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Interval type-2 fuzzy logic based multiclass ANFIS algorithm for real-time EEG based movement control of a robot arm

Saugat Bhattacharyya [a,b,*], Debabrota Basu [a], Amit Konar [a], D.N. Tibarewala [b]

[a] Department of Electronics & Telecommunication Engineering, Jadavpur University, Kolkata, 700032, India
[b] School of Bioscience & Engineering, Jadavpur University, Kolkata, 700032, India

HIGHLIGHTS

- Multi-class classification of motor imagery EEG signal.
- Adaptive neural fuzzy inference system (ANFIS) using one-vs-one and one-vs-all methods.
- Proposed an interval type-2 fuzzy fusion with ANFIS to improve uncertainty handling.
- Experimented on an online control task of moving a robot towards a target.
- The success rate of the robot reaching the target is above 60% for most subjects.

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ABSTRACT

Brain–computer interfacing is an emerging field of research where signals extracted from the human brain are used for decision making and generation of control signals. Selection of the right classifier to detect the mental states from electroencephalography (EEG) signal is an open area of research because of the signal's non-stationary and Ergodic nature. Though neural network based classifiers, like Adaptive Neural Fuzzy Inference System (ANFIS), act efficiently, to deal with the uncertainties involved in EEG signals, we have introduced interval type-2 fuzzy system in the fray to improve its uncertainty handling. Also, real-time scenarios require a classifier to detect more than two mental states. Thus, a multi-class discriminating algorithm based on the fusion of interval type-2 fuzzy logic and ANFIS, is introduced in this paper. Two variants of this algorithm have been developed on the basis of One-Vs-All and One-Vs-One methods. Both the variants have been tested on an experiment involving the real-time control of robot arm, where both the variants of the proposed classifier, produces an average success rate of reaching a target to 65% and 70% respectively. The result shows the competitiveness of our algorithm over other standard ones in the domain of non-stationary and uncertain signal data classification.

1. Introduction

Human–machine interaction (HMI) [1] is rapidly evolving as a potential field of research in applied biomedical and cognitive science. In this paper, we have dealt with an emerging trend of HMI called brain–computer interfacing (BCI), where the user interacts with a computing device or robot directly through mental intentions (or commands), generated as signals, from the brain [2].

A BCI technology is broadly composed of four basic processes, viz., recording the mental activity (*Signal Acquisition*); extraction of the intended action or desired features from that activity (*Signal Processing*); generation of the desired action (*Mental state detection*); and feedback, either through intact sensation, such as vision, or generated and applied by the prosthetic device (*Feedback*) [3]. Each of the aforementioned processes requires highly efficient techniques of signal processing, machine learning and control theory whose functions are to unveil the information embedded within the brain signals for various applications, like in robotics, communication, and gaming [4–7]. But BCI will be most helpful in neuro-rehabilitation [8,9] of physically challenged patients, like those suffering from paralysis, Amyotrophic Lateral Sclerosis, cerebral palsy, loss of limb [10]. These brain signals are extracted, decoded and studied with the help of various brain

* Correspondence to: School of Bioscience and Engineering, Jadavpur University, Raja S.C. Mullick Road, Jadavpur, Kolkata, 700032, India. Tel.: +91 9932866197.
E-mail addresses: saugatbhattacharyya@live.com (S. Bhattacharyya), basudebabrota29@gmail.com (D. Basu), konaramit@yahoo.co.in (A. Konar), biomed.ju@gmail.com (D.N. Tibarewala).

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measures like Magnetoencephalography, functional Magnetic Resonance Imaging, Electro-corticography, and Electroencephalography (EEG) [11,12]. In our analysis, we have preferred to use EEG signal over other measures because it is portable, easy to use, inexpensive, and has a higher temporal resolution [10,13].

For every cognitive task performed by the user, a characteristic brain modality is generated from the brain at different locations. A BCI technology aims at decoding these brain modalities to control a robotic device and the selection of brain modalities for a specific control task is an important issue in BCI research. Examples of few frequently used modalities are *steady-state visually evoked potential* (SSVEP), *slow cortical potential* (SCP), *P300*, *event related desynchronization/synchronization* (ERD/ERS) and *error related potential* (ErRP) [10,14]. In the current study, we aim to control the movement of a robot arm using five motor imagery mental commands: Forward, Backward, Left, Right and No movement. Using these commands the subject would attempt to move the arm towards a randomly positioned target (placed within the reach of the robot arm). ERD/ERS signals originates during movement planning, movement imagination or movement execution (collectively, referred to as *motor imagery* signals) [14,15]. Thus, this modality have relevance for control purpose in our present study.

In this paper, we have also delineated the importance of multiclass classification [16,17] in real world problems and how it can be employed efficiently. In real time scenarios, we often come across situations, which requires the classifier to detect more than one mental states. So in case of BCI systems, multiclass classification is quite important and has a wide scope of usage.

The brain signals recorded using EEG are non-linear, complex, non-stationary and non-Gaussian. Thus, they are quite challenging to classify and the problem is nothing but a conundrum. Adaptive neural fuzzy inference system (ANFIS) is a neural network [18,19] inspired classifier, which is used to classify complex datasets using fuzzy inference systems. ANFIS, is a strong and standard neural fuzzy inference tool but due to its Type-1 fuzzy membership pattern, it fails to handle noise and uncertainty in case of chaotic and Ergodic signals. Also, ANFIS is dependent and sensitive to the parameter sets defined by the user [18]. These shortcomings of the classical ANFIS algorithm inspired us to associate type-2 fuzzy [20,21] sets with classical ANFIS for BCI application.

In this paper, we have proposed two novel classification method based on the fusion of interval type-2 fuzzy system with the ANFIS structure for multiclass classification. In classical multiclass literature, 'one vs all' and 'one vs one' methods [10] are commonly used among researchers and these methods amalgamates the results of smaller binary classifiers to give the final hyperplane. Here, we have used ANFIS architecture for each of the binary classifiers and then the outputs of each individual binary classifiers are combined using a type-2 fuzzy to yield the final output.

Here, the EEG features are classified using our proposed type-2 fuzzy sets with the fuzzy inference system of ANFIS to minimize the adverse effects of uncertainty. This has made our algorithm a better tool to handle and classify EEG signals. It is more robust, efficient, user independent and handles the uncertainty of EEG signals much better than the previous model (classical ANFIS). Our proposed classifier also shows its competitiveness to discriminate between multiple classes as compared to other state-of-art classification algorithms.

The rest of the paper is arranged as follows. In Section 2, we describe the acquisition system and the robot arm used in this paper. In Section 3, we discuss on the experimental and data processing techniques used for offline classification and online control of the robot arm. Our proposed multiclass ANFIS networks and their working procedures are described in Section 4 of this paper. A discussion on the results of the offline and online experiments using our proposed classification algorithm are mentioned in Section 5, followed by the concluding remarks in Section 6.

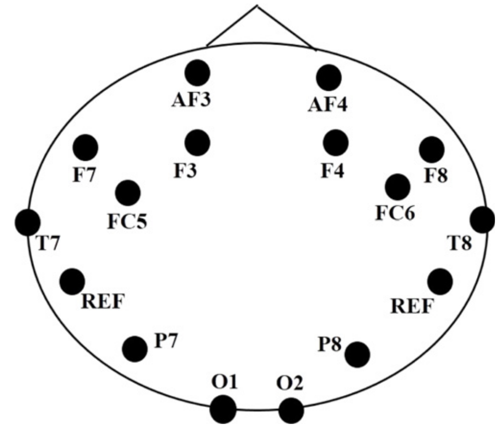

Fig. 1. Electrode locations in the Emotiv Epoc system.

2. Materials and control methods

In this study, the subject controls the movement of a Jaco robot arm [22,23] using five motor imagery signals related to following movement states: forward, backward, left, right and no movement. This section gives a brief background on the EEG acquisition system and the Jaco Robot arm, followed by a discussion on the control strategy implemented in this study.

2.1. EEG data acquisition system: Emotiv Epoc

The mental states of the users in form of EEG signals are recorded using an Emotiv Epoc System. It is a high resolution, multi-channel, wireless neuro-headset which uses a set of 14 sensors (electrodes) and 2 references. The electrodes are arranged according to the standard 10–20 electrode system [24] and their locations are AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4 (Fig. 1). The sampling rate of the EEG system is 128 Hz with a resolution of 0.51 μV. The system comprises of a built-in digital 5th order sinc filter with a bandwidth of 0.2–45 Hz and a digital notch filter at 50 and 60 Hz.

2.2. Jaco Robot Arm

Jaco Robot Arm, developed by Kinova, is a 6-axis robotic manipulator with a three fingered hand. The arm has six degrees of freedom in total with a maximum reach of 90 cm radius sphere and maximum speed of 30 cm/s. It is made of three sensors: force, position and acceleration. This arm is suitable for a person with a disability of the upper arm and can be placed on a wheelchair. The upper arm of the robot is made of three links which is similar to the upper limb of the human body, as shown in Fig. 2. An API is provided from the manufacturers which allows greater freedom of control by users [22,23].

2.3. Online control scheme

As mentioned earlier, the subject needs to control the movement of the robot arm towards a given target by using five mental (motor imagery) commands: Forward (F), Backward (B), Left (L), Right (R) and No movement (N). To stop the movement of robot arm, the subject would generate a No Movement command by relaxing. The rest of the commands are employed to move the robot arm in their respective directions. For example, if the subject wants to move the robot arm in the forward direction, he would need to imagine moving forward, which would generate a forward command from the brain signals. The control signals generated according to the mental commands are given in Table 1.