A novel three dimensional probability-based classifier for improving motor imagery-based BCI

Adrian L. Ashley[1], Mahnaz Arvaneh[2], and Lyudmila S. Mihaylova[3]

Abstract— *Objective:* **Motor imagery BCI based assistive robotics solution has the potential to empower the upper mobility independence of a disabled person. The objective of this work was to compare the classification performance of well-established classifiers with a novel prototype classifier.** *Approach:* **We developed an adaptive decision surface ADS classifier with the future objective to augment an assistive robotic prosthetic hand to open and close to grasp an object in cooperation with LIDAR sensors. The ADS was trained with a training data set from the BCI competition IV dataset 2a from Graz University of Technology.***Main results:* **The classification accuracy in the offline tests reached 76.06 % class 1 and 81.50 % class 2 using a non-adaptive ADS and 79.55 % class 1 and 99.69 % class 2 using an adaptive ADS classifiers. We show a prototype adaptive decision classifier used with motor imagery datasets.**

I. INTRODUCTION

The possibility of detecting the changes in brain activity following muscle movements such as moving an arm or leg is well known in research as shown in [1]. Changes in the cortex area of the brain occur when a person moves their limbs can be detected with EEG [2]. Sensorimotor rhythms associated with oscillations in brain activity involving both sensory and motor functions comprises:

μ **(7.5 - 12.5)** Located over the motor cortex of the brain are synchronized patterns of electrical activity associated with a person's voluntary movement such as opening and closing your right hand.

β **Range in frequency from (12 - 30 Hz)** discovered by Hans Berger he also invented EEG in 1924. During early experiments, it was noticed that when a person's eyes were closed the alpha waves with neural oscillation in 7.5 - 12.5 Hz reduced with movement or imagined movement and open eyes. Moreover, the alpha wave is replaced by the beta wave with reduced amplitude and higher frequency was observed when the person opened their eyes. Beta waves are associated with muscle movement furthermore beta waves increase when a person is voluntarily suppressing or resisting movement β **Low Beta Waves (12.5 - 16 Hz)** associated with various levels of conciseness. β **Beta Waves (16.5 - 20 Hz)** associated with various levels of conciseness. β **High Beta Waves (20.5 - 28 Hz)** associated with various levels of conciseness.

These Sensorimotor rhythms can be detected in the EEG during physical movement or imagined movement [3]. Before a person moves there is a decrease in μ (7.5 - 12.5) and β (12 - 30 Hz) rhythms in the cortical area. The decrease is labeled as event-related desynchronization (ERD). After the movement followed by relaxation the rhythm increases and is known as event-related synchronization (ERS) [3]. In addition, ERD and ERS can occur by imagining the physical movement [1], [4]. Hence an application in BCI can enable the detection of a person intentions and therefore restore physical movement via the BCI and assistive robotic device. Furthermore, a BCI is able to detect an error-related potential (ErrP) when those intentions are not interpreted. Ang et al [5] showed a method for using a filter bank common spatial patterns (FBCSP) algorithm using 4 progressive stages that incorporated signal processing and machine learning using EEG data from the BCI competition 2008 Datasets 2a and 2b. The filter bank [5] comprising Chebyshev Type II bandpass filters, spatial filtering used a CSP algorithm, CSP feature selection. A CSP projection matrix for each filter band, the discriminative CSP features and the classifier model labeling the training data according to the motor imagery. The acquired parameters during the training phase are used in the evaluation phase [5]. There are other motor imagery data sets available, however, the Graz dataset A is well known in the BCI research community.

The remainder of this paper is organized as follows. Section II describes the proposed method. Section III presents the results followed by a discussion in Section IV.

II. METHODOLOGY

A disabled person unable to move their limbs such as their arms, hands, feet like they used to do in the past must be a debilitating condition. Previously the person may have been fully able-bodied such that the person will have learned during the early stages of their life how to move their limbs. Having the prior skills of physical movement the disabled person has the knowledge in their brains. Supporting a person's disability can be achieved in the following steps. Firstly, with this prior knowledge, a disabled person can imagine

[1]Adrian.L.Ashley is an MPhil student at Automatic control and system Engineering Department, University of Sheffield , Sheffield, United Kingdom alashley1@sheffield.ac.uk

[2]Mahnaz Arvaneh Lecturer at Automatic control and system Engineering Department, University of Sheffield , Sheffield, United Kingdom m.arvaneh@sheffield.ac.uk

[3]Lyudmila S Mihaylova Professor at Automatic control and system Engineering Department, University of Sheffield , Sheffield, United Kingdom b.d.researcher@ieee.org

opening or closing their left or right hand. Secondly, a brain-computer interface using motor imagery will be able to determine the imagined movement. Finally, an assistive device may support the disabled person's objectives.

A. MI-BCI Improving performance with Spatial filters

The purpose of spatial filters is to reduce unnecessary spatial EEG electrical activity and highlight a particular location of interest. In addition, the spatial filter will maximize the signal to noise ratio such that accuracy of EEG-based communication will be improved shown in [6]. The classification process will benefit from the improved EEG signal with a more accurate classification.

B. Motor Imagery Adaptive decision surface(MI-ADS) mathematical definition

Training set of vertices

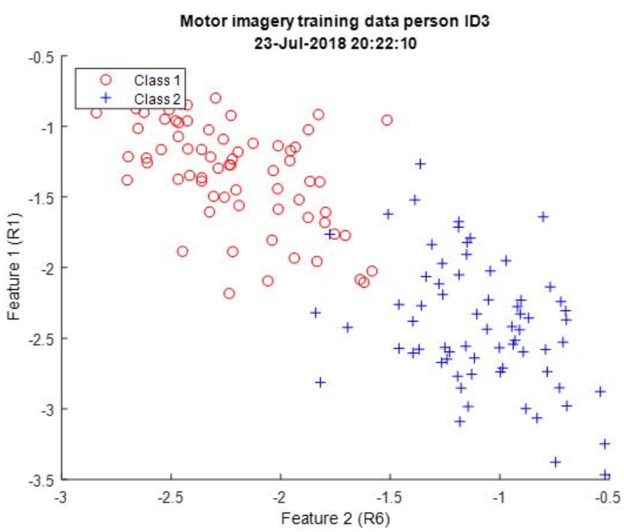

Fig. 1: Training data Class 1 and Class 2

$$V_{Train} = \{C_1, C_2\} \tag{1}$$

where,
C_1 = Class 1, Right hand motor imagery
C_2 = Class 2, Left hand motor imagery

$$C_1 = \{\vec{v}_1, \vec{v}_2, .., \vec{v}_n\} \tag{2}$$

$$C_2 = \{\vec{v}_1, \vec{v}_2, .., \vec{v}_n\} \tag{3}$$

Classification 1, Right hand motor imagery

$$\vec{\mu_{C_1}} \in C_1 \tag{4}$$

$$\vec{\mu_{C_1}} = \begin{pmatrix} f_1 \\ f_2 \end{pmatrix} \tag{5}$$

where,
$f_1 = \mu_{feature1}$
$f_2 = \mu_{feature2}$

$$\vec{\mu_{C_1}} = \frac{1}{n} \sum_{i=n}^{n} \vec{v}_i \tag{6}$$

Classification 2, Left hand motor imagery

$$\vec{\mu_{C_2}} \in C_2 \tag{7}$$

$$\vec{\mu_{C_2}} = \begin{pmatrix} f_1 \\ f_2 \end{pmatrix} \tag{8}$$

where,
$f_1 = \mu_{feature1}$
$f_2 = \mu_{feature2}$

$$\vec{\mu_{C_2}} = \frac{1}{n} \sum_{i=n}^{n} \vec{v}_i \tag{9}$$

The adaptive decision surface ADS represented by a 3 dimensional space

$$S \subseteq \mathbb{R}^3 \tag{10}$$

where,

$$S = [x_{min}, x_{max}] \times [y_{min}, y_{max}] \times [z_{min}, z_{max}] \tag{11}$$

$$V \in S \tag{12}$$

A Bivariate Gaussian distribution data structure is projected on to S around $\vec{\mu_{C_1}} \in C_1$ and $\vec{\mu_{C_2}} \in C_2$

C. Building 'Likelihood' bias into the ADS model for motor imagery

When the ADS is used for motor imagery the likelihood is shown in Fig 2 The bias will be adaptable in a future decision processing system.

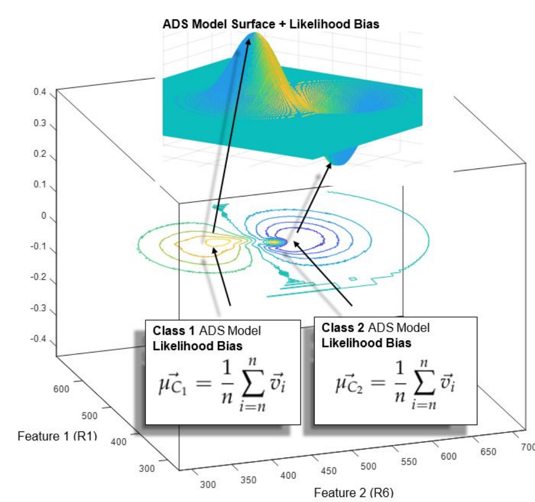

Fig. 2: Adaptive Decision Surface ADS, incorporating a 'Likelihood' bias for motor imagery

D. A constructed motor imagery adaptive decision surface model

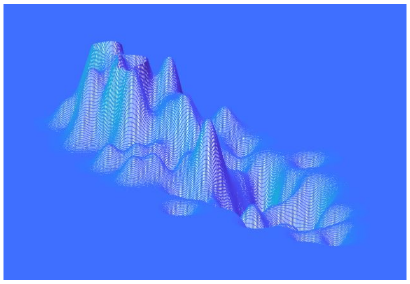

Fig. 3: Trained motor-imagery adaptive decision surface

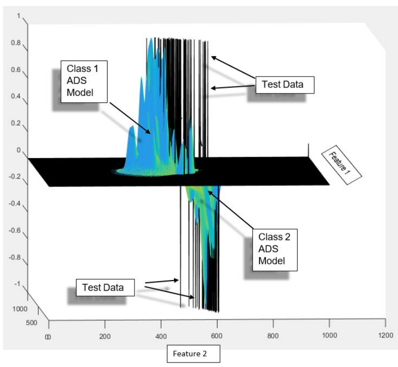

Fig. 4: Trained motor-imagery adaptive decision surface with test data

E. Adapting the surface of the ADS

The ADS classifier has the option to adapt the surface during classification. After the acquisition of the input vector feature, the ADS will classify the unknown vector. The adaptation will occur if the surface reading is above a certain threshold for the particular class.

Algorithm 1 *Adaptive Decision Surface (ADS) Adapter algorithm*

1: *A set of coefficients were estimated heuristically*
 C1ass 1 threshold = $th1$
 C1ass 2 threshold = $th2$
2: *Acquire the unknown feature coordinate*
if $AdaptiveDecisionsSurface > 0$ **then**
  Classify as class 1
  if $AdaptiveDecisionsSurface > thresholdth1$ **then**
   input feature coordinate
   Plot a Gaussian scaled by c1GS on the ADS ,Fig 3
if $AdaptiveDecisionsSurface < 0$ **then**
  Classify as class 2
  if $AdaptiveDecisionsSurface < thresholdth2$ **then**
   input feature coordinate
   Plot an inverted Gaussian scaled by c2GS on the ADS ,Fig 3

III. RESULTS

A. Results from the motor imagery adaptive decision surface MI ADS

The classification accuracy in the offline tests reached 76.06 % class 1 and 81.50 % using a non adaptive ADS and 79.55 % class 1 and 99.69 % using an adaptive ADS classifiers.

	Classifier	Class 1	Class 2
1	SVM Coarse Gaussian	83.49	77.16
2	Subspace discriminant	82.41	77.62
3	SVM Medium Gaussian	81.94	77.78
4	SVM Cubic	81.17	77.78
5	SVM Linear	80.86	79.17
6	SVM Quadratic	80.56	79.32
7	SVM Fine Gaussian	80.55	74.69
8	KNN Weighted	79.78	76.23
9	Linear Discriminant (LDA)	79.63	79.01
10	Quadratic Discriminant(QDA)	79.63	79.47
11	**ADS Adaptive v3**	**79.55**	**99.69**
12	Logistic Regression	79.17	79.94
13	KNN Cubic	78.24	83.95
14	KNN Coarse	78.08	78.55
15	KNN Medium	77.93	84.26
16	KNN Fine	77.62	72.84
17	KNN Cosine	76.85	81.95
18	Ensemble Bagged Tree	76.70	77.78
19	Decision Tree Coarse	76.24	77.78
20	**ADS None adaptive**	**76.07**	**81.50**
21	Decision Tree Simple	75.92	80.71
22	Decision Tree Medium	75.77	78.55
23	Subspace KNN	67.44	76.08
24	Ensemble Boosted Tree	59.41	64.97
25	RUSBoosted Trees	58.49	67.44

Fig. 5: BCI competition IV dataset 2a from Graz University of Technology

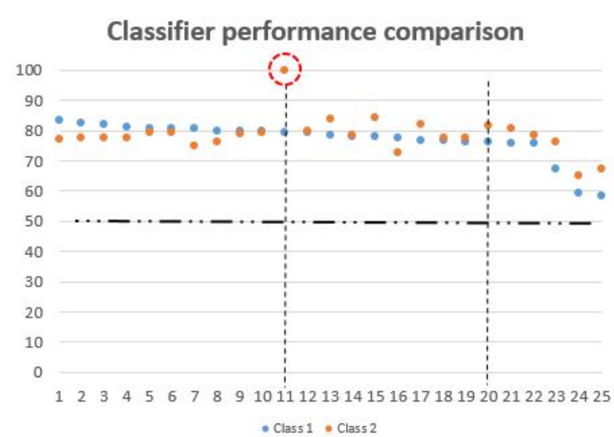

Fig. 6: BCI competition IV dataset 2a from Graz University of Technology

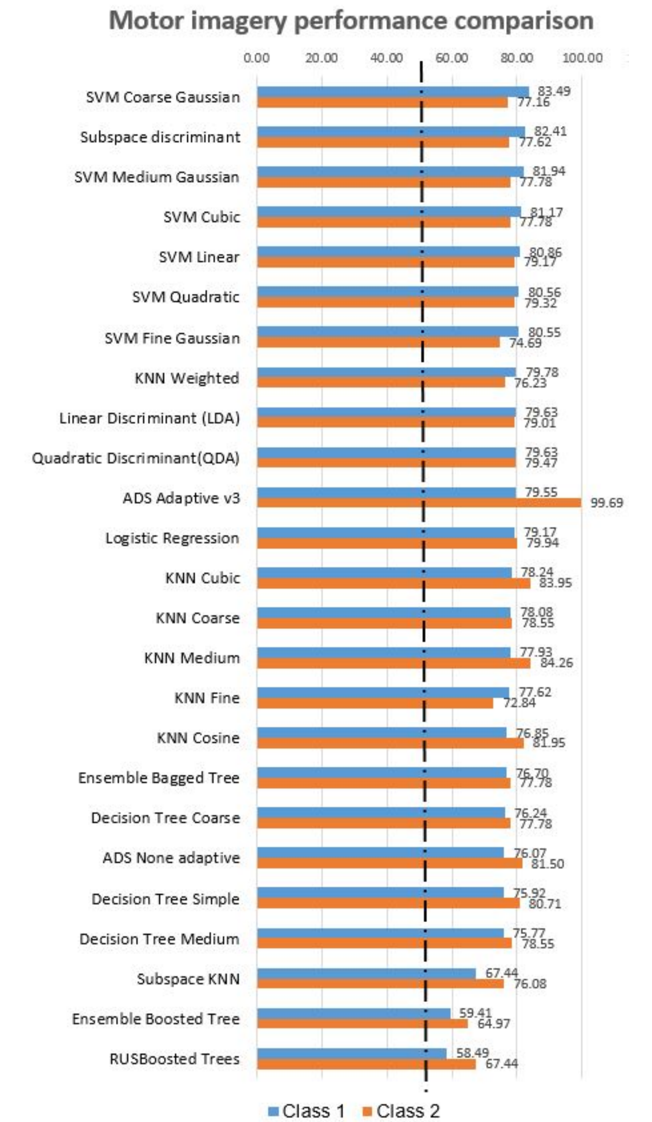

Fig. 7: 25 Classifier MI performance comparison BCI competition IV dataset 2a from Graz University of Technology

IV. DISCUSSION

This paper showed a probability-based classifier for improving motor imagery based BCI performance compared with other classifiers. The classification accuracy in the offline tests reached 76.06 % class 1 and 81.50 % class 2 using a non-adaptive ADS and 79.55 % class 1 and 99.69 % class 2 using an adaptive ADS classifier. Finally, a direction for future development an artificial intelligent controller and this classifier is shown in Fig 9. This AI controller could decide to combine proximity sensor data to augment certain features to close the prosthetic hand on a nearby object Fig 8. Other inputs such as electromyogram could be part of a multi-modal input used by an AI controller. In addition AI control may update the trained ADS classifier in the event of error correction during usage.

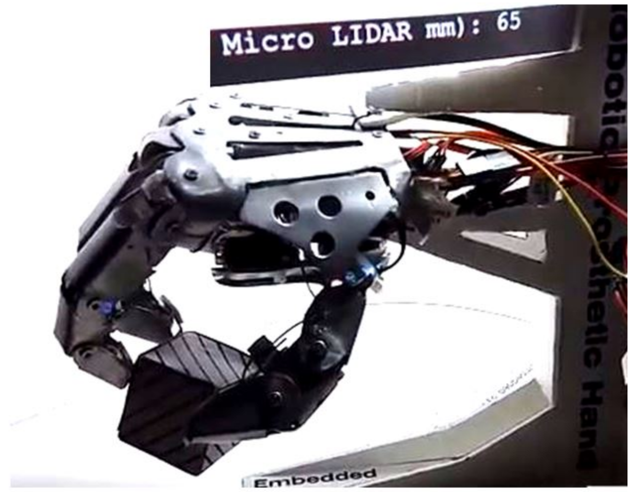

Fig. 8: Prosthetic hand with a LIDAR sensor.

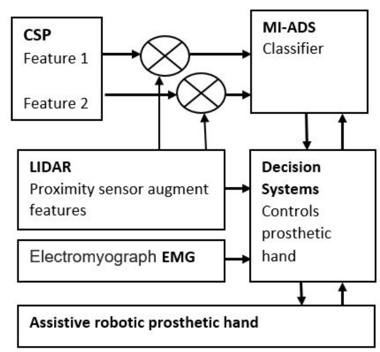

Fig. 9: BCI intelligent controller system.

ACKNOWLEDGMENTS

The authors would like to thank the Sheffield University Mathematics and Statistics Help (MASH) department Mr. Dan Wilson, Mr. Mustabsar Awais, Dr. Basile Marquier and Ellen Marshall.

REFERENCES

[1] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain-computer interfaces for communication and control." *Clinical neurophysiology : official journal of the International Federation of Clinical Neurophysiology*, vol. 113, no. 6, pp. 767–91, 2002.

[2] I. Dokare, "Classification of EEG Signal for Imagined Left and Right Hand Movement for Brain Computer Interface Applications," vol. 2014, pp. 291–294, 2014.

[3] D. J. McFarland, L. a. Miner, T. M. Vaughan, and J. R. Wolpaw, "Mu and beta rhythm topographies during motor imagery and actual movements." *Brain topography*, vol. 12, no. 3, pp. 177–186, 2000.

[4] A. Bashashati, M. Fatourechi, R. K. Ward, and G. E. Birch, "A survey of signal processing algorithms in brain-computer interfaces based on electrical brain signals," *Journal of Neural Engineering*, vol. 4, no. 2, 2007.

[5] K. K. Ang, Z. Y. Chin, C. Wang, C. Guan, and H. Zhang, "Filter bank common spatial pattern algorithm on BCI competition IV datasets 2a and 2b," *Frontiers in Neuroscience*, vol. 6, no. MAR, pp. 1–9, 2012.

[6] D. J. McFarland, L. M. McCane, S. V. David, and J. R. Wolpaw, "Spatial filter selection for EEG-based communication," *Electroencephalography and Clinical Neurophysiology*, vol. 103, no. 3, pp. 386–394, 1997.