Emotion Recognition Model Using Source-Temporal Features and Fuzzy

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Abstract. This paper aims to evaluate the performance of Electroencephalographic (EEG) emotion recognition system (EEG-ER) using source-temporal domain with Takagi- Sugeno-Kang (TSK) fuzzy model. Ten healthy subjects aged 5-6 years were participated in this study. Emotion elicitation procedure has done using the Radbound faces database (RafD). The selected emotions were happy, sad, and neutral and fear. The results were compared with wavelet coefficients (WC) as feature extraction method and Regularized Least Square (RLS) and Multi-Layer Perception (MLP) neural network classifiers from our previous work. Another comparison was done between affective model of Russell and RafD. The results show the efficiency of using source-temporal features in emotion recognition system hence there was a slight difference in accuracy among different classifier; MLP, RLS and TSK however MLP and TSK results were with high accurate and stable. Moreover Russell model which is based on positive-negative dimensions shows high accuracy than RafD model that has positive dimensions. The accuracy was around 97% using Russell model.

Keywords: Emotion, EEG, Relative source temporal features, Takagi-Sugeno-Kang fuzzy approach.

1 Introduction

Emotion is one of the mysterious that has no specific psychology and physiology definition. However, it is involved in human cognition, perception and experience. Consequently it is affected on human learning process and human physical and mental health. Emotion can be expressed using verbal function like words “happy, sad …etc” or non-verbal function based on facial expression and behavior. However it is difficult to people with disability to express their feeling to others. Therefore identify others emotion is important task. Many studies have been done using bio-signals to recognize emotion state such as speech, skin temperatures, heart rate [1-3]. Recent studies concern on using EEG signal in emotion recognition system (ER) [4-8] hence EEG measures the signal from the central nervous system (CNS) making it a suitable tool for studying human emotions.

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Our previous study [9] shows the efficiency of using spatial source domain to present the dynamic brain activity which is consistent with the distribution theory where emotion is produced through interactions among brain regions rather than simply a function of a specific brain location [10]. The proposed model is based on applying Time Difference of Arrival (TDOA) approach [11] with EEG signals to extract the relative spatial source domain in terms of (x, y, z) coordinates which named Relative Source Temporal (RST) features. The previous work shows significant results using MLP [12] and RLS [13] classifiers. Fuzzy system [14] has been used widely in many applications such as control system and pattern recognition problems. In this study we apply TSK fuzzy model which is knowing of its generalization and simplicity to model complex system as well as its generated rules from given input-output data set based on subtractive clustering [15, 16]. Emotion has been modeled based on many theories. The majority of them which is based on psychology perspective consider emotion as discrete values or basic emotions while other theories are characterized emotion as continues domain which can be presented by many dimensions. One of the most widely model is 2 dimension affective model of Russell [17] that categorizes every kind of emotions in a two-dimensional model; valence (V) that reflect the cognitive perception and arousal (A) that reflect the physiological component. Russell model divided the valence and arousal to positive and negative. In this study we use Russell model and we use also RafD model [18] which is also 2dimension affective model but with positive values hence the values of valence and arousal were taken based on self –assessment test with score from (1-5). The first goal of this study is to investigate the performance of RST features with TSK fuzzy classifier and compared it with our previous results. The second goal is to examine the affection of Russell and RafD model to predicate the values of valence and arousal for each emotion.

2 Method and Materials

2.1 EEG Data Descriptions

EEG data was collected from ten healthy subjects aged (5-6) from the preschool (Malaysia International Islamic preschool) using BMCI model device. Data was recording from eight channels; F3, F4, C3, C4, P3, P4, T7, T8 placed according to international 10-20 system with Cz as references. Emotion of participant has evoked using eight pictures of children faces for each emotion states with different valence and arousal that selected from RafD [18]. Each subject asked to sit and watch sequence of these pictures on screen away 75 cm. The time for each session was 1 min. sampling rate was 250 and recorder frequency from 0.5-50 Hz. The collected data are filter using IIR filter to alpha band (7-13) Hz for RST model and filtered to the range (0.5-30) Hz for wavelet model.

2.2 Feature Extraction Methods

Relative Source –Temporal Features (RST): This technique is based on using TDOA approach with EEG signals to extract the spatial sources and temporal information. Theoretical of this technique was explained in our previous studies [9]. Brief illustration will show here.

- Initial four site electrode location and their *x, y* and *z* coordinates is taken from [19].
- Compute the time delay among the channels using Cross-Correlation (CC) [20]. One second movement window are used with 125 sample movement. Thus the time delays are computed for each one second sample within 50 sec. However the time delay among EEG signals are expected to be in less than mille-second and because of our sampling rate was 250 Hz, time delay in some epoch cannot be capture within 1 second interval. To solve this, we use regression model (polynomial function with order 3) to fit our CC data.
- Apply TDOA principle as explained in [9], three linear equations are produced which can be solved using Gaussian elimination methods to get *x,y* and *z* variables [21]. The linear equation for three receivers have (x_1, y_1, z_1), (x_2, y_2, z_2) and (x_3, y_3, z_3) coordinates with speed v and time delay t_{12} and t_{13} is given by :

$$R = Ax + By + Cz \tag{1}$$

Hence

$$R = vt_{13} - vt_{12} + \left(\frac{x_1^2 + y_1^2 + z_1^2}{t_{13}} - \frac{x_3^2 + y_3^2 + z_3^2}{t_{13}}\right) - \left(\frac{x_1^2 + y_1^2 + z_1^2}{t_{12}} - \frac{x_2^2 + y_2^2 + z_2^2}{t_{12}}\right) \tag{2}$$

$$A = 2\left[\frac{(x_2 - x_1)}{vt_{12}} - \frac{(x_3 - x_1)}{vt_{13}}\right] \tag{3}$$

$$B = 2\left[\frac{(y_2 - y_1)}{vt_{12}} - \frac{(y_3 - y_1)}{vt_{13}}\right] \tag{4}$$

$$C = 2\left[\frac{(z_2 - z)}{vt_{12}} - \frac{(z_3 - z_1)}{vt_{13}}\right] \tag{5}$$

- Choose another 4 different electrodes site locations and repeat the previous procedures.

This procedure is repeated 20 times with different electrodes sites each. At the end, 20 features with time samples are computed for three variables *x, y* and *z* that called in this work the virtual sources for the alpha wave activities.

Wavelet Coefficients based features (WC): For comparison reason, emotion recognition based wavelet transform are applied [7] .Wavelet transform decompose the signal to its component with different scale giving multi resolution analysis for EEG signal. Discreet wavelet transform with the Daubechies fourth order was applied to decompose the EEG signal to four frequencies band and the extracted coefficient (C) corresponding to alpha band (7-13) was used to compute energy (EN)and the entropy (ET) .

$$EN(j) = \sum_{i=n-1}^{N} C_j(i)^2 \tag{6}$$

$$ET(j) = -\sum_{i=n-1}^{N} C_j(i)\log C_j(i) \tag{7}$$

2.3 Fuzzy Logic Model

Takagi, Sugeno and Kang [15, 16] , introduced fuzzy model which is known (TSK)fuzzy system. TSK fuzzy model based on using simple rules generates from the input –output data. These rules consequences with a simple linear regression model to predicate the output. In TSK approach , subtractive cluster methods [16] are used to cluster the input data by finding the center of each cluster which is represent the point with highest number of neighborhood , consequently , the second cluster will be the second point of highest neighborhood. After using the subtractive cluster to identify number of cluster and its location the rules for TSK fuzzy are extracted from training data. For example, the rules of j cluster can express as:

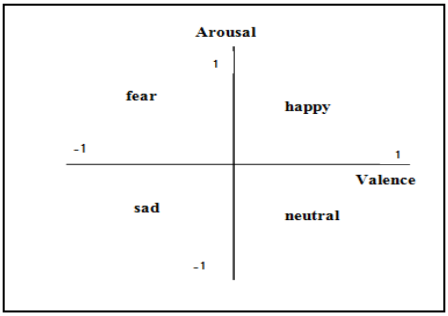
IF x_1 is in A^j_1 and x_2 is in A^j_2 and x_3 is in A^j_3 …… x_n is in A^j_n

Then: $$y^j = p_0 + p_1^j x_1 + p_2^j x_2 + p_3^j x_3 + \cdots + p_n^j x_n \tag{8}$$

where x is the input variables from 1 to n, y is the output variable, A^j_n is the membership function for the cluster j and p^j_n is the regression parameters for *jth* rules. For this study the input variables are the extracted features that explained in the previous section which contain 60 features and the output is labeled to two values indicate valence and arousal for each emotion states that will explain in next section. TSK fuzzy-subtractive approach was applied to the input-output variables to cluster the data and model the memberships which is that associated with each variable and clusters. There are all of these statistical techniques and we have tested some of these for the comparison and others are being implemented as part of the PhD work... however, the purpose here is to present a soft-computing based techniques more academically speaking, the data is quite noisy as well as extremely unpredictable in other words, Fuzzy. Therefore the fuzzy classification was utilized

2.4 Classification Set up

The classification process was done to separate among four emotion or classes. In this study two affective models were used to extract the label of each class. Fig.1 show the label of each class based on Russell model while Fig.2 shows the labels extracted from RafD model, hence the label present the mean value of valence and arousal for the selected images of each emotion.



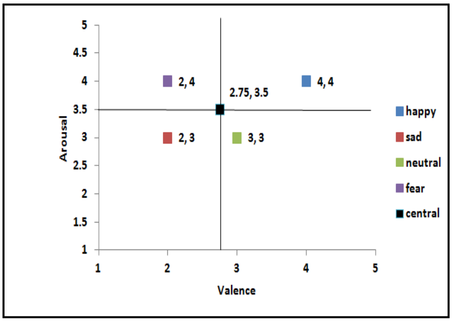


Fig. 1. 2DE affective model of Russell

Fig. 2. D affective model of RafD

3 Results and Discussion

In this study we consider user-independent case. Features are extracted from each subject and normalized using z-score then feed to classifier. The labeled for each emotion states are identified based on Russell model. For simplicity we used 56 epochs from each emotion state per subject. We use 10 fold cross –validation with 70% of data as training and 30% of data as test. Table 1 shows the results of the classification using TSK compared with wavelet coefficients. Clearly RST –EC has high accuracy than WC-ER. Emotion recognition using TSK fuzzy model was compared with our previous work using MLP and RLS classifiers for both RST features and WC as shown in Fig.3 and Fig.4. The three classifiers combined with RST features have high accuracy to detect different emotion states compare with WC features which indicates the efficiency of spatial source domain to recognize high cognitive task like emotion. Adding data-driven classifier such as MLP and TSK are more efficiency with RST features than RLS classifier which is depends on modeling the features using Gaussian kernel. However RLS and TSK show high accuracy than MLP for WC-ER system. So far all the results were discussed before is based on predication two dimensions; valence and arousal for each emotion states using Russell model. Another scenario has been done to predicate the same dimension by using RafD model that was shown in Fig.3 hence each class or emotion states is labeled by the center of each state. Table 2 shows the classification rate for each emotion using RST features combined with different classifiers. There is slight different between the models. RafD model shows good accuracy even though all emotions labeled are positive and their values near from each others. However, RafD model show low ability to discriminate different emotion using WC as illustrated in Table 3.

Table 1. Classification rate values in parentage of each emotion of the proposed RST features compare with wavelet coefficient features using TSK Fuzzy as RST-EC up and WC-EC down

	Happy	**sad**	**neutral**	**fear**
	98.67	0	1.33	0
happy	**60.34**	7.32	23.25	9.09
	0	**97.75**	2.25	0
Sad	27.24	**60.65**	5.77	6.34
	1.5	1.67	**96.83**	0
neutral	10.4	15.25	**64.01**	10.34
	0	2.16	0.6	**97.24**
Fear	15.62	5.33	18.3	**60.75**

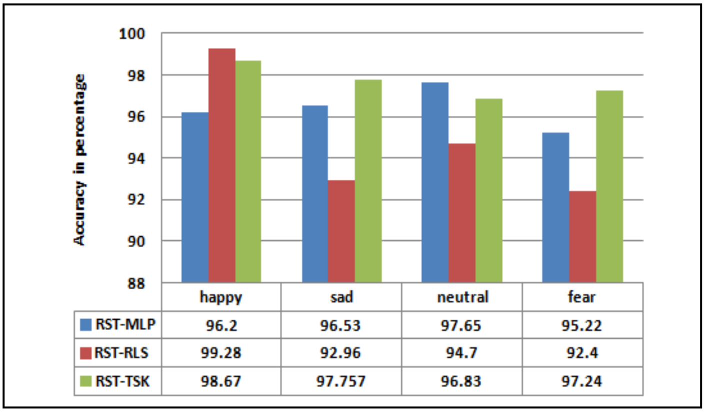


Fig. 3. Classification rate of each emotion using RST with different classifier

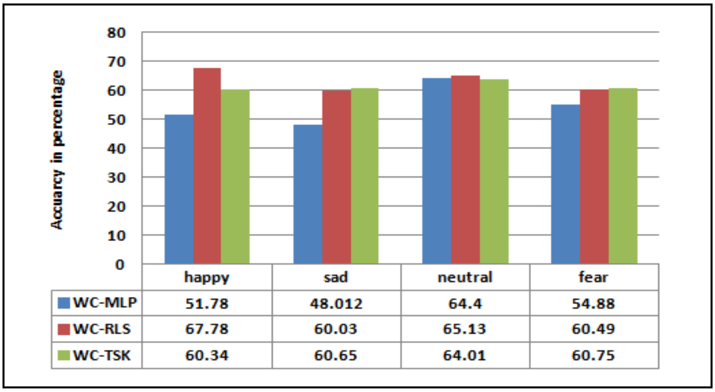


Fig. 4. Classification rate of each emotion using WC with different classifier

Table 2. Classification rate of each emotion uisng RafD and Russell model with RST

	RafD model					**Russell model**				
classifier	happy	sad	neutral	fear	A.C	happy	sad	neutral	fear	A.C
RST-TSK	97.24	98.1	94.4	94.9	96.21	98.67	97.7	96.8	97.2	97.6
RST-RLS	90.30	100	92.9	93.2	94.12	99.28	92.9	94.7	92.4	94.3
RST-MLP	97.09	98.31	96.2	97.3	97.24	96.53	96.5	97.6	95.2	96.4

Table 3. Classification rate of each emotion uisng RafD and Russell model with WC

	RafD model					Russell model				
classifier	Happy	sad	neutral	Fear	A.C	happy	sad	neutral	fear	A.C
WC-TSK	57.18	58.10	50.6	60.09	56.50	60.34	60.65	64.0	60.7	61.4
WC-RLS	28.59	73.39	57.7	26.66	46.6	67.78	60.03	65.1	60.4	63.3
WC-MLP	52.90	51.83	39.2	50.91	48.7	51.78	48.01	64.4	54.8	54.7

4 Conclusion and Future Work

This study evaluates the performance of RST features with TSK fuzzy inference system to detect brain activity under different emotion states using EEG signals. The results were so promising and show the robust and the efficiency of RST features to discriminate different classes. Also, it is noticed that RST give good results using data-driven classifier. Moreover, this study show that 2 D affective model of Russell to present the valence and arousal in positive and negative dimension help to distinguishes among emotion states more than RafD model. Future work will consider on user-dependent case and more kind of emotions states.

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