EEG EMOTIONS RECOGNITION SYSTEM

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ABSTRACT

This paper proposes an emotion recognition system based on time domain analysis of the bio-signals for emotion features extraction. Subjects are first prime prior to collecting the EEG signals. Three different types of emotions, (happy, relax and sad) are classified and results are compared using five different algorithm based on the RVM, MLP, DT, SVM, Bayes. Experimental results show the potential of using the time domain analysis for real-time application.

1. Introduction

Emotions accompany us in our daily life, playing a key role in non-verbal communication. Assessing emotions is thus essential to the understanding of human behavior. In order to achieve an intelligent man-machine interface system that recognizes nonverbal information, such as the intentions, emotions and affections of a user, this paper aims to present an emotion recognition system by means of pattern recognition and classification techniques.

Human electroencephalography (EEG) measures both the frequency and amplitude of electrical activity generated from the human brain. The benefits of using EEG to conduct experiments testing are noninvasive, simple, fast, and inexpensive. It is neither painful nor uncomfortable or time-consuming for the subjects. For these reasons, EEG has become a preferred method in studying the brain's responses to emotional stimuli.

In this paper, four popular neural networks from WEKA toolbox have been used on the EEG bio-signals' time domain data, in order to determine the optimal selection of experiment parameters.

By considering the results from different neural networks, the sampling length, overlapping rate of sampling and the initial length of signals that need to be removed can be obtained. Using these methods, the selection of experiment parameters is usually more robust and informative.

Finally, experiments are conducted to find important features that classify the three different emotions.

The paper is organized as follows. After the brief introduction in section **Error! Reference source not found.**, section 2 will describes the data collection we are using in the experiments. *Relevance vector machine* (RVM) model is briefly discussed in section 3. After that, the experiment and the result analysis are presented in section 4. We concluded the whole paper in section 5.

2. Emotional Data Collection

Experimental Setup

Figure 1 shows the overview of the process for gathering bio-potential signals in emotion recognition experiments. First, subjects are asked to put on the headgear shown in Figure 2(a) to obtain their relevant brainwave activities. An EEG device shown in Figure 2(b) will then transmit the bio-signals to the PC for recording. Another PC is then used to present visual and aural stimulus to excite the respective emotions for the subject.

Bio-signal data were collected over four dry electrodes shown in Figure 3 from the points F4, T3, T4 and P4 according to the International 10-20 standards. Fp2 was the ground channel and the left ear lobe was used as the reference. The impedances of the electrodes are ensured to be below 40 throughout the experiment.

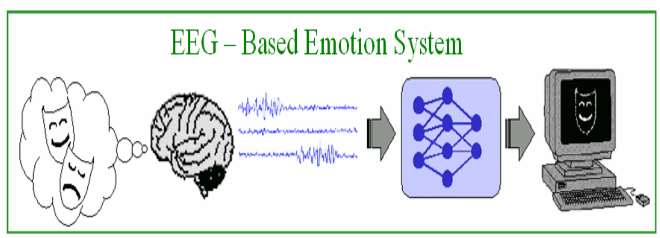

Figure 1: The process of EEG data collection

Figure 2: Overview of Equipments from: g.MICROelements (Left), g.USBamp (Right)

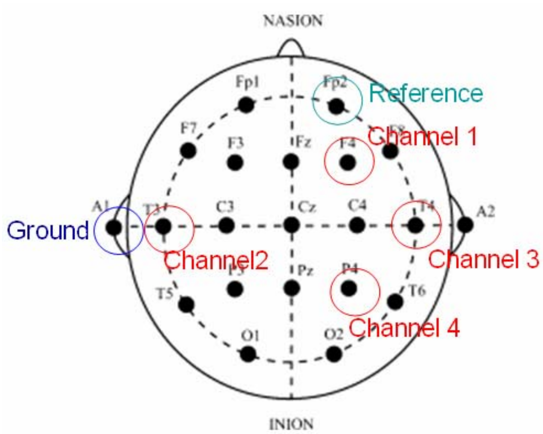

Figure 3: Placement of Electrodes for EEG

Psychological Experiments

The experiments were carried out in a private laboratory. The EEG bio-signals were gathered under psychological experiments that used visual and aural stimulus for exciting the respective emotions.

Three selected videos from www.youtube.com were used as stimulus for each emotion. A survey was conducted among 30 human subjects who did not participate in the experiments to evaluate the integrity of the videos to invoke the respective emotions among 10 individuals. The results can be seen in Table 1. The average results of the three emotions are around 70%. This is still acceptable as different people have different threshold towards each emotion, which are built over a long time through adaptive learning in uncontrolled environment.

Table 1: Emotion survey by human subjects

Sampling	18 Males		12 Females
Emotions	Happy	Relaxed	Sad
Average Rating (1-10)	7.066667	7.333333	7.233333

The participants consist of a total of 3 males and 2 females, all native Chinese between the ages of 19 to 25. The raw EEG bio-signals were collected from each subject for each of the three emotions. Each electrode on the head records electrical signals which are then recorded in a channel. Figure 4 shows examples of EEG bio-signals measured from a subject while he received the stimulus. Raw EEG data shown in Figure 4 is hard to draw generalization about. Using a high level programming language called Matlab, it is possible to build a graphical user interface to the EEG data as well as easily create transformation files to manipulate the EEG data in virtually any way.

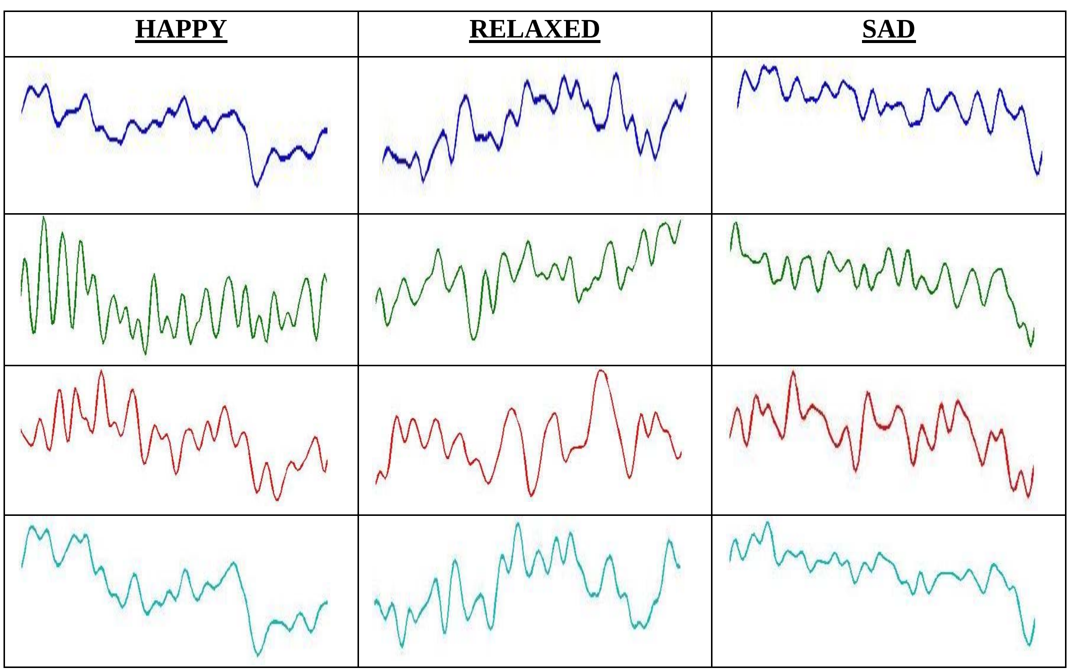

Figure 4: Example of bio-signals: Channel 1 (Top row), Channel 2 (Second row), Channel 3 (Third row), Channel 4 (Forth row)

Feature Extraction

In order to make use of neural network, there must be availability of inputs and outputs data for training. This paper will make use of the feature extraction method proposed in [1] in time domain. According to [1], six features can be extracted in each bio-signal.

$$\mu_X = \frac{1}{T}\sum_{t=1}^{T} X(t)$$
$$\sigma_X = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(X(t)-\mu_X\right)^2}$$
$$\delta_X = \frac{1}{T-1}\sum_{t=1}^{T-1}\left|X(t+1)-X(t)\right|$$
$$\bar{\delta}_X = \frac{1}{T-1}\sum_{t=1}^{T-1}\left|\bar{X}(t+1)-\bar{X}(t)\right| = \frac{\delta_X}{\sigma_X}$$
$$\gamma_X = \frac{1}{T-2}\sum_{t=1}^{T-2}\left|X(t+2)-X(t)\right|$$
$$\bar{\gamma}_X = \frac{1}{T-2}\sum_{t=1}^{T-2}\left|\bar{X}(t+2)-\bar{X}(t)\right| = \frac{\gamma_X}{\sigma_X}$$

Where t is the sampling number and T is the total number of sample. By using these feature values, a total of 24 features, 6 for each channel can be determined. No noise-filtering methods are used in preprocessing because our learning model can aid in reducing the noise level.

Selection of Experiment Parameters

Several parameters need to be determined before extracting features from the original dataset, including:

(1) Sampling Length

(2) Overlapping rate of sampling

(3) Initial length of signal that needs to be removed (The first several seconds of signal record are invalid due to EEG equipment)

For parameter (3), the first 2000 samples in all bio-signals were consistently removed. To determine parameter (1) and (2), a simple experiment was conducted to find out the optimal one.

It can be deduced that for most popular models that were used in the experiment, the trend is that the larger the (1) sampling length, the larger the (2) overlapping rate, the better the performance. Thus in the experiment, a sampling length of 5k and an overlapping rate of 70% are chosen.

3. RVM Model

As a Bayesian sparse kernel technique, the *relevance vector machine* (RVM) [2] shares a lot of characteristics with *support vector machine* (SVM) [3] and *Gaussian Process models* (GP) [4]. As discussed in [4] (Chap 6.6), the RVM can actually be viewed as a special case of GP, with the covariance function form as:

$$k(\boldsymbol{x},\boldsymbol{x}') = \sum_{j=1}^{N}\frac{1}{\alpha_j}\phi_j(\boldsymbol{x})\phi_j(\boldsymbol{x}')$$

where α_j are hyperparameters and the N basis functions $\phi_j(\boldsymbol{x})$ are usually but not necessarily taken to be Gaussian shaped basis functions centered on each training data point

$$\phi_j(\boldsymbol{x}) = \exp\left(-\frac{\left|\boldsymbol{x}-\boldsymbol{x}_j\right|^2}{2l^2}\right)$$

where l is a length-scale hyperparameter controlling the width of the basis functions and $\boldsymbol{x}_j$ are the *j*th input instance.

Due to the similarities of RVM to SVM and GP, there are some advantages of RVM compared to other learning models such as MLP and Decision Trees. For example, as a special case of GP, RVM can avoid the overfitting by marginalizing rather than cross validation. In this way, the model selection step can use all the training data, without the need for a validation set. The computation cost in RVM is also much reduced than the models based on cross validation. For our empirical experience, the RVM model can be several times faster than a MLP based on the 10-folder cross validation.

Another merit of RVM and SVM is due to their sparse solutions, in which a lot of instances/features play no role [5]. For RVM, by setting different length-scale hyperparameters for different input components, a significant portion of them will go to infinity in the evidence maximization solution, which means the corresponding input component play no role in the final solution. In this way, RVM can be used as a classifier and also a feature selection method. In the following experiments we will see that only 1/3 features are selected by RVM. And without the non-significant features, the classification performances of all learning models in the experiments didn't deteriorate much. However, by only using those significant features, the computation costs have been much reduced.

As the demerits of all kernel methods, we usually need to store the training samples during training of RVM, which may prolong the evaluation time. More details about RVM and GP can be referred to [4, 5].

4. Experiments Results

In this section, we are using four popular neural network models as well as a new learning model based on Relevance Vector Machines (RVM) [2]. The four popular models are multilayer perceptron, decision tree, Bayes network and support vector machine. In all experiments, the accuracies are estimated by the 10-folder cross validation to avoid overfitting, which reflects the performance on both training and unseen data and the methods are implemented using WEKA toolbox.

Default settings were all used in WEKA for Multilayer perceptron (MLP), Decision Tree (C4.5) and Bayes Network (BayesNet). But for Support Vector Machine (SMO), the buildLogisticModels is set to True, the filterType is set to Standardize training data and the rest uses default value.

The resultant confusion matrix of each model in the experiment is listed in Table 2. The training time of each model is calculated by taking the average training time of running the experiments five times, which is shown in Table 3.

Table 2: Confusion Matrix of RVM, Multilayer Perceptron, Support Vector Machine and Bayes Network

	Happy vs Relaxed		Relaxed vs Sad		Happy vs Sad	
RVM	86	9	130	6	95	0
	0	136	1	128	0	129
Accuracy	96.10%		97.36%		100.00%	
MLP	91	4	134	4	93	2
	2	134	7	122	3	126
Accuracy	97.40%		95.85 %		97.77 %	
DT	91	4	126	10	91	4
	5	131	16	113	5	124
Accuracy	96.10%		90.19 %		95.98 %	
SVM	81	14	117	19	80	15
	3	133	22	107	9	120
Accuracy	87.45 %		75.85 %		84.38 %	
Bayes	75	20	108	28	85	10
	1	135	31	98	0	129
Accuracy	90.91 %		77.74 %		95.55 %	

Table 3: Training time in seconds of RVM, Multilayer Perceptron, Support Vector Machine and Bayes Network

	Happy vs Relaxed	Relaxed vs Sad	Happy vs Sad
RVM	60.49s	74.9s	145.65s
	Total Training Time = 281.04s		
MLP	162.77s	189.06s	161.64s
	Total Training Time = 513.47s		
DT	0.42s	0.66s	0.4s
	Total Training Time = 1.48s		
SVM	36.76s	31.72s	35.66s
	Total Training Time = 104.14s		
Bayes	0.3s	0.8s	0.4s
	Total Training Time = 1.5s		

From Table 2, it can be seen that both the results of RVM and MLP are relatively near and both give better results than the rest. However in Table 3, the total training time of MLP is almost 1.5 times more than RVM. This is due to the nature of each model, where RVM can do training and cross validation at the same time while MLP can only do each at a time. Hence in terms of computational cost, RVM would be the better choice.

Next, we try to identify the useful features out of the 24 features, by using RVM. The experimental results can be shown in Table 4.

Table 4: Experimental results of RVM

Happy vs Relaxed		Relaxed vs Sad		Happy vs Sad	
Confusion Matrix:		Confusion Matrix:		Confusion Matrix:	
86	9	130	6	95	0
0	136	1	128	0	129
Total Accuracy:		Total Accuracy:		Total Accuracy:	
96.10%		97.36%		100.00%	
Features	Importance	Features	Importance	Features	Importance
C11	0.0001	C11	0.0111	C11	0
C12	0	C12	0.0239	C12	0
C13	**202.321**	C13	**71.9024**	C13	**5.5198**
C14	0.0067	C14	0.4269	C14	0.0038
C15	**13.2155**	C15	0.0351	C15	**3.819**
C16	0.0018	C16	0.1131	C16	0.0011
C21	0.0001	C21	0.0022	C21	0
C22	0	C22	0.0701	C22	0.0001
C23	0.0656	C23	**11.2806**	C23	0.016
C24	0.005	C24	0.2564	C24	0.0044
C25	0.0018	C25	0.0829	C25	**19.5637**
C26	0.0014	C26	0.0939	C26	0.0015
C31	0.0079	C31	0.1388	C31	0.0001
C32	0	C32	0.0002	C32	0.001
C33	**5.6478**	C33	0.8149	C33	0.0001
C34	0.0037	C34	0.1181	C34	0.0196
C35	**9.605**	C35	**23.2826**	C35	0
C36	0.001	C36	0.0621	C36	0.0057
C41	0.0001	C41	0.0021	C41	0
C42	0	C42	0.0003	C42	0.0422
C43	**40.2034**	C43	**74.3512**	C43	0.0001
C44	0.0166	C44	0.3375	C44	0.0097
C45	0.0054	C45	**1.1293**	C45	0
C46	0.0033	C46	0.1283	C46	0.0027

As byproducts, RVM can also give the relative importance of features. Fortunately and amazingly, most of the input features are not significant in our experiment. Besides, the significant features for different classification tasks seem consistent in some degree. In summary, the most important features are:

(a) δ_X for ch1
(b) γ_X for ch1
(c) δ_X for ch2 (only for Relaxed vs Sad)
(d) γ_X for ch2 (only for Happy vs Sad)
(e) δ_X for ch3 (only for Happy vs Relaxed)
(f) γ_X for ch3
(g) δ_X for ch4
(h) γ_X for ch4 (only for Relaxed vs Sad)

We can see that for all channels, only δ_X and γ_X are important, all the other 4 can be generally ignored—this is quite significant. Among the 4 channels, ch1 is the most important, after that is ch3 and ch4. Ch2 is partly useful for differentiating relaxed and sad. We will try to verify the feature selection results by comparing the performances with full feature set and those with selected features. The results can be shown in Table 5.

Table 5: Confusion Matrix based on features selected by RVM

	Happy vs Relaxed		**Relaxed vs Sad**		**Happy vs Sad**	
RVM	80	15	133	3	77	18
	0	136	4	125	0	129
Accuracy	93.50 %		97.36 %		91.96 %	
MLP	87	8	131	5	94	1
	3	133	2	127	5	124
Accuracy	95.24 %		97.36 %		97.32 %	
DT	91	4	127	9	91	4
	3	133	13	116	4	125
Accuracy	96.97%		91.70 %		96.43 %	
SVM	74	12	114	22	67	28
	5	131	9	120	13	116
Accuracy	88.75 %		88.30 %		81.70 %	
Bayes	79	19	94	42	87	8
	6	130	29	100	1	128
Accuracy	89.18 %		73.21%		95.98 %	

Table 6: Comparison of RVM's training time between selected features and original features

RVM	**Happy vs Relaxed**	**Relaxed vs Sad**	**Happy vs Sad**
24 Original Features	60.49s	74.9s	145.65s
	Total Training Time = 281.04s		
8 Selected Features	12.58s	16.44s	32.72s
	Total Training Time = 61.74s		

By comparing the confusion matrix in Table 5 and Table 2, it can be observed that both results are relatively similar. The average accuracy of the 24 original features is 97.82%, while the average accuracy of the 8 selected features is 94.27%. Furthermore, in Table 6, the total training time of the 8 selected features is about 4.5 times more than the one with the 24 original features. Hence, these support the idea that the output can be classified by just using the useful features from RVM.

Based on [1], an accuracy of 41.7% using SVM is achieved from classifying 5 types of emotions as shown in Table 7. In this paper, we use SVM in our experiments too. Based on the 8 selected features, SVM is able to give an average accuracy of 86.25% to classify 3 types of emotions, which are happy, relaxed and sad. The percentage difference in accuracy is almost doubled. This low accuracy in [1] might be because of the additional emotions, anger and fear. Firstly, the data collection for anger and fear might not be convincing. It is hard to really invoke anger or fear from subjects by showing stimulus, especially anger. It can be observed that the two emotions with the highest accuracy in Table 7 are joy and relaxed, which are considered as positive emotions. On the other hand, anger, sadness and fear are considered to be negative emotions.

According to [6], positive emotions are implemented by more left hemispheric, negative emotions by more right-hemispheric activity. This means there are three negative emotions that generate high activity in the right hemispheric, while two positive emotions generating high activity in the left hemispheric. Perhaps this explains why the accuracy for all the negative emotions is much lower as compared to the positive emotions. From [7], it states that happy emotions showed strong activities in the left too. Hence, from Table 5, it can be observed from RVM and MLP that *Relaxed vs Sad* gives the highest accuracy, as it involves classifying a positive and negative emotion.

According to [8], sad and happy emotions were associated with distinct subdivisions within the same brain regions. This may explain why an accuracy of 100% in RVM is achieved for *Happy vs Sad* by using all the 24 original features, shown in Table 2. However, an accuracy of 91.96% is achieved when using the 8 selected features; nevertheless this accuracy is good enough as a trade-off for lesser training time. The speed of the training time is increased by almost 2.5 times.

Table 7: EEG Emotion recognition results in [1]

Emotions	**Accuracy**
Joy	58.3%
Anger	33.4%
Sadness	25.0%
Fear	41.7%
Relaxed	50.0%

5. Conclusions

This paper proposes an emotion recognition system from EEG signals in time domain. Three emotion, happy, relaxed and sad, were conducted in this experiment. In order to compare the accuracy results, five different models were used and they are relevance vector machine (RVM), multi layer perception (MLP), decision tree (DT), support vector machine (SVM) and bayes network. Based on the experiments, RVM and MLP both gave the highest accuracies, with relatively similar results. However, it was concluded that RVM is a better choice over MLP. The reason being RVM's training time is 1.5 times faster. RVM also generated the relative importance of features, which identifies 8 important features. The experiment was rerun again with the 8 selected features to verify the accuracy. The average accuracy is 97.82% for the 24 original features, while the average accuracy for the 8 selected features is 94.27%. It was also observed that the training time for the latter is almost 4.5 times faster than the other one. Considering the trade-off from the accuracy for the increased in speed of the training time, the experimental results were satisfying.

Next, for future work, a comparison between time domain and frequency domain could be carried out. Additional of anger and fear emotions are be considered, if the data collection process is more convincing. Increasing more EEG electrode locations could be explored to achieve a better understanding.

6. References

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