FUZZY LOGIC BASED EMOTION CLASSIFICATION

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ABSTRACT

Emotions affect many aspects of our daily lives including decision making, reasoning and physical wellbeing. Researchers have therefore addressed the detection of emotion from individuals' heart rate, skin conductance, pupil dilation. tone of voice. facial expression and electroencephalogram (EEG). This paper presents an algorithm for classifying positive and negative emotions from EEG. Unlike other algorithms that extract fuzzy rules from the data, the fuzzy rules used in this paper are obtained from emotion classification research reported in the literature and the classification output indicates both the type of emotion and its strength. The results show that the algorithm is more than 90 times faster than the widely used LIBSVM and the obtained average accuracy of 63.52 % is higher than previously reported using the same EEG dataset. This makes this algorithm attractive for real time emotion classification. In addition, the paper introduces a new oscillation feature computed from local minima and local maxima of the signal.

Index Terms- Emotions, Fuzzy Logic, Classification

1. INTRODUCTION

Emotions play an important role in our daily lives influencing decisions [1], reasoning and attention [2]. Emotions have been associated with the wellbeing of people [3] and their quality of life [4]. Researchers have also indicated that emotions are associated with the body immune system. Experimental results show that people who typically report experiencing negative emotions are at greater risk of disease than those who typically report positive emotions [5]. Furthermore, people with a more negative affective style (negative emotional state) have a weaker immune response than those with a more positive affective style (positive emotional state) [6]. A recent publication has also indicated that people who frequently experience positive emotions live longer and healthier lives [7]. All these findings have enticed researchers to better understand human emotions and make good for use in areas such as human-computer interaction and affective computing.

Researchers have detected emotions from individuals' heart rate, skin conductance, pupil dilation, tone of voice, facial expression and EEG using various techniques. Most of these techniques emerge from the machine learning and pattern recognition fields. Classification algorithms such as k-nearest neighbors (kNN) [8], Naïve Bayes [8], neural network [9], support vector machines (SVM) [10] and others [11], [12] have been used in detection of emotions. Fuzzy logic based methods, which are widely used in the area of control, have also been used in emotion detection [13]-[15]. Fuzzy based emotion classifications from EEG have also been proposed due to its advantage of assigning patterns into more than one class with certain degree of membership. In [16] the authors proposed EEG-based emotion classification using fuzzy clustering algorithms (Fuzzy K-Means and Fuzzy C- Means), and [17] presented a method of extracting emotion from the EEG using incremental neural fuzzy inference system.

In this paper, a new fuzzy based classification algorithm of positive and negative emotion from EEG is presented. In previous contributions both the fuzzy rules and fuzzy membership functions were generated from the data. In this work, however, fuzzy rules are defined based on research showing that there is a correlation of negative and positive emotions with activation of the right and left hemispheres of the human head. The algorithm has three main advantages: (1) direct use of intuitive rules that can be obtained from the literature or from expertise and additionally, new rules can be added as required, (2) the classification output gives two types of information: type of emotion and the strength of that emotion, and (3) it has low computation times and hence is suitable for portable devices and for real time applications.

This paper is organized as follows. Section 2 presents the methodology providing the background on Fisher's discriminant analysis (FDA) and fuzzy logic systems followed by the implementation of the algorithm. Section 3 presents the testing and evaluation methods of the proposed algorithm and finally Section 4 presents the results and conclusions.

2. METHODOLOGY

2.1. Semi-supervised Fisher's discriminant analysis

FDA [18] is a common and robust method for reducing high dimension data into a lower dimension subspace using a projection matrix, W. As it was pointed out by Fukunaga [12], there are equivalent variants of FDA to find the projection matrix that maximises the feature separation criteria. In this paper, the following FDA method was used [12]:

 $W = \operatorname{argmax}_{W} \{ (|W^{\top}S^{B}W|)(|W^{\top}S^{T}W|)^{-1} \}$ where:

$$S^{B} = \sum_{i=1}^{C} n_{i} (\mu_{i} - \mu) (\mu_{i} - \mu)^{\top}$$
(2)

(1)

is the between-class scatter matrix, and

$$S^{T} = \sum_{j=1}^{N} (x_{j} - \mu) (x_{j} - \mu)^{\top}$$
(3)

is the total scatter matrix, *C* is the total number of classes, n_i is the sample number of the class *i*, μ_i is the mean of the class *i*, μ is the global mean, *N* is the total number of training samples in matrix *X* with elements x_j , $\forall j = 1, 2, ... N$ and the symbol τ is the transpose.

The new algorithm in this paper uses FDA to reduce the high dimension feature space into low dimension space. As FDA is a supervised dimension reduction method, W was computed using labeled training samples. Then W is updated continuously to take into account changes that might occur over time in the stream of unlabeled samples. In order to update $S^{\mathcal{B}}$ (see eqn. 2) using unlabeled samples, μ_i was kept constant, as proposed in [19]. S^T , on the other hand, was updated every time a new sample, x(t) was acquired. So eqn 3 was modified to

$$S_{(t)}^{T} = \frac{(t-1)}{t} \left(S_{(t-1)}^{T} + \frac{(x(t)-\mu(t-1))(x(t)-\mu(t-1))^{\top}}{t} \right)$$
(4)

where $\mu(t-1)$ is the past global mean computed recursively, t = N+1, N+1, N+2, ..., N being total number of training samples. The derivation of eqn 4 cannot be shown here due to limited space, but it is inspired from [20]. The reduced dimension feature, z(t), was calculated using eqn 5 and then normalized to $\overline{z(t)}$, using eqn 6.

$$z(t) = x(t)W^{\top} \tag{5}$$

$$\widetilde{z(t)} = \exp(z(t)) \times \{\sum \exp(z(t))\}^{-1}$$
(6)

2.2. Fuzzy rule based classification

In standard pattern recognition, classes are mutually exclusive [21], that is, a sample or pattern is assumed to belong to only one of the classes. However, in fuzzy classification, a pattern can belong to several classes with a certain degree of membership. In this paper, the fuzzy classifier of the following form will be used [22]:

$$IF x_1 is A_1 AND \dots x_m is A_n \quad THEN \ C is Y \tag{7}$$

where $x_1, \ldots x_m$ are features, $A_1, \ldots A_n$ and Y are linguistic variables (e.g. small, medium, and large), C is the class. The number of *IF-THEN* rules depends on the number of linguistic variables and the number of features. For example, if there are m linguistic variables for each feature and n number of features, then there are m^n possible number of rules.

There two reasons fuzzy logic classification was chosen: (1) it has intuitive linguistic rules which are easy to understand and be obtained from experts and in the literature, (2) emotions are subjective and continuously varying and this variation can be well reflected using the degree of membership property of fuzzy classification.

2.3 Proposed fuzzy logic based emotion classification

This algorithm was developed based on a valence-arousal emotion classification model which is widely used in the literature. Based on this model, it has been reported that the right hemisphere of the brain is more active during negative emotions (low valence) and the left hemisphere is more active during positive emotions (high valence) [23]–[25]. This has been supported by experimental results in the literature. Trainor et al [26] reported that both joy and happiness emotions showed relatively greater left frontal alpha activation whereas both fear and sadness showed greater right alpha activation. In other words, the alpha wave of the left hemisphere decreases with positive emotions and that of the right hemisphere decreases with negative emotions. In [27] the authors reported that there existed a left and right difference in the relative power of the alpha wave for left and right hemispheres and the alpha wave decreased only at the right side in the happy state. Also, in [28] alpha power was greater in the left than in the right frontal region during experience of negative emotions. These findings and others reported in the literature can be used to devise rules which can be used as a fuzzy classifier to classify emotions from the EEG signal. The highlighted text above are good indicators of the linguistic variables of the fuzzy system. Therefore, the table of rules (see Table 1) was developed using two input features (one from the left hemisphere (LEFT), the other from the right hemisphere (RIGHT) and one output (VALENCE). Three linguistic variables: low, medium, and high were used for the input features and five linguistic variables: very low, VL, low, L, medium, M, high, H, and very high, VH, were used for the valence. The membership functions corresponding to these linguistic variables are shown in Figure 1 and 2 for input features and valence respectively.

		RIGH		
		LOW	MEDIUM	HIGH
	LOW	М	L	VL
EFT	MEDIUM	Н	М	L
	HIGH	VH	Н	М

Table 1: IF-THEN fuzzy rules used for emotion classification





Figure 2. Output membership functions

To put this in context, if it is assumed that the signal power from the EEG alpha band is taken from FP1 (electrode at frontal left hemisphere) and FP2 (at frontal right hemisphere) channels, then based on equation 7, example of rules from Table 1 could be linguistically interpreted as:

Rule 1: If left alpha power is low and right alpha power is high, then valence is very low.

Rule 2: If left alpha power is medium and right alpha power is high, then valence is low.

The fuzzy logic based emotion classification algorithm, FLEC, was implemented using FDA for feature dimension reduction and Fuzzy logic using the rules shown in Table 1 for classification and was implemented using Mamdani-type inference system [29]. The FLEC algorithm can be summarized as follows: *Step 1*: Compute global mean, μ , of labelled feature matrix X

Step 2: Calculate S^B and S^T using eqns 2, and 3 respectively. *Step 3*: Calculate the projection matrix, W using eqn 1.

- *Step 4*: For every unlabeled feature vector, *x*(*t*)
 - 1. Compute S^{B} using eqn 2, (using fixed μ_{i} and global mean)
 - 2. Update $S^{T}(t)$ using eqn 4.
 - 3. Update the projection matrix, W
 - 4. Reduce the dimension of x(t) using eqn 5
 - 5. Normalize z(t) using eqn 6
 - 6. Classify z(t) using fuzzy rules of Table 1
 - 7. Update the global mean

Step 5: If there are more features, repeat Step 4.

3. EXPERIMENT

3.1. Signal acquisition and feature extraction

The algorithm was tested using real EEG data which was obtained from a dataset for the analysis of human affective states managed by Queen Mary University of London [30]. The data was acquired from 32 participants while watching music video clips to induce different emotions. Each participant in the experiment watched 40 one minute long music video clips while his or her physiological signals being recorded using a 32 channel EEG. Then, participants rated each video in terms of arousal, valence, like/dislike, dominance and familiarity. More details and the EEG dataset can be obtained from [8] and [30].

In this experiment 14 asymmetrical channel pairs, named according to the 10-20 International standard of electrode placements [31], { (FP1,FP2), (AF3,AF4), (F3,F4), (F7,F8), (FC3,FC4), (FC1,FC2), (C3,C4), (T7,T8), (CP5,CP6), (CP1,CP2), (P3,P4), (P7,P8), (PO3,PO4), (O1,O2) } were used. From each channel, the alpha band (8 Hz to 12 Hz) was filtered using a finite impulse response filter with 127 filter coefficients. Then the following statistical features were extracted from the obtained alpha band: mean, standard deviation, mean of the absolute values of the first differences, mean of the absolute values of the second differences. Formulae for computing these features can be found in [32]. In addition, the signal power of the alpha band was also computed as a feature.

In this paper, we also propose a new feature that will be referred as the oscillation feature. This was obtained by finding all local maxima and local minima of the signal and this gives an insight of how signal power is related to oscillations and activation and inactivation of certain areas of the brain. Therefore, the correlation of the signal power and oscillation features is an indication that both features originate from the same emotion activity. This feature is obtained using an algorithm shown below:

Get the signal x(t), with t = 1, 2, ...N samples Set local minima, $L_{min} = 0$ Set local maxima, $L_{max} = 0$ FOR t = 1 to N-2

$$IF x(t) > x(t+1) AND x(t+2) > x(t+1)$$

$$THEN L_{min} = L_{min} + 1$$

$$IF x(t) < x(t+1) AND x(t+2) < x(t+1)$$

$$THEN L_{max} = L_{max} + 1$$

$$END FOR$$

Then, the oscillation feature, *O*, was calculated as in eqn. 8

$$O = N/(L_{min} + L_{max})$$
(8)

3.2. Feature selection and classification

For each video trial there were six features per channel and so a total of twelve features per channel pair. To reduce the classification computation cost without compromising the accuracy, we reduced the number of features from twelve to four. This was done by computing the FDA ratio for all possible combinations of features (${}^{12}C_4 = 495$) and those with the highest discrimination ratio were chosen. It was observed that feature combinations which contained the signal power and oscillation features had higher discrimination ratios than other features. Thus the power and oscillation features of the alpha band from each channel were used for classification.

To test the performance of the proposed algorithm, subject independent classification was performed on all video trials using our classification algorithm, FLEC, and its performance was compared using standard classifiers such as Naïve Bayes, Matlab inbuilt support vector machine (SVM), and LIBSVM [34] which are widely used for emotion classifications [10]. For every channel pair, classification was performed for all subjects and a 10-fold cross validation was used to determine and compare the performance of each of the four classification methods.

4. RESULTS AND CONCLUSION

4.1. Results and discussion

Table 2 shows the 10-fold cross validation results obtained by classifying positive and negative emotions using features extracted from channel pairs as discussed in section 3.2. The classification output from FLEC is continuous, ranging from 0 to 1 for negative and positive valence respectively and the actual value indicates the corresponding emotion strength. To compare FLEC with other classification algorithms, the continuous values were converted into crisp values, that is, any value less or equal to 0.49 was taken as negative valence (class 1) otherwise, it was taken as positive valence (class 2). Table 2 also shows classification results from BAYES, SVM and LIBSVM classifiers. From these results it can be observed that LIBSVM has highest average accuracy of 63.13% followed by FLEC, BAYES and SVM with average classification accuracy of 62.62%, 59.64% and 50.62% respectively. While classifying the data, the computation time was measured on a standard PC running window 7 64 bits with Intel i7 3.4 GHz processor. On average, FLEC was 92 times faster than LIBSVM as shown in Table 3.

Table 2: Accuracy averaged over 10 - fold cross validation

	ALGORITHM			
CHANNEL PAIR	FLEC	BAYES	SVM	LIBSVM
FP1-FP2	63.05	62.66	51.25	63.10
AF3-AF4	63.52	62.97	55.00	63.13
F3-F4	63.20	61.72	49.38	63.12
F7-F8	62.59	59.53	55.70	63.13
FC3-FC4	62.50	61.95	53.05	63.12
FC1-FC2	62.97	60.23	52.81	63.12
C3-C4	61.80	61.56	47.19	63.13
Т7-Т8	62.19	60.86	52.58	63.12
CP5-CP6	61.02	45.23	44.53	63.13
CP1-CP2	63.44	60.55	55.55	63.13
P3-P4	62.89	61.88	48.75	63.12
P7-P8	62.27	55.86	49.53	63.12
PO3-PO4	62.50	60.31	42.73	63.13
01-02	62.81	59.61	50.63	63.12
MEAN	62.62	59.64	50.62	63.13

Table 5. Average computation in	Table 3:	Average	computation	time
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	FLEC	BAYES	SVM	LIBSVM
Time [ms]	1.94	17.11	427.58	178.84
Speed [Relative to FLEC]	1	9	220	92

4.2. Conclusion

A continuous negative and positive emotion classifier is presented in this paper. The classifier has comparable classification accuracy with a robust LIBSVM library. An average of 62.62% of negative and positive classification accuracy is obtained using FLEC which is higher than the 57.60% previously reported in [8] using the same dataset. In addition, the proposed classifier has less computation time, a feature desirable for real time or near real time classification tasks. Finally, the paper has also proposed a new oscillation feature, which was found to have higher FDA ratio than other statistical features. Further investigation of the FLEC classifier and oscillation algorithm will be performed for real time emotion classification on wearable EEG sensor nodes in the future.

5. REFERENCES

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