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4-CLASS MOTOR IMAGERY CLASSIFICATION FOR POST STROKE REHABILITATION USING BRAIN-COMPUTER INTERFACE

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ABSTRACT

Brain-Computer Interface (BCI) is a mechanism that helps in the control/communication of one's environment through the brain signals obtained directly from the brain via an EEG signal acquisition unit. A BCI incorporating Motor Imagery for post-stroke rehabilitation of upper limbs and knee in fully disabled patients is designed. It helps in restoring some of the activities of the daily living. It aids post-stroke sufferers to carry out functionalities like movement of right and left hands, right and left knee, grabbing things, etc. Till now, the post-stroke rehabilitation is possible in partially impaired patients. The therapy was given to the damaged cortical area in the brain directly by the therapist moving the hand of the patient. This is not suitable as it requires the presence of therapist, can be done only in a hospital leading to high cost, muscle fatigue, slow recovery of the damaged area. In this paper, a survey of various BCIs is done and an optimum design is devised. Also the overall accuracy of the system is calculated to be approximately 91%.

KEYWORDS: Brain Computer Interface, Motor Imagery, Support Vector Machines.

INTRODUCTION

In today's world, it is possible for the paralyzed people to interact with the environment as a normal person. They are able to carry out some of their activities of daily living on their own. The advance of technology has brought this into a reality: Humans can use the electrical signals from brain activity to interact with, influence, or change their environments. This technology commonly known as the Brain-Computer Interface is an emerging field where new experiments are going on to improve the efficiency and to incorporate new applications.At present, BCI allow individuals, who are unable to speak and/or use their limbs, to once again communicate or operate assistive devices like mouse, wheel chair, robotic arms, sensor attached shoes etc for walking and manipulating objects.

Brain-computer interface research is an area of high public awareness. It improves the lives of many disabled persons affected by a number of different disease processes. They may eventually be used routinely to replace or restore useful function for people severely disabled by neuromuscular disorders; they might also improve rehabilitation for people with strokes, head trauma, and other disorders.

The available methodologies for the design of BCI are many and it is the designer's decision and knowledge in this area that leads to the most comprehended design which takes care of all the existing short-comings and improve the working and the use of the BCI.

EXISTING METHODS

The Brain-Computer Interface (BCI) includes acquisition of brain signals, band-passing the acquired signals to obtain the significant frequency band, extracting the feature vectors corresponding to the concerned activity and using these to classify the incoming brain signals. Further, this can be given as a command signal to an assistive device like a wheel chair, computer keyboard, mouse, robotic hands or sensor attached shoes to carry out the action. In the present scenario, either the therapist gives the simulated signal corresponding to an action or the brain waves of the patients when they move their eyelids in a trained way is used to carry out the action. Yet in some BCIs, the partially impaired patient is asked to do the action with healthy hand and the corresponding signal is processed to carry out the action for the other hand. Usually Electroencephalography (EEG) is used to acquire signals from brain due to its reliability when compared to other signal acquisition methods. This is band-passed using any of the available filters like Butterworth band-pass filter, Chebyshev filter or using window functions like Hamming window, Hanning window etc to get the concerned frequency band where the brain activity is maximum during an activity. The features are obtained by taking either power spectral density or log-variance or any method that distinguish the variation in the brain rhythm during the concerned activity. The various feature extraction methods available include Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Fisher's Discriminant Analysis (FDA) etc. Classification algorithms used in BCI designs include linear classifiers like Support Vector Machine (SVM), neural network classifiers, non-linear Bayesian classifiers etc. Thus there are many methods available at each step of BCI design and choosing the best methodology to get better classification accuracy is a difficult task. Till now; the post-stroke rehabilitation is possible only in partially impaired patients. Most of the existing designs focus on the rehabilitation of upper limbs and classify feature vectors between any two movements. The therapy is given to the damaged cortical area in the brain by moving the hand of the patient. This is not suitable as it requires the presence of therapist and can be done only in a hospital leading to high cost, muscle fatigue, slow recovery of the damaged area etc. This also leads to patients discontinuing the rehabilitation programme and only partial recovery is attained in post-stroke patients. At present, the striking achievements of BCI research and development remain confined almost entirely to the laboratory, and the bulk of work to date comprises data gathered from able-bodied humans or animals. Studies in the ultimate target population of people with severe disabilities have been largely confined to a few limited trials closely overseen by research personnel. The translation of the exciting laboratory progress to clinical use, to BCI systems that actually improve the daily lives of people with disabilities, has barely begun. This essential task is perhaps even more demanding than the laboratory research that produces a BCI system. It must show that a specific BCI system can be implemented in a form suitable for long-term independent home use, define the appropriate user population and establish that they can use the BCI, demonstrate that their home environments can support their use of the BCI and that they do use it, and establish that the BCI improves their lives. This work requires dedicated, well-supported, multidisciplinary research teams that have expertise in the full range of relevant disciplines, including engineering, computer science, basic and clinical neuroscience. Brain-Computer Interfaces may eventually be used routinely to replace or restore useful function for people severely disabled by neuromuscular.

METHODOLOGY

The methodology followed in this paper combines the advantages of frequency sub-bands and channel selection using common spatial pattern algorithm. In the proposed method, the movement is evoked by the zero-mobility patient directly by imagining the movement. Motor imagery corresponds to a set of EEG signals generated in the sensory motor cortex area of the brain when the person is imagining a movement. This set of EEG signals usually lies in the mu-beta range (8-30 Hz). These EEG signals corresponding to the upper limbs and knee movements are used in this work. The datasets are first divided into trial and test datasets. The trial datasets are used to design the BCI by assuming that the classes are known beforehand. The trial datasets are first passed through a band pass filter bank to separate it to a sub-band of 4 Hz each in the frequency range 4-40 Hz. Here a filter bank of Gabor band pass filter is used which has a centre frequency of 4 Hz and the range is from 4-40 Hz. Thus 9 sub-bands are obtained at the end of this stage. Each sub-band is then passed through Common Spatial Pattern algorithm (CSP) to select the optimal subset of channels where relevant information is found. This is done by sorting out the CSP coefficients. Out of 118 channels used in this case, 2 channels were selected based on the condition that the coefficients should have maximum variance ratio among the classes.

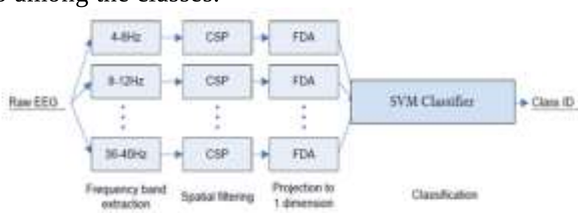

Fig.3.1. Block diagram of the system

This subset is used in the design purpose and the rest of the channels are discarded. Each channel is then used to obtain the feature vector for each sub-band. Thus at the end of CSP, two features are obtained for each sub-band. The features used in this case are log-variance of the normalized channels. The features are then dimensionally reduced using Fischer's Discriminant Analysis (FDA), to reduce further computational complexities. FDA searches for direction in the data that have largest variance and subsequently project the data onto it. This reduced feature vectors are then used to train the SVM classifier.

Finally, the dimensionally reduced features were passed through the Support Vector Machine (SVM) to classify the data into right hand, left hand, right knee or left knee imagined movement. This can be further used to drive the assistive devices like wheelchairs, mouse etc. Thus, communication of paralyzed people with the external world is made possible. This type of classification is known as supervised classification. After training, a SVM model is created. SVM model uses a hyperplane to classify the feature vectors. The feature vectors above the hyperplane are classified as one class and the feature vectors below the hyperplane is classified as the other class. This model is used to classify the test datasets, i.e; the test dataset is first passed through the filter bank, optimal subset of channels are selected by passing through the CSP, feature vectors computed, dimensionally reduced and finally classified. Using this design, the recovery of damaged area of brain is faster as the patient himself is carrying out the therapy. This method is further extended to knee movement. Thus a four class implementation of the motor imagery classification is made – the designed BCI is capable of distinguishing the left hand, right hand, left knee and right knee imagined movements.

RESULTS

The design is verified for 100 datasets each of left hand, right hand, left knee and right knee imagined movements. Further the accuracy of the whole system is measured in terms of the movement achieved versus the desired movement. The accuracy of the design obtained while distinguishing left hand imagined movement from the rest was 90%, right hand imagined movement from the rest was 93.33%, left knee imagined movement from the rest was 92% and right knee imagined movement from the rest was 88.89%. The overall accuracy of the designed BCI was 91.11%.

Motor Imagery	Total	Left hand	Right hand	Left knee	Right knee
Trial data	40	10/10	10/10	10/10	10/10
Test data	360	81/90	84/90	83/90	80/90

Fig.4.1. Final result obtained when various trials were experimented

Using this design, zero-mobility patients can be rehabilitated at home. This reduces muscle fatigue as the patient is doing the task and necessary breaks, as and when required, can be taken. Also there is no need of a therapist or heavy hospital equipments to give simulated signals. The cost of rehabilitation is reduced and more movements are included in the rehabilitation programme. Since the rehabilitation programme can be continued at home with simple equipments, there is more chance for the patient to complete the programme and complete recovery of the patient can be ensured. Further, this work can be extended to include visually evoked potentials along with MI signals. Here the patient is trained to blink once or twice when imagining a particular movement and the signals corresponding to both the activities can be used to classify the activities to one of the concerned actions. By doing so, it is assumed that the classification will be a lot easier and the chances of error is minimized but at the cost of more intermediate processing steps.

In this paper, the datasets obtained from BCI competition IV were used. There were 400 datasets comprising right hand, left hand, right knee and left knee motor imageries. The datasets were divided into trail and test sets.

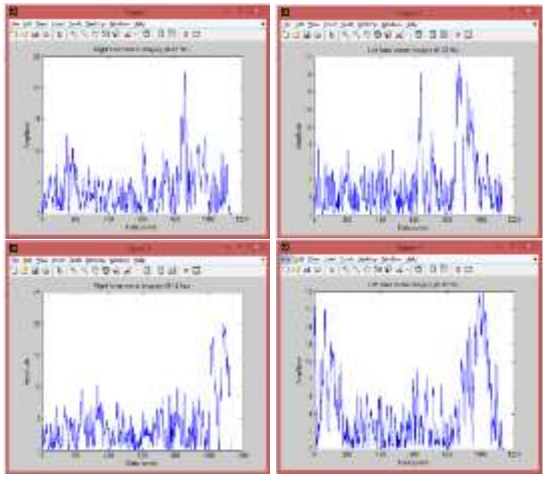

Fig.4.2. Sub-band frequency of 8-12 Hz corresponding to right, left hands, right and left knees

The trial sets were used to define the design of the BCI while test sets were used to verify the design and to check the accuracy of the whole setup.

COMPARISONS

The previous works focused on the neuro - motor rehabilitation of patients taking input for the BCI from a therapist. The main disadvantages included Muscle Fatigue, High Cost, Safety Issues, patients need to have some type of movement and no Home-Based Rehabilitation was possible. The idea of the novel approach is to use Enhanced Feedback using steady state visually evoked potentials and motor imagery to help patient who are completely bed-driven to communicate with the environment via devices like robotic arms. It also helps in the restoration of some of the damaged cortical areas in the brain of the patient. Further rehabilitation is provided for both the upper limbs and knee as opposed to the previous work where only the upper limb rehabilitation was considered. The training can be continued at home without the need of therapist / hospital equipment. Active participation of the patients is guaranteed as there is no muscle fatigue and whole set up is user-friendly and safe to handle.

REFERENCES

[1] Tianyou Yu et al., "Enhanced Motor Imagery Training Using A Hybrid BCI With Feedback", IEEE Trans. Biomedical Eng., vol. PP, no. 5, pp.1-13, 2015
[2] Wanjoo Park, Gyu Hyun Kwon, Da-Hye Kim, Yun-Hee Kim, Sung-Phil Kim, and Laehyun Kim, "Assessment of Cognitive Engagement in Stroke Patients From Single-Trial EEG During Motor Rehabilitation", IEEE Trans. Neural Systems and Rehabilitation Eng., vol. 23, no. 3, pp.351-362, 2015
[3] Denis Renato de Moraes Piazentin and Joao Luis Garcia Rosa, "Motor imagery classification for Brain-Computer Interfaces through a chaotic neural network", IEEE International Joint Conference on. IEEE., pp.4103-08, 2014
[4] V. Squeri, L. Masia, P. Giannoni, G. Sandini, and P. Morasso, "Wrist rehabilitation in chronic stroke patients by means of adaptive, progressive robot-aided therapy", IEEE Trans. Neural Syst. Rehabil. Eng., vol. 22, no. 2, pp.312-325, 2014
[5] Oana-diana Eva, Roxana Aldea and Anca Lazăr , "Detection And Classification Of Mu Rhythm For Motor Movement/Imagery Dataset" , Institute for Knowledge Discovery, Graz University of Technology, Graz, Austria; Neuroelectrical Imaging and BCI Lab (F.P., D.M.), Fondazione Santa Lucia IRCCS, Rome, Italy; University of Graz, Graz, Austria, Fasc. 2, 2014
[6] Roxana Aldea and Monica Fira , "Classifications of Motor Imagery Tasks in Brain Computer Interface Using Linear Discriminant Analysis", (IJARAI) International Journal of Advanced Research in Artificial Intelligence, Vol. 3, No.7, 2014
[7] Jonas Richiardi, Sophie Achard, Horst Bunke, and Dimitri Van De Ville, "Machine Learning with Brain Graphs", IEEE Signal Processing Magazine, 1053-5888/13, pp. 58-70, May 2013

[8] Mohammad H. Alomari, Aya Samaha, and Khaled AlKamha, "Automated Classification of L/R Hand Movement EEG Signals using Advanced Feature Extraction and Machine Learning", International Journal of Advanced Computer Science and Applications, vol. 4, no. 6, pp. 207-13 2013
[9] Martin Steinisch, Maria Gabriella Tana and Silvia Comani, "A Post-Stroke Rehabilitation System Integrating Robotics, VR and High Resolution EEG Imaging", IEEE Trans. Neural Syst. Rehabil. Eng., vol. 21, no. 5, pp.849-859, 2013
[10] S.Bermúdezi Badia, A. García Morgade, H.Samaha, and P. F. M. J. Verschure, "Using a Hybrid BCI and Virtual Reality System to Monitor and Promote Cortical Reorganization through Motor Activity and Motor Imagery Training" , IEEE Trans. Neural Systems And rehabilitation Eng., vol. 21, no. 2, pp. 174-181, 2013
[11] Yunyong Punsawad , "Hybrid SSVEP-Motion Visual Stimulus based BCI system for intelligent wheelchairs", IEEE EMBS, pp.7416-19, July, 2013
[12] Hiroshi Higashi, "Study of Feature Extraction for Motor-Imagery EEG Signals", Tokyo University Of Agriculture And Technology, December 2013
[13] Martina Tolić and Franjo Jović, "Classification Of Wavelet Transformed EEG Signals With Neural Network For Imagined Mental And Motor Tasks" , Classification of wavelet transformed EEG... Kinesiology 45(2013) 1:130-138
[14] Nandish.M, Stafford Michahial, Hemanth Kumar P, Faizan Ahmed, "Feature Extraction and Classification of EEG Signal Using Neural Network Based Techniques", International Journal of Engineering and Innovative Technology (IJEIT), SSN: 2277-3754, vol.2, Issue 4, pp. 1-5, 2012
[15] Vera Kaiser, Ian Daly, Floriana Pichiorri, Donatella Mattia, Gernot R. Muller-Putz, Christa Neuper , "Relationship Between Electrical Brain Responses to Motor Imagery and Motor Impairment in Stroke", Institute for Knowledge Discovery, Graz University of Technology, Graz, Austria; Neuroelectrical Imaging and BCI Lab (F.P., D.M.), Fondazione Santa Lucia IRCCS, Rome, Italy; University of Graz, Graz, Austria, 2012
[16] Siuly, " Analysis and Classification of EEG Signals ", University of Southern Queensland, Australia , July 2012
[17] F. Cincotti, F. Pichiorri, P. Arico, F. Aloise, F. Leotta, F. de Vico Fallani, "EEG-based Brain-Computer Interface to support Post-stroke motor rehabilitation of the upper limb", IEEE EMBS, pp.4112-15, Sept 2012
[18] Cristina Rodríguez-de-Pablo, Joel C. Perry, Francesca I. Cavallaro, Haritz Zabaleta and Thierry Keller , "Development of Computer Games for Assessment and Training in Post-stroke Arm Telerehabilitation ", IEEE EMBS Conference on Neural Eng., pp.4571-74, 2012
[19] Kai Keng Ang, Zheng Yang Chin, Haihong Zhang, and Cuntai Guan, "Filter Bank Common Spatial Pattern (FBCSP) algorithm using online adaptive and semi-supervised learning", Proceedings of International Joint Conference on Neural Networks, pp. 392-96, 2011
[20] Mahnaz Arvaneh, Cuntai Guan, Kai Keng Ang and Chai Quek, "Optimizing the Channel Selection and Classification Accuracy in EEG-Based BCI", IEEE Transactions On Biomedical Engineering, vol. 58, No. 6, pg 1865-1873, 2011
[21] A.K. Mohamed, T. Marwala, and L.R. John, "Single-trial EEG Discrimination between Wrist and Finger Movement Imagery and Execution in a Sensorimotor BCI", Journal of Neural Engineering, Institute of Physics: Hybrid Open Access, August 13, 2010.
[22] Girijesh Prasad, Pawel Herman, Damien Coyle, "Using Motor Imagery Based Brain-Computer Interface for Post-stroke Rehabilitation", IEEE EMBS Conference on Neural Eng., pp.258-262, 2009
[23] Shuxiang Guo and Zhibin Song, "A Novel Motor Function Training Assisted System for Upper Limbs Rehabilitation", IEEE Conference on Intelligent Robots and Systems, pp.1025-1030, 2009
[24] Zhendong Mu Dan Xiao Jianfeng Hu, "Classification of Motor Imagery EEG Signals Based on Time–Frequency Analysis ", International Journal of Digital Content Technology and its Applications Volume 3, Number 4, December 2009
[25] Bao-Guo Xu & Ai-Guo Song, "Pattern recognition of motor imagery EEG using wavelet transform", J. Biomedical Science and Engineering, vol.1, pages 64-67, 2008
[26] Fabien Lotte, Marco Congedo, Anatole Lecuyer, Fabrice Lamarche, "A review of classification algorithms for EEG-based brain - computer interfaces", Journal of Neural Engineering, Institute of Physics: Hybrid Open Access, vol.4, pp.1-24, 2007

[27] Reinhold Scherer, Andrea Mohapp, Peter Grieshofer, Gert Pfurtscheller and Christa Neuper , “Sensorimotor EEG patterns during motor imagery in hemiparetic stroke patients ” , International Journal of Bioelectromagnetism, Vol. 9, No. 3, pp. 155 - 162, 2007

[28] Saeid Sanei and J.A.Chambers, “EEG Signal Processing”, Centre of Digital Signal Processing, Cardiff University, UK, John Wiley & Sons, Ltd, 2007

[29] Naoki Tomida, Toshihisa Tanaka and Shunsuke Ono, “Active Data Selection for Motor Imagery EEG Classification”, IEEE Transactions on Biomedical Engineering Journal Of Latex Class Files, vol. 6, NO. 1, pp. 1 10, 2007

[30] Yijun Wang, Bo Hong, Xiaorong Gao, and Shangkai Gao, “Implementation of a Brain-Computer Interface Based on Three States of Motor Imagery”, Proceedings of the 29th Annual International Conference of the IEEE EMBS, pp.23-26, 2007

[31] Moritz Grosse-Wentrup and Martin Buss, “Multi-class Common Spatial Patterns andInformation Theoretic Feature Extraction”, Clinical Neurophysiology, vol.8, No.5, pp.1-10, 2006

[32] Wolpaw et al., “Brain-Computer Interfaces for Communication and Control”, Clinical Neurophysiology, vol. 113 , pp.77-791, 2002