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Neural Control using EEG as a BCI Technique for Low Cost Prosthetic Arms

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Keywords: Brain Computer Interface, Prosthetic Arm, Kinematics, EEG, Iterative Algorithm, Machine Learning.

Abstract: There have been significant advancements in brain computer interface (BCI) techniques using EEG-like methods. EEG can serve as non-invasive BMI technique, to control devices like wheelchairs, cursors and robotic arm. In this paper, we discuss the use of EEG recordings to control low-cost robotic arms by extracting motor task patterns and indicate where such control algorithms may show promise towards the humanitarian challenge. Studies have shown robotic arm movement solutions using kinematics and machine learning methods. With iterative processes for trajectory making, EEG signals have been known to be used to control robotic arms. The paper also showcases a case-study developed towards this challenge in order to test such algorithmic approaches. Non-traditional approaches using neuro-inspired processing techniques without implicit kinematics have also shown potential applications. Use of EEG to resolve temporal information may, indeed, help understand movement coordination in robotic arm.

1 INTRODUCTION

Brain Computer Interfaces (BCI) is a novel fast evolving technology connecting the brain to a computing devices (Birbaumer, 2006; Wolpaw et al., 2002), now seen as a ubiquitous detection and diagnostics tool. The domain of EEG-based BCIs include several applications like controlling a cursor on the screen (Yuanqing Li et al., 2008), selecting letters from keyboard playing games (Donchin et al., 2000), controlling a prosthetic arm (Bi et al., 2013; Muller and Blankertz, 2006). BCI devices are used in multiple modes including invasive or non-invasive (Leuthardt et al., 2004; Owen and Coleman, 2008; Pfurtscheller et al., 2010), synchronous and asynchronous (Md Norani et al., 2010) modes in current BCI applications. Prosthetic articulators based on EEG play a vital role in the area of haptics and sensorimotor control (Wolpert and Flanagan, 2010). In this position paper, we discuss the evolution of EEG-based BCI techniques for control of neuro-prosthetic articulators and include our case study on a low-cost robotic arm model.

Electroencephalography (EEG) is a widely used neuroimaging technique, owing to its high temporal resolution, low cost, high portability and has become a practical choice for BCI. The quality of EEG signals are usually affected by noise from scalp, skull and a significant contribution from background noise (Nicolas-Alonso and Gomez-Gil, 2012). Various EEG-based BCIs differ based on user intent to extract neuro-electrical activity. Techniques commonly used are based on recognition of specific pattern in EEG to a particular task (Millán et al., 2002; Pfurtscheller et al., 2003; Wolpaw et al., 2002), identification of characteristic waveforms in EEGs which follow an event (Birbaumer et al., 2003; Farwell and Donchin, 1988), and the presence of periodic waveforms in EEGs in the range of frequencies of an oscillatory signal corresponding to a light flash stimulus (Friman et al., 2007). EEG signals, based on specific responses related to a task-related stimulus, serve as an input for BCI systems to control prosthetic arms (Figure 1). EEG patterns can be extracted using Sensory Motor Rhythms (SMR). Motor movement or imaginary movement changes the oscillatory patterns of EEG, resulting in

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suppression of amplitude (ERD) or enhancement in amplitude (ERS) for mu or beta rhythms. (McFarland et al., 2000; Pfurtscheller et al., 2006; Wolpaw et al., 2002).

1.1 Implementation Issues regarding EEG Based Techniques

Although EEG is portable (Nicolas-Alonso and Gomez-Gil, 2012; Tanaka et al., 2005) and cost effective (Bi et al., 2013; Vespa et al., 1999) for research purposes, poor signal to noise ratio or artefacts are recorded during signal acquisition. For statistical significance, EEG analysis require complex data analytics and significantly large dataset with a fair number of subjects (Schlögl et al., 2002). Due to low spatial resolution, EEG signals need elaborate interpretation in order to functionally hypothesize on areas activated by particular response (Srinivasan, 1999). Pre-recording setup times are also significantly long.

Noise in the signals plays an important role in EEG signal analysis and interpretation of data (Repovs, 2010). There is a necessity for efficient strategies towards noise prevention and removal.

1.2 Neurological Mechanisms Used in BCI

Control signals generated by BCI methods correspond into 5 main categories namely sensorimotor activity (ERD/ERS), VEP, P300, SCP, activity of neural cell (Wolpaw et al., 2002), and furthermore into two additional categories, mental arithmetic tasks (non-movement) and multiple neural mechanisms (Anderson, 1995; Gysels et al., 2005).

Previous studies (Anderson, 1995; Choi, 2012; Craig and Nguyen, 2007; Leeb et al., 2007; Pires et al., 2008; Tanaka et al., 2005) have shown that these neurological mechanisms were used in different motor-related tasks. A previous work (Tanaka et al., 2005) had extracted ERD/ERS neurological phenomena for pattern classification of turn-left and turn-right events concerning a BCI-enabled wheel chair. Similar methods were employed for moving-forward and moving-backward tasks but used SVM (Choi, 2012), Linear classifier (Leeb et al., 2007), Artificial Neural Network(ANN) (Craig and Nguyen, 2007). Methods using EEG-based techniques involved low-pass filtering(7 Hz) of the P300 wave and feature-extraction using windowing or normalization (Pires et al., 2008).

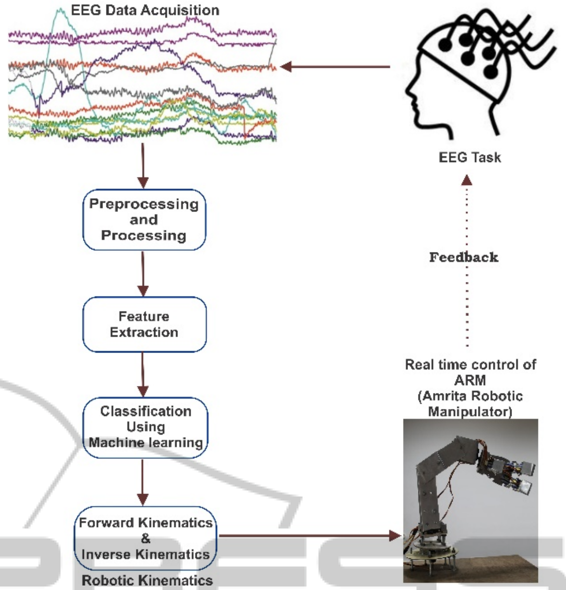

Figure 1: Schematic representation of a BCI-controlled low-cost robotic upper arm model.

Datasets were then classified using Bayesian classifier for categorizing multi-class movement data. A motor–task study using SSVEP-based methods (Middendorf et al., 2000), employed feature extraction using Welch periodogram (512 FFT points) and involved SVM-based classification of turning right/going forward and stopping (Dasgupta et al., 2010). Neural Networks with back-propagation learning have been shown to classify arithmetic calculation task features, extracted using Burg method/Levison algorithm (auto-regression models) (Anderson, 1995). Studies on word-generation and motor activity used Butterworth filter (1-40 Hz) coefficients and phase locking values(PLV) (Lachaux et al., 1999) as features and classified the dataset using SVM (Gysels et al., 2005). Laplacian algorithms have also been used for movement-related tasks (McFarland et al., 2000).

1.3 Prosthesis & Control with EEG Signal

Brain computer interface (BCI) have been employed to control prosthetic arms (Wolpert and Flanagan, 2010) in order to do specialized tasks, namely, reaching the target with an optimal feedback (Mitrovic et al., 2010), examining the different parameters of an object (Saal and Vijayakumar, 2010). Prosthetic or robotic arms consist of a series of links which were equipped by an end-effector to move in a 3D space (AbuQassem, 2010; Wolpert and Flanagan, 2010). Links were driven by motors changing the orientation of the manipulator (Megahed, 2013).

Modeling of robotic arm behavior for prosthetic devices involved kinematics of the robotic links (Kay, 2005). Different algorithms have been proposed to solve the robotic kinematics; DH method (Iqbal et al., 2012), homogenous method (Mitra, 2012) for forward kinematic model and analytical method (Iqbal et al., 2012) for inverse kinematics model. Analytical methods are subcategorized into geometric and algebraic approaches. Geometric approach has been applied to simple robotic structures with few DOF, whereas algebraic approach were used for greater DOF (Kucuk and Bingul, 2006). Triangulation and CCD (Cyclic Coordinate Descent) algorithms (Muller-Cajar and Mukundan, 2007) have been used to solve inverse kinematics with a scalable number of links. Quaternion algebraic approach (Sahu et al., 2008) has been shown to be computationally cost-effective compared to homogenous methods.

A feedback system was shown to control grip force of a gripper/ grasper (Westling and Johansson, 1984). Controllers like PID (open loop optimization), OFC (closed loop optimization) have been used to optimize the motor commands with the help of cost functions like iterative linear quadratic Gaussian (ILQG) which use trajectory planning and execution in multiple steps (Mitrovic et al., 2010) instead of using sensors. Stochastic optimal control is another application which is now widely being used for planning and controlling of robotic systems (Rawlik et al., 2012). It has been demonstrated that Kullback-Leibler divergence minimization algorithm could present a solution towards stochastic optimal control (Rawlik et al., 2012).

1.4 Non-Traditional BCI Methods

Models of spiking neural networks (SNN) take advantage of precise timing of spikes to produce rich dynamic behavior(Kasabov et al., 2013). The study of enriched cognitive systems embodied interaction with environment could be achieved by employing SNN. Futuristic design of hybrid architecture inspired by the working human brain have led to complex structures and significant models of internal dynamics has seen in representation of the model kinematics structures such as the cerebellum (Furber et al., 2014; Shepherd et al., 1998).

The key contribution to this direction of study will be a method for simulating a spiking neural network with high parallelism relying on data organization has seen in internal representation mimicking the motor circuit in the brain. An evaluation of user configurable structures resemble primary circuit of movement coordination such as the cerebellum or the V1 motor cortex may suggest discrete spike based transformation models generating responses appropriate to kinematic algorithms via data classification technique such circuits may have ranges modified by nature of input and delays configuring the plasticity of adaptive responses as seen in biological neural circuit.

CMAC (Albus, 1975) had proposed a pattern separation algorithm based on internal representation model of the cerebellar neurons that perform movement coordination tasks. While spiking neuron models of CMAC-like algorithms are being elaborated, benchmark nonlinear tests have shown to function using simple neural microcircuit models (Joshi and Maass, 2005).Such neural circuits may perform indifferently to the kind of feedback received compared to the control performance of traditional techniques. A trend of novel spiking neural circuit based methods for SLAM techniques may help bridge the gap for the BCI devices and such low-cost articulator models.

1.5 Implementation Issues for Low Cost Prosthetic Devices

For sensorimotor control, the primary aim was to accomplish a task of reaching a specified target. Targets for low economic cost prosthetic arms include an ability of generalization of tasks (say grasp task) without significant precision or high accuracy. Adapting variability models in kinematic algorithms and using learning methods, some of the issues may be overcome (Vijayan et al., 2013). Position feedback is measured in some robotic arms using sensors (Mitrovic et al., 2010). In devices without sensor-based feedback of real-time localization, effective prediction-correction schemes may be needed (Kalanovic et al., 2000).

Although a major humanitarian necessity, the major challenges faced when designing a low cost prosthetic devices include the economic cost for research and development, local availability of components, device functionality, prediction of time of failure, design simplicity (D'Apuzzo et al., 2012). Avoiding sensory feedback decreased cost but increased the localization variability in models. However, with a low-cost prosthesis implementation issues such as position control, simultaneous localization models and power management pose additional challenges post-design. We have however regarded a task-based control model in the context of this paper.

2 CASE STUDY: LOW-COST PROSTHETIC ARM CONTROL USING EEG

In our study, we used a indigenously designed robotic ARM (Amrita Robotic Manipulator), a part of remotely-triggered experiments available online (Vijayan et al., 2013) with 6 DOF as a prototype for a prosthetic upper arm. We tested the kinematic behavior of the manipulator with DH method and algebraic method (AbuQassem, 2010) for forward kinematics and triangulation algorithm (Muller-Cajar and Mukundan, 2007) for inverse kinematics.

We used F3 and F4 channels data for extracting movement patterns. Signal pre-processing was done using band-pass filtering from 6 to 30 Hz to obtain Mu and beta rhythms.

To extract features, we used power spectral density and cross-correlation analysis from preprocessed signal data (Hosni et al., 2007). Movement of the arm to left or right directions were categorized as two classes. We used classification (Vijayan et al., 2013) for translating imagery to robotic articulation (Figure 2). In our study, prosthetic arm had a localization variability of ±5 cm variability. Mapping and localization of end-effector positions were corrected using error minimization algorithms (work in progress).

Previous studies on pattern classification of signals related to motor tasks used to train prosthetic devices like wheelchairs have shown a high level of accuracy (~80%) (Tanaka et al., 2005).The scalability of similar techniques on high-end devices like the DLR JUSTIN arm or DARPA ARM may need detailed studies and outreach modifications.

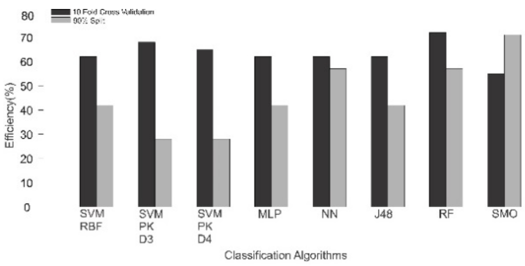

Figure 2: Accuracy of robotic arm dataset for different classification algorithms.

3 CONCLUSIONS

The paper aims to highlight the current progress in a humanitarian challenge of redesigning a low economic cost neuro-prosthetic arm that could be controlled using EEG-based signal re-classification. Usual techniques include applications of machine learning and adaptive feature extraction methods to process EEG real-time and using a learned system to control the arm using kinematic techniques. Such methods have their performance and training issues. While data reliability and over-learning can cause issues, the device variability requires prediction-correction or other iterative approaches. The issues may be solved using feedback via sensors but that would add considerable financial and computational overload to the design and implementation. To keep the low-cost target, internal representation models may be needed to help the prediction-correction process. Our case-study using a home developed (<$50 ARM) suggests the common issues seen with any low-cost project while allowing us to use the platform for testing the potential solutions. The suggestions are as follows: Firstly, while EEG based tests are reliable for some event-related tasks, a learned feature extraction approach may help reduce the noise in the dataset. Secondly, classification has to have simple mechanisms such as testing using SVM or ANNs. Thirdly, better approximations are to be favored over precision. Iterative processing of kinematics movements may substitute the sensory-motor feedback model. Spiking neural network based internal representation models may help overcome some of the internal representation issues. While traditional approaches have their own performance and implementation issues, a novel non-traditional approach seems inevitable.

As a final word, we indicate that control mechanisms using BCI may change the design of kinematics for robotic articulators. It may, therefore, need a dual-styled approach of classification and interpretation from EEG to the arm and an internal representation model to predict the kinematics of the arm based on the feature-triggered categorization of movement dynamics.

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REFERENCES

AbuQassem, M.R., 2010. Simulation and Interfacing of 5 DOF Educational Robot Arm. Islamic University of Gaza.

Albus, J.S., 1975. A New Approach to Manipulator Control: The Cerebellar Model Articulation Controller(CMAC). J. Dyn. Syst. Meas. Control.

Anderson, C., 1995. EEG signal classification with different signal representations. In: Neural Networks for Signal Processing. *IEEE, Cambridge*, MA, pp. 475–483.

Bi, L., Fan, X.-A., Liu, Y., 2013. EEG-Based Brain-Controlled Mobile Robots: A Survey. *IEEE Trans. Human-Machine Syst.* 43, 161–176.

Birbaumer, N., 2006. Breaking the silence: brain-computer interfaces (BCI) for communication and motor control. Psychophysiology 43, 517–32.

Birbaumer, N., Hinterberger, T., Kübler, A., Neumann, N., 2003. The thought-translation device (TTD): neurobehavioral mechanisms and clinical outcome. *IEEE Trans. Neural Syst. Rehabil*. Eng. 11, 120–3.

Choi, K., 2012. Control of a vehicle with EEG signals in real-time and system evaluation. Eur. J. Appl. Physiol. 112, 755–66.

Craig, D.A., Nguyen, H.T., 2007. Adaptive EEG thought pattern classifier for advanced wheelchair control. In: Annual International *Conference of the IEEE Engineering in Medicine and Biology Society*. pp. 2544–7.

D'Apuzzo, M., Liccardo, A., Bifulco, P., Polisiero, M., 2012. Metrological issues concerning low cost EMG-controlled prosthetic hand. In: 2012 *IEEE International Instrumentation and Measurement Technology Conference Proceedings. IEEE*, pp. 1481–1486.

Dasgupta, S., Fanton, M., Pham, J., Willard, M., Nezamfar, H., Shafai, B., Erdogmus, D., 2010. Brain controlled robotic platform using steady state visual evoked potentials acquired by EEG. In: 2010 Conference *Record of the Forty Fourth Asilomar Conference on Signals, Systems and Computers. IEEE*, pp. 1371–1374.

Donchin, E., Spencer, K.M., Wijesinghe, R., 2000. The mental prosthesis: assessing the speed of a P300-based brain-computer interface. *IEEE Trans. Rehabil. Eng. 8*, 174–179.

Farwell, L. a, Donchin, E., 1988. Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials. Electroencephalogr. Clin. Neurophysiol. 70, 510–23.

Friman, O., Volosyak, I., Gräser, A., 2007. Multiple channel detection of steady-state visual evoked potentials for brain-computer interfaces. *IEEE Trans. Biomed. Eng.* 54, 742–50.

Furber, S.B., Galluppi, F., Temple, S., Plana, L.A., 2014. *The SpiNNaker Project. Proc. IEEE* 102, 652–665.

Gysels, E., Renevey, P., Celka, P., 2005. SVM-based recursive feature elimination to compare phase synchronization computed from broadband and narrowband EEG signals in Brain–Computer Interfaces. Signal Processing 85, 2178–2189.

Hosni, S.M., Gadallah, M.E., Bahgat, S.F., AbdelWahab, M.S., 2007. Classification of EEG signals using different feature extraction techniques for mental-task BCI. *2007 Int. Conf. Comput. Eng. Syst*. 220–226.

Iqbal, J., Islam, R., Khan, H., 2012. Modeling and Analysis of a 6 DOF Robotic Arm Manipulator. Can. J. Electr. Electron. Eng.

Joshi, P., Maass, W., 2005. Movement generation with circuits of spiking neurons. Neural Comput. 17, 1715–1738.

Kalanovic, V.D., Popoviic, D., Skaug, N.T., 2000. Feedback Error Learning Neural Network for Trans-femoral Prosthesis. *IEEE Trans. Rehabil. Eng. 8,* 71–80.

Kasabov, N., Dhoble, K., Nuntalid, N., Indiveri, G., 2013. Dynamic evolving spiking neural networks for on-line spatio- and spectro-temporal pattern recognition. Neural Netw. 41, 188–201.

Kay, J., 2005. Introduction to Homogeneous Transformations & Robot Kinematics.

Kucuk, S., Bingul, Z., 2006. Robot Kinematics: Forward and Inverse Kinematics. In: Industrial-Robotics-Theory-Modelling-Control. pp. 117–148.

Lachaux, J.P., Rodriguez, E., Martinerie, J., Varela, F.J., 1999. Measuring phase synchrony in brain signals. Hum. Brain Mapp. 8, 194–208.

Leeb, R., Friedman, D., Müller-Putz, G.R., Scherer, R., Slater, M., Pfurtscheller, G., 2007. Self-paced (asynchronous) BCI control of a wheelchair in virtual environments: a case study with a tetraplegic. Comput. Intell. Neurosci. 79642.

Leuthardt, E.C., Schalk, G., Wolpaw, J.R., Ojemann, J.G., Moran, D.W., 2004. A brain-computer interface using electrocorticographic signals in humans. J. Neural Eng. 1, 63–71.

McFarland, D.J., Miner, L. a, Vaughan, T.M., Wolpaw, J.R., 2000. Mu and beta rhythm topographies during motor imagery and actual movements. Brain Topogr. 12, 177–86.

Md Norani, N.A., Mansor, W., Khuan, L.Y., 2010. A review of signal processing in brain computer interface system. In: *2010 IEEE EMBS Conference on Biomedical Engineering and Sciences (IECBES). IEEE*, pp. 443–449.

Megahed, S.M., 2013. Mechanical Design & Production Department.

Middendorf, M., McMillan, G., Calhoun, G., Jones, K.S., 2000. Brain-computer interfaces based on the steady-state visual-evoked response. *IEEE Trans. Rehabil. Eng. 8*, 211–4.

Millán, J., Franzé, M., Mouriño, J., Cincotti, F., Babiloni, F., 2002. *Relevant EEG features for the classification of spontaneous motor-related tasks. Biol. Cybern.* 86, 89–95.

Mitra, A.K., 2012. Joint Motion-based Homogeneous Matrix Method for Forward Kinematic Analysis of Serial Mechanisms. Int. J. Emerg. Technol. Adv. Eng. 2, 111–122.

Mitrovic, D., Nagashima, S., Klanke, S., Matsubara, T., Vijayakumar, S., 2010. Optimal Feedback Control for Anthropomorphic Manipulators. In: Int. Conf. Robot. Autom. 2010). Alaska, USA.

Muller, K.-R., Blankertz, B., 2006. Toward noninvasive brain-computer interfaces. *IEEE Signal Process.* Mag. 23, 128–126.

Muller-Cajar, R., Mukundan, R., 2007. Triangulation : A new algorithm for Inverse Kinematics. In: *Proceedings of Image and Vision Computing New Zealand*. pp. 181–186.

Nicolas-Alonso, L.F., Gomez-Gil, J., 2012. Brain computer interfaces, a review. Sensors (Basel). 12, 1211–79.

Owen, A.M., Coleman, M.R., 2008. Using neuroimaging to detect awareness in disorders of consciousness. Funct. Neurol. 23, 189–94.

Pfurtscheller, G., Allison, B.Z., Brunner, C., Bauernfeind, G., Solis-Escalante, T., Scherer, R., Zander, T.O., Mueller-Putz, G., Neuper, C., Birbaumer, N., 2010. The hybrid BCI. Front. Neurosci. 4, 30.

Pfurtscheller, G., Brunner, C., Schlögl, A., Lopes da Silva, F.H., 2006. Mu rhythm (de)synchronization and EEG single-trial classification of different motor imagery tasks. Neuroimage 31, 153–9.

Pfurtscheller, G., Neuper, C., Müller, G.R., Obermaier, B., Krausz, G., Schlögl, A., Scherer, R., Graimann, B., Keinrath, C., Skliris, D., Wörtz, M., Supp, G., Schrank, C., 2003. Graz-BCI: state of the art and clinical applications. *IEEE Trans. Neural Syst. Rehabil.* Eng. 11, 177–80.

Pires, G., Castelo-Branco, M., Nunes, U., 2008. Visual P300-based BCI to steer a wheelchair: a Bayesian approach. In: Conference Proceedings : ... *Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society.* Conference. pp. 658–61.

Rawlik, K., Toussaint, M., S, V., 2012. On Stochastic Optimal Control and Reinforcement Learning by Approximate Inference. In: *Robotics: Science and Systems Conference*.

Repovs, G., 2010. Dealing with Noise in EEG Recording and data analysis. Inform. Medica Slov. 15, 18–25.

Saal, H.P., Vijayakumar, S., 2010. Active estimation of object dynamics parameters with tactile sensors. In: *2010 IEEE/RSJ Int. Conf. Intell. Robot. Syst. IEEE*, pp. 916–921.

Sahu, S., Biswal, B.B., Subudhi, B., 2008. Computational Intelligence , Control and Automation A Novel Method for Representing Robot Kinematics using Quaternion Theory A Novel Method for Representing Robot Kinematics using Quaternion Theory. *IEEE Spons. Conf. Comput. Intell. Control Comput. Vis. Robot. Autom.*

Schlögl, A., Slater, M., Pfurtscheller, G., 2002. Presence research and EEG Properties of EEG recordings.

Shepherd, G.M., Mirsky, J.S., Healy, M.D., Singer, M.S., Skoufos, E., Hines, M.S., Nadkarni, P.M., Miller, P.L., 1998. The Human Brain Project: neuroinformatics tools for integrating, searching and modeling multidisciplinary neuroscience data. Trends Neurosci. 21, 460–468.

Srinivasan, R., 1999. Methods to Improve the Spatial Resolution of EEG. Int. J. Bioelectromagn. 1, 102–111.

Tanaka, K., Matsunaga, K., Wang, H.O., 2005. Electroencephalogram-Based Control of an Electric Wheelchair. *IEEE Trans. Robot.* 21, 762–766.

Vespa, P.M., Nenov, V., Nuwer, M.R., 1999. Continuous EEG monitoring in the intensive care unit: early findings and clinical efficacy. J. Clin. Neurophysiol. 16, 1–13.

Vijayan, A., Nutakki, C., Medini, C., Singanamala, H., Nair, B., 2013. Classifying Movement Articulation for Robotic Arms via Machine Learning. J. Intell. Comput.

Westling, G., Johansson, R.S., 1984. Factors influencing the force control during precision grip. Exp. brain Res. 53, 277–84.

Wolpaw, J.R., Birbaumer, N., McFarland, D.J., Pfurtscheller, G., Vaughan, T.M., 2002. Brain-computer interfaces for communication and control. Clin. Neurophysiol. 113, 767–91.

Wolpert, D.M., Flanagan, J.R., 2010. Q&A: Robotics as a tool to understand the brain. BMC Biol. 8, 92.

Yuanqing Li, Chuanchu Wang, Haihong Zhang, Cuntai Guan, 2008. An EEG-based BCI system for 2D cursor control. In: *2008 IEEE International Joint Conference on Neural Networks (IEEE World Congress on Computational Intelligence). IEEE*, pp. 2214–2219.