_stavisky,daniel_bacher,leigh_hochberg}@brown.edu

John Donoghue
Dept. of Neuroscience, Brown University, Providence, RI, e-mail: john_donoghue@brown.edu

John Simeral, Sergey Stavisky, Leigh Hochberg and John Donoghue
Rehabilitation R&D Service Dept. Veterans Affairs Med. Ctr., Providence, RI

John Simeral, Sergey Stavisky, and Leigh Hochberg
Neurology, Massachusetts General Hospital, Boston, MA

Leigh Hochberg
Neurology, Brigham & Women's and Spaulding Rehabilitation Hospitals, Harvard Medical School, Boston, MA

1 Motivation

Enabling individuals with tetraplegia to control a robot arm and hand as an assistive device for manipulation tasks by use of intracortical motor signals could provide significant autonomy capabilities to the concerned person. The ultimate goal is to re-enable the person to move an assistive device *naturally*, instantiated by a robotic arm with dexterous robotic hand, as if it was their own and grasp and manipulate real-world objects. By using the higher-order control capabilities of the human brain, i.e., selection of the goal; hand posture; global trajectory planning; etc., grasping and object handling in unstructured environments need not be implemented in artificially cognitive robotic systems. Rather, the robotic system should take care of the low-level intelligence, including motion and interaction control, collision handling, and the performance of stable grasps. Consequently, the person can depend entirely on the safe and stable behaviour of the robot [1].

In this paper we demonstrate for the first time continuous control of a robot arm and hand by intracortical motor signals of a person with tetraplegia, which we believe is an important step towards the aforementioned goal.

Control of various devices by the use of intracortical and electrocorticographic brain-computer interfaces (BCI) has been an ongoing research area for many years. With respect to EEG-based approaches, the intra/epicortical methods excel in their increased bandwidth, accuracy of the signal, and not requiring adaptation by the participant. It has been shown in various studies that with intracortical BCIs humans can move, e.g., a computer cursor on a screen or similar two-dimensional tasks [2, 3, 4]. Furthermore, motion control of hardware devices such as a wheelchair has been demonstrated [5, 3]. Furthermore, on-off control of the opening of a prosthetic hand and simple movement of a robotic arm based on neural cursor control was shown [4]. However, continuous motor control of a full robotic arm with the possibility to exhibit physical interaction has previously only been demonstrated under direct cortical control by neurologically intact non-human primates [6]. This difference is fundamental. In the case of non-human primates, the data to map the correspondence between intracortical activity and the correlated motion of the controlled limbs can be recorded, on the one side using intracortical recordings, on the other by visually tracking the movement of the hand and fingers of the primate. In people with tetraplegia, however, the second set of data cannot, due to the impairment of the extremities, be gathered, and a different method of correlation is required. Thereto the “embodiment” of the robotic limb by the participant plays a central role, which has to be quantified.

2 Technical Approach

In this study our goal is to enable a person with tetraplegia to control a robotic hand-arm system and use it as assistive device for everyday activities. Exemplary for this long-term goal the task is to move the robot towards a bottle which is placed on a table, grasp it, and move it to another position.

2.1 Robotic assistive device

In our experiments we use the DLR Light-Weight Robot III (LWR-III) with the DLR Five-Finger Hand as robotic platform. It has been designed at the German Aerospace Center (DLR) [7] and is particularly well-suited for operation in unknown environments which necessitate high safety capabilities [8]. The LWR-III is a 14kg, 7 degree-of-freedom robotic arm which can lift its own weight. It is equipped with torque sensors in each joint, enabling various "Soft Robotics" control schemes such as Cartesian impedance control and collision detection and reaction [9, 10, 11]. Its various soft-robotics control schemes are embedded in a human-friendly state-based control architecture [12] which allows us to develop complex interaction scenarios. In our research, the LWR-III is equipped with the modular DLR Five-Finger Hand to grasp and hold objects. Similar to the robot, this hand is equipped with joint torque sensors in each active joint, allowing it to be also used in impedance control. During manipulation tasks this makes it robust against uncertainties in the environment such as the position of objects to be grasped. Furthermore, this facilitates automatic, impedance-driven grasping methods.

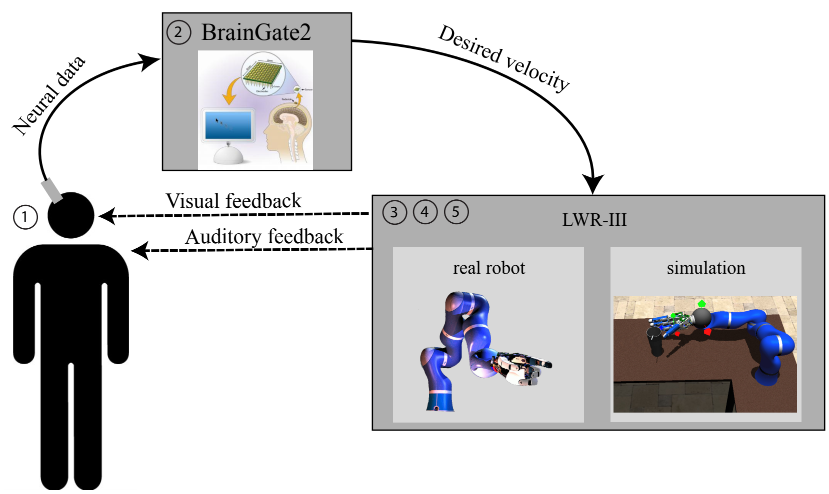

Fig. 1 Closed-loop control by neural data.

2.2 Cortical recording and decoding

Commanding the robot by the human via decoded neural data is done with the BrainGate2 Neural Interface System (CAUTION: Investigational Device. Limited by Federal (U.S.) Law to Investigational Use). In the BrainGate2 system, a 10×10-electrode array (4×4mm platform, 1.5mm electrode length) implanted in the human motor cortex records spikes of nearby neurons.

As the electrode array records the extracellular voltage fluctuations from multiple neurons, a manual spike sorting is performed to isolate single units for each electrode. Spike sorting of intracortically recorded signals is still a subject of ongoing research [13, 14]. Despite the fact that there are algorithms for automated spike sorting, we preferred to use a manual sorting in these experiments, because this proved to be functional in other BrainGate2 experiments [4]. Spikes from single units were isolated when possible, but occasionally spiking activity from more than one neuron may have been grouped together as a single unit [4, 2, 15]. Spikes from each channel were then summed in non-overlapping 100ms bins.

During training, the subject was asked to attempt moving the arm in tandem with the robot arm, matching its velocity as closely as possible. End-point velocity $\mathbf{x}$ of the robot arm along with binned spike rate $\mathbf{z}$ was used to build a Kalman filter [16]. Briefly, the Kalman filter predicts the current velocity of the subject's attempted arm movement using both its previous prediction and the current binned spike rate. More specifically, the predicted velocity is the solution to dual linear equations

$$\mathbf{z}_t = H\mathbf{x}_t + Q, \tag{1}$$

$$\mathbf{x}_{t+1} = A\mathbf{x}_t + W \tag{2}$$

Both W and Q are zero-mean, Gaussian-distributed noise matrices, H linearly relates velocity to spike rate, while A linearly relates how the velocity changes across a single time-step. Details on how to calculate these matrices along with filter implementation can be found in [17]. In addition, a linear discriminant analysis classifier decodes imagined grasps into a binary signal which can be used as a control input, e.g., for clicking or grasping.

2.3 Integrated system

In previous studies it has been shown that it is possible to continuously control a computer cursor (with click) via BrainGate [2, 3, 4]. The closed-loop control scheme, incorporating the human action and perception is depicted in Figure 1. The loop consists of following entities:

1. Participant with tetraplegia imagines making desired motion with her own arm/hand;
2. Neural data is decoded to desired velocity by BrainGate2;
3. Robot is controlled to follow the encoded velocity profile, while

4. Virtual Environment limits the robot workspace to a defined area; and
5. Grasping of objects is performed when triggered by cortex-decoded grasp intention (a pre-programmed sensor based grasp strategy is performed).

The overall system structure is depicted in Figure 2. It consists of the BrainGate2 which sends desired endpoint velocities to the robot and receives the current status of the robot via UDP. This feedback from the robot is used when the robot hits the virtual workspace boundaries. It triggers an auditory feedback to the participant and resets the Kalman history to erase any previous momentum in the direction of the boundary. The robot is controlled by a high-level hybrid state-machine in combination with the low-level robot control kernel that incorporates safe collision handling [12].

The connection to the control core of the robot is realized via the real-time communication protocol Ardnet [18] which was developed at DLR. Using a hybrid state-machine provides an simple-to-use interface, with which we create complex robot interaction scenarios. All task-relevant parameters such as, e.g., configuration of the virtual environment, velocity limits and reaction strategies in case of collision can easily be defined depending on the current state of the task execution. This high-level part of the controller architecture runs on a Windows PC at a soft-realtime rate of $\approx$ 100Hz.

On the hard-realtime control kernel, which uses VxWorks as an operating system, all algorithms run at a 1kHz rate and handle the motion control, virtual environment, collision avoidance, detection and reaction.

As the joint torque sensors of the robot enable to directly command on joint torque level, we use a virtual environment that generates repulsive wrenches for limiting the robot workspace. These virtual walls create a repelling Cartesian wrench depending on the relative distance and velocity between the robot and the wall. Via the transposed Jacobian, the Cartesian wrench is mapped into joint torques which then can be easily added to the desired torques generated by the nominal Cartesian impedance controller.

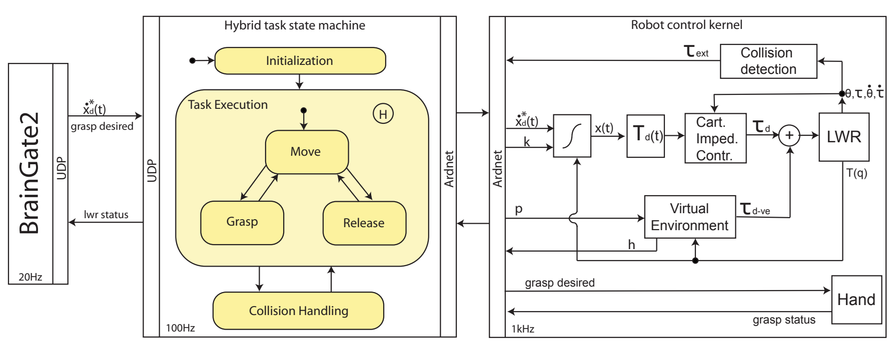

Fig. 2 Simplified system overview

Furthermore, the joint torque sensors together with a good dynamic model of the robot allow for the detection and estimation of external forces applied by real world objects, such as an object to be grasped or the table the object is placed on. Depending on the task such a contact can be unexpected and trigger a human-safe reactive behaviour, or it can be intentional, for instance when putting down a bottle. Thereby this modality can be used to induce the robotic hand to release the grasp in a pre-programmed motion sequence.

2.4 Neural Decoder Building

To set up the model parameters for the decoders, a short filter-building procedure (10–15min) is required. During this period the participant is told to watch a pre-programmed motion of the robot and mentally imagine performing a corresponding arm motion, by attempting to follow the robot hand's motion with her own wrist.

The motion of the robot consists of center-out-and-back movements with a sinusoidal velocity profile. The training space consists of four targets in the table top plane and one target above the center position. This sums up to five possible trajectories, given that the robot moves back to the center position after reaching one of the targets. The targets are colour-coded as depicted in Fig. 3. To minimize reaction time issues, the target the robot will move to is vocally announced shortly before the robot starts moving towards it.

The filter-building procedure is divided into different blocks wherein the sequence of trajectories is randomly permuted. The peak velocity of the motion is kept constant within one block and a training period consists of blocks with either slower

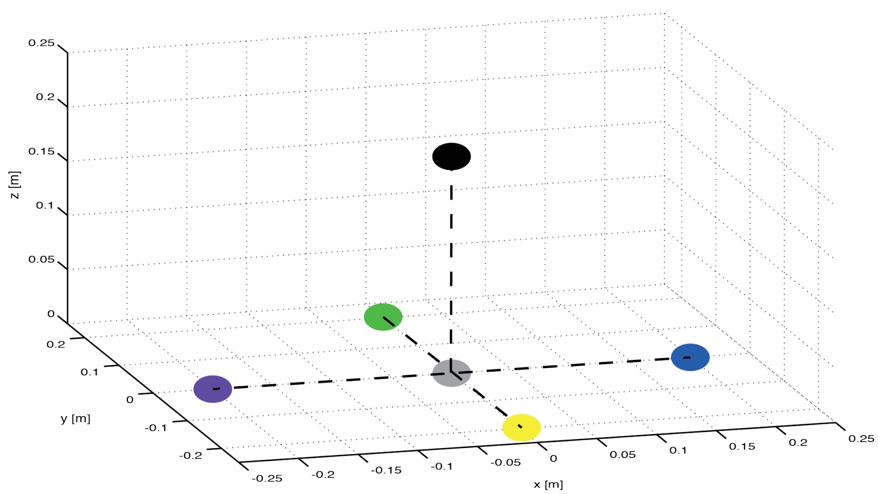

Fig. 3 Trajectories uses for filter-building procedure

(0.1m/s) or faster (0.2m/s) peak velocity. Furthermore grasp encoding, instructing the robotic hand to close, is trained in a separate set of blocks. These training blocks are run at the larger velocity. When the center position is reached, the robot automatically performs a grasp motion, during which the participant is asked to imagine a short but firm grasp.

As the filter-building paradigm relies on motion imagination which should mimic the real, participant-observed robot motion, our training approach provides an intuitive and physically relevant interface for robot control.

3 Experiments and Results

To validate the functionality of our approach, we executed a sequence of steps in various research sessions during the last years. Initially, encoded recorded intracortical data was used offline to control the simulated robot arm and hand in a realistic scenario. This software implements a full dynamics simulation of the robotic system, allowing us to quantify the viability of the approach and usability of the encoded cortical data. Furthermore, it allowed us to define velocity and positional scaling factors to ensure safe and convenient interfacing between the participant and the robot.

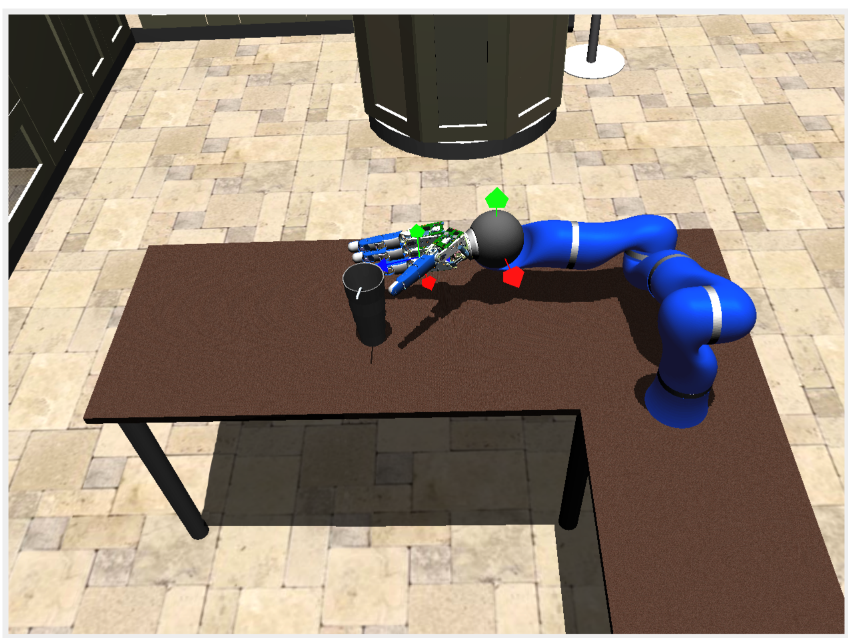

Fig. 4 Screenshot of the full dynamics robot simulation

In a second set of experimental sessions, the participant was given BrainGate-based control over the aforementioned robot simulator. In these sessions a virtual environment illustrating a kitchen scenario (see Fig. 4) was shown to the participant on a computer screen. In this environment the robot was mounted on top of a table. The task was to grasp a glass standing on the table, move it to a target position, and release it again. A series of research sessions validated the success of the approach, and allowed us to further adjust the robot control parameters.

In order to perform tasks similar to those in the simulator sessions, the participant was given direct BrainGate-based control over the real DLR-LWR-III with Hand in a third set of experiments

The setup with the real robotic system is depicted in Fig. 5. We will refer to individual days in which the participant controlled the robot as sessions.

From the data collected in the training phase as described above, the neural decoder is parameterized and the participant is given control over the robot. The participant is initially restricted to moving the robot in single x, y and z Cartesian dimensions. This allows us to evaluate the functionality of the decoders and enabled the participant to more easily explore the mapping between neural activity (i.e.,

Fig. 5 Experimental setup with the participant observing the LWR-III with hand

intended movement) and robot motion. The grasp/click decoding is evaluated separately in a simple grasp/no grasp task.

After the functionality of the decoder is validated, the participant is asked to either move towards a target drawn on the table, or a bottle filled with water was placed on the table to be grasped and moved to another location. The grasping and lifting of the object was triggered by the grasp decoder and then autonomously performed by the robot, provided the object was detected in the robotic hand.

As the workspace of the robot was limited by a set of virtual walls; an acoustic signal indicated when the robot touched one of these walls.

A typical session lasted approximately 3–4 hours and consisted of several repetitions of training and evaluation phases.

The results we report on are still very preliminary. They are based on a very limited set of research sessions done with one participant only. In particular, the results we present here are based on five sessions with simulated robot and three sessions with the real robot system.

Figure 6 shows clippings of a video taken during a research session in which the participant moved the robot towards a bottle, successfully grasps it, and brings it over to a target location. Though this trial only covers one-dimensional control plus click/grasp control of the robot, it clearly demonstrates the functionality of the overall system.

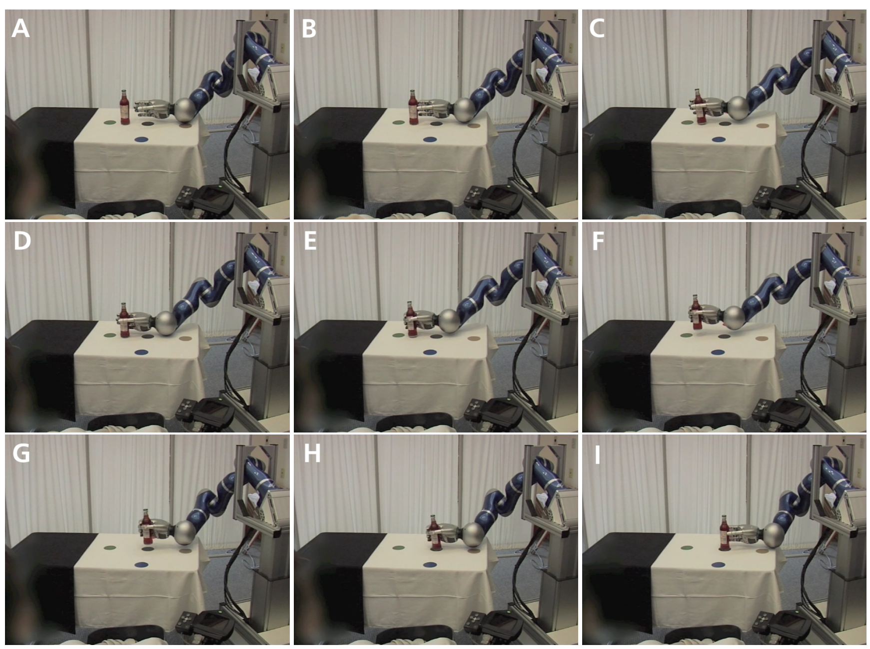

Fig. 6 Stills taken from a video showing 1D control plus grasp by picking up a bottle

As can be seen in Fig. 6 (A), the task starts with the robot hand placed in the center of the workspace and the bottle located ≈ 20 cm left of it. Moving towards the bottle (B), the robot reaches it and slightly tilts it over (C). The participant sees that and (D) corrects the robots position so that the bottle stands stably between the fingers of the hand for the participant to initiate a grasp command (E). The lifting of the bottle (F) is autonomously performed as soon as the robotic hand detects the successful grasp using its integrated torque sensors. After the bottle is lifted the participant is requested to put it down on the black target in the center of the workspace. This is successfully done as can be seen in (G)(H)(I).

Fig. 7 shows the robot end-effector position over time. The figure clearly shows an overshoot when reaching for the bottle. This indicates that there could be some inertia or time delay affecting the decoded velocities, which we presume to be caused by the nature of the Kalman filter. We can also see that the participant is able to correct for this overshoot, and can eventually, though preceded by some aberrant motion, put the bottle down almost perfectly in the center of the target location.

These experimental results demonstrate the ability of the participant to move to the bottle, initiate a grasp when needed, and put the bottle down at a defined target location. Other trials have, however, also demonstrated considerable aberrant motion. Several factors may have contributed to suboptimal performance, including a relatively small neuronal unit count when compared to recent non-human primate results [6], non-stationarities in the response properties of neural units to intended movement, and imperfect sorting of individual neural units. Furthermore, we suspect that a suboptimal experimental setting, in which the participant must be kept outside the reach space of the robot, negatively influences the results, since they sig-

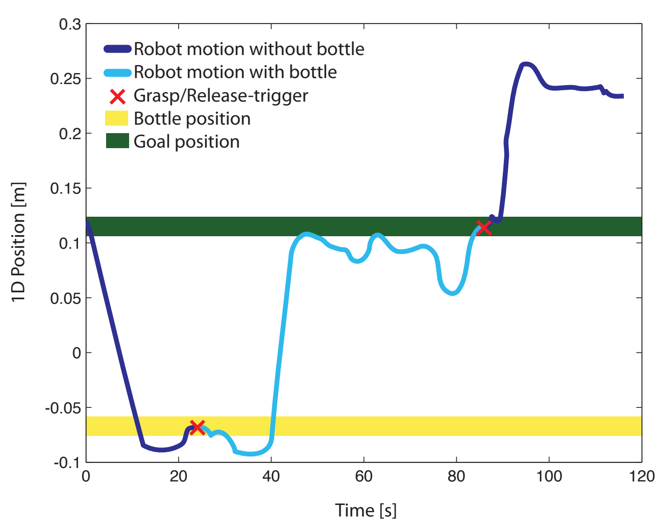

Fig. 7 Robot end-effector position over time

nificantly reduce the interpretation of the three-dimensional visual scene. We intend to address these issues in future research sessions.

4 Conclusion

In this paper we have described a method to enable a tetraplegic participant using the BrainGate2 cortical implant to control a robotic assistive device consisting of the DLR Light-Weight Robot III and DLR Five-Finger Hand II. Preliminary research, in which the participant, after a short training period, is given control of the robot arm and hand, are encouraging and show the ease of integration between the system and the participant: with only learning required at the system side, the participant can immediately use the system to regain very basic grasping and handling capabilities.

Even though these results are still very preliminary, they are very promising. Our insights are based on six simulator sessions and three sessions with the actual robotic system, all having been done with the same participant. Despite the fact that in all research sessions the number of active neurons was significantly less compared to non-human primate experiments [6], all experiments demonstrated the ability of the participant to obtain usable control of the robotic arm through visual feedback. Furthermore, our preliminary results suggest a correlation between the control accuracy and feedback gains of the robotic system (i.e., the responsiveness of the mechanical system to external stimuli). Moreover, the shaping of the visual scene seemed to play a non-negligible role. Further research sessions are planned to parameterise these effects.

A detailed description of the results obtained in these experiments will be published in subsequent papers.

References

1. S. Haddadin, A. Albu-Schäffer, and G. Hirzinger. Requirements for safe robots: Measurements, analysis and new insights. *International Journal on Robotics Research*, 28(11-12):1507–1520, 2009.
2. S.P. Kim, J.D. Simeral, L.R. Hochberg, J.P. Donoghue, and M.J. Black. Neural control of computer cursor velocity by decoding motor cortical spiking activity in humans with tetraplegia. *Journal of Neural Engineering*, 5:455, 2008.
3. J.P. Donoghue, G.M. Friehs, A.H. Caplan, J. Stein, J.A. Mukand, D. Chen, R.D. Penn, and L.R. Hochberg. BrainGate neuromotor prosthesis: first experience by a person with brainstem stroke. *Soc Neurosci Abs*, 256, 2006.
4. L.R. Hochberg, M.D. Serruya, G.M. Friehs, J.A. Mukand, M. Saleh, A.H. Caplan, A. Branner, D. Chen, R.D. Penn, and J.P. Donoghue. Neuronal ensemble control of prosthetic devices by a human with tetraplegia. *Nature*, 442:164–171, 2006.
5. K. Choi and A. Cichocki. Control of a wheelchair by motor imagery in real time. In *Intelligent Data Engineering and Automated Learning IDEAL 2008*, pages 330–337. Springer, 2008.
6. M. Velliste, S. Perel, M.C. Spalding, A.S. Whitford, and A.B. Schwartz. Cortical control of a prosthetic arm for self-feeding. *Nature*, 453(7198):1098–1101, 2008.

7. A. Albu-Schäffer, S. Haddadin, C. Ott, A. Stemmer, T. Wimböck, and G. Hirzinger. The DLR lightweight robot: design and control concepts for robots in human environments. *Industrial Robot: An International Journal*, 34(5):376–385, 2007.
8. S. Haddadin, A. Albu-Schäffer, and G. Hirzinger. Safety analysis for a human-friendly manipulator. *International Journal of Social Robotics*, 2:235–252, 2010.
9. A. Albu-Schäffer, C. Ott, and G. Hirzinger. A unified passivity-based control framework for position, torque and impedance control of flexible joint robots. *The International Journal of Robotics Research*, 26(1):23, 2007.
10. S. Haddadin, A. Albu-Schäffer, A. De Luca, and G. Hirzinger. Collision detection and reaction: A contribution to safe physical human-robot interaction. *IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, Nice(France), 2008.
11. S. Haddadin, S. Parusel, J. Vogel, R. Belder, T. Rokahr, A. Albu-Schäffer, and G. Hirzinger. Holistic design and analysis for the human-friendly robotic co-worker. *IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, Taipeh(Taiwan), 2010.
12. S. Haddadin, M. Suppa, S. Fuchs, T. Bodenmüller, A. Albu-Schäffer, and G. Hirzinger. Towards the robotic co-worker. In *International Symposium on Robotics Research*, 2009.
13. F. Wood, M.J. Black, C. Vargas-Irwin, M. Fellows, and J.P. Donoghue. On the variability of manual spike sorting. *Biomedical Engineering, IEEE Transactions on*, 51(6):912–918, 2004.
14. F. Wood and M.J. Black. A nonparametric bayesian alternative to spike sorting. *Journal of neuroscience methods*, 173(1):1–12, 2008.
15. J.D. Simeral, S-P. Kim, S.D. Stavisky, J.P. Donoghue, and L.R. Hochberg. Assessment of BrainGate-enabled neural control of a point-and-click cursor by a person with tetraplegia 1000 days after array implant. In Program No. 181.5, editor, *Neuroscience Meeting Planner*, Chicago, IL, 2009. Society for Neuroscience.
16. W. Wu, Y. Gao, E. Bienenstock, J.P. Donoghue, and M.J. Black. Bayesian population decoding of motor cortical activity using a Kalman filter. *Neural Computation*, 18:80–118, 2006.
17. W. Wu, M.J. Black, Y. Gao, E. Bienenstock, M. Serruya, and J.P. Donoghue. Inferring hand motion from multi-cell recordings in motor cortex using a Kalman filter. In *SAB'02-Workshop on Motor Control in Humans and Robots: On the Interplay of Real Brains and Artificial Devices*, pages 66–73, 2002.
18. B. Bäuml and G. Hirzinger. When hard realtime matters: Software for complex mechatronic systems robotics and autonomous systems. *Robotics and Autonomous Systems*, 56:5–13, 2008.