Investigation of Time Interval Size Effect on SVM Model in Emotion Norm Database

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Abstract. Few studies have focused on investigating the time interval effects on support vector machine (SVM) model in emotion recognition. This study tested original averaged value models and difference value models with three different time-intervals (5 seconds, 10 seconds, and 30 seconds) for SVM emotion recognition in our developed emotion norm database. Forty one elementary school students were recruited as participants to see some emotion pictures in international affective picture system (IAPS), and to collect their affective information—attention, meditation, electroencephalography (EEG), electrocardiogram (ECG), and SpO2 for developing the affective norm recognition system. This study selected 5480 IPAS photos physiological data as the tested dataset from our emotion norm database. The bio-physiology signals were averaged by seconds or difference the value by second and then to serve as the input variables value for C-SVM with RBF kernel function. The results showed that the original averaged models have better performance than the difference models. In addition, the original averaged value model with 30 seconds time interval is the optimal classification model. This study suggested that future research can adopt 30 seconds as the time interval for determining the size of time interval for their training dataset in emotion recognition problem.

Keywords: EEG (Electroencephalography); ECG (Electrocardiogram), Affective Computing, Support Vector Machine, Emotion and Attention Recognition System, Eye Tracker, Time interval.

1 Introduction

Since Affective Computing was proposed, there has been a burst of research that focuses on creating technologies that can monitor and appropriately respond to the affective states of the user (Picard, 1997). Because of this new Artificial Intelligence area, computers are able to recognize human emotions in different ways. Why is human emotion an important research area? The latest scientific findings indicate that emotions play an essential role in decision-making, perception, learning, and more [1]. However, how to develop an efficient emotion recognition system? Suited time-interval for setting the optimal training data for emotion recognition system and classifiers are unknown.

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Therefore, this study compared two types of models--original averaged value models and difference value models with three different time-intervals (5 seconds, 10 seconds, and 30 seconds) for SVM emotion recognition in our developed emotion norm database [2] to determine the optimal size of time-interval for SVM emotion recognition system.

2 The Physiological Input Signals for Emotion Recognition

The physiological input signals of eye movement, EEG and ECG will be selected to input our learning state recognition system. Attention and emotion is a complex phenomenon. A single physiological parameter can't evaluate the state of attention and emotion. For including more objective physiological indices when recognize learning state, several techniques need to be combined for classifying the state of attention and emotion based on the past studies. .With the emergence of Electroencephalography (EEG) technology, learner's brain characteristics could be accessed directly and the outcome may well hand-in-hand supported the conventional test, recognize a learner's Learning Style [3]. The arousal state of the brain [4], alertness, cognition, and memory [5, 6] also can be measure. Heart rate variability (HRV) from ECG, has gained widespread acceptance as a sensitive indicator of mental workload [7]. The positive emotions may change the HF components of HRV [8].

3 Method

3.1 Participants and Procedure

Forty-one elementary school students in the fifth grade participated in this study. Participants were tested individually. On arrival and after attaching physiological sensors, Participants will be asked to rest quietly. Participants will be told that pictures differing in emotional content would be displayed for 5 seconds on a screen in front of them, and that each picture should be viewed during this moment. Each rating will be preceded by a 5 seconds preparatory slide showing the number (1–24) of the next photograph to be presented (baseline period). The photograph will be rated and then be screened for 5 seconds (stimulus period), while the physiological responses will be recorded. The inter-trial interval was set at 30 seconds permitting recovery from the previous slide on all physiological measures. Slide presentation will be randomized for all subjects. Prior to the onset of the experimental trials, three pictures (highly pleasant-arousing, neutral on both valence/arousal, and highly unpleasant-arousing) will serve as practice stimuli. We collected participant's physiology signals (EEG, ECG, heart beating, SpO2) during the experiment every one second.

3.2 Materials

The aim of emotion norm construction is to determine (calculate) the relations between physiological changes and subjective ratings of International Affective Picture System (IAPS) photographs. Providing a standardized pool of affective and attention stimuli, the International Affective Picture System (IAPS) has become a highly useful methodological tool used in numerous investigations [9] IAPS includes normative ratings of each photograph with respect to valence (pleasure), arousal, and dominance and consists of over 700 standardized color photographs evoking a range of affective responses.

A total number of 18 IAPS were used in the experiment. The pictures were divided into three different groups; 6 pleasant, 6 neutral and 6 unpleasant pictures [10]. Twenty-four International Affective Picture System (IAPS) photographs are grouped into 3 sets of 8 photographs: highly pleasant-arousing, neutral on both valence/arousal, and highly unpleasant-arousing ones. IAPS picture sequence: 1750(pleasant), 5480(pleasant), 1740(neutral), 1050(unpleasant), 9584(unpleasant), 6260(unpleasant), 2210(neutral), 7004(neutral), 7330(pleasant), 1300(unpleasant), 7050(neutral), 1670(neutral), 1463(pleasant), 7460(pleasant), 6370(unpleasant), 7150(neutral), 9592(unpleasant), 1710(pleasant) [11]. We selected 5480 picture as our testing database in our study.

4 Database

We used the emotion norm database in our previous studies [2] via NeuroSky. The database includes 10 brainwave variables (attention score, meditation score, delta1, theta, beta1, beta2, alpha1, alpha2, gamma1, gamma2), heart beating, SpO2, and emwave emotion variable.

Based on the distribution of frequency zones, when a learner's emotional state is negative, peaceful or positive, the Coherence score will be calculated as 0, 1 and 2, respectively .The value of Heart Rate Artifacts (HRAs) is zero when the human emotion detected is in normal situations, whereas the value of HRAs is one when the human emotion is detected in abnormal situations. The emWave system identifies learner emotional states every 5 s. In this study, identifying the percentages spent in positive or negative emotions was applied to assess the effects of two learning methods on learning emotions. In computing the percentages of positive and negative emotions, the Accumulated Coherence Score (ACS) has the key role, whereas the method for computing ACS based on different coherence states and HRAs is as follows:

$$CV(t) = \begin{cases} -1\text{, if Coherence}(t) = 0 \text{ and HRA}(t) = 0 \text{ (negative emotion)} \\ +1\text{, if Coherence}(t) = 1 \text{ and HRA}(t) = 0 \text{ (peaceful emotion)} \\ +2\text{, if Coherence}(t) = 2 \text{ and HRA}(t) = 0 \text{ (positive emotion)} \end{cases}, CV(0) = 0, t = 0, 1, 2, \ldots, m \quad (1)$$

The entire emotion norm database that collected data from 42 elementary school students. Each student was asked to see 20 IAPS pictures. The database included brain wave data, hear beating data, SpO2, and emotion data. There are totally 14972 records in this database. We selected photo number 5480 and average all the participants' physiological data by second as our tested dataset. Our tested Dataset that selected from our emotion norm database [2] is shown in Table 1. There are totally 59 records in this tested dataset.

Table 1. Our tested dataset that selected from our emotion norm database

Photo Id	Attention	Meditation	Delta1	Theta	Beta1	Beta2	Alpha1	Alpha2	Gamma1	Gamma2	Emwave	HeartBeat	SPO2	Output
5480	53	61	44.9	2.1	0.6	1.4	1.1	0.2	0.2	0.1	0	87	98	2
5480	51	61	44.9	2.1	0.6	1.4	1.1	0.2	0.2	0.1	0	87	98	2
5480	51	50	44.9	2.1	0.6	1.4	1.1	0.2	0.2	0.1	0	87	98	2
5480	51	50	86.8	11.1	1.4	0.5	1.7	0.8	0.2	0.4	0	87	98	2
5480	51	50	86.8	11.1	1.4	0.5	1.7	0.8	0.2	0.4	0	85	98	2
5480	51	50	86.8	11.1	1.4	0.5	1.7	0.8	0.2	0.4	0	85	98	2
5480	51	57	86.8	11.1	1.4	0.5	1.7	0.8	0.2	0.4	0	85	98	2
5480	51	57	67.9	14.9	2.7	9.4	5.8	1.3	0.8	0.4	0	85	98	2
5480	51	57	67.9	14.9	2.7	9.4	5.8	1.3	0.8	0.4	0	82	98	2

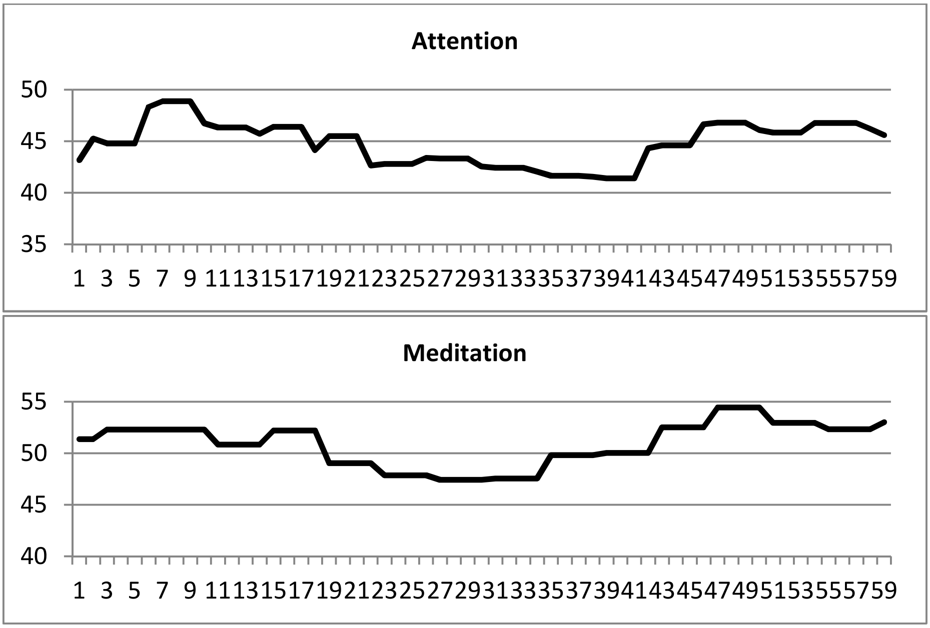

Fig. 1. Trend of Physiological Signals in Photo 5480 (Average by 41 students)

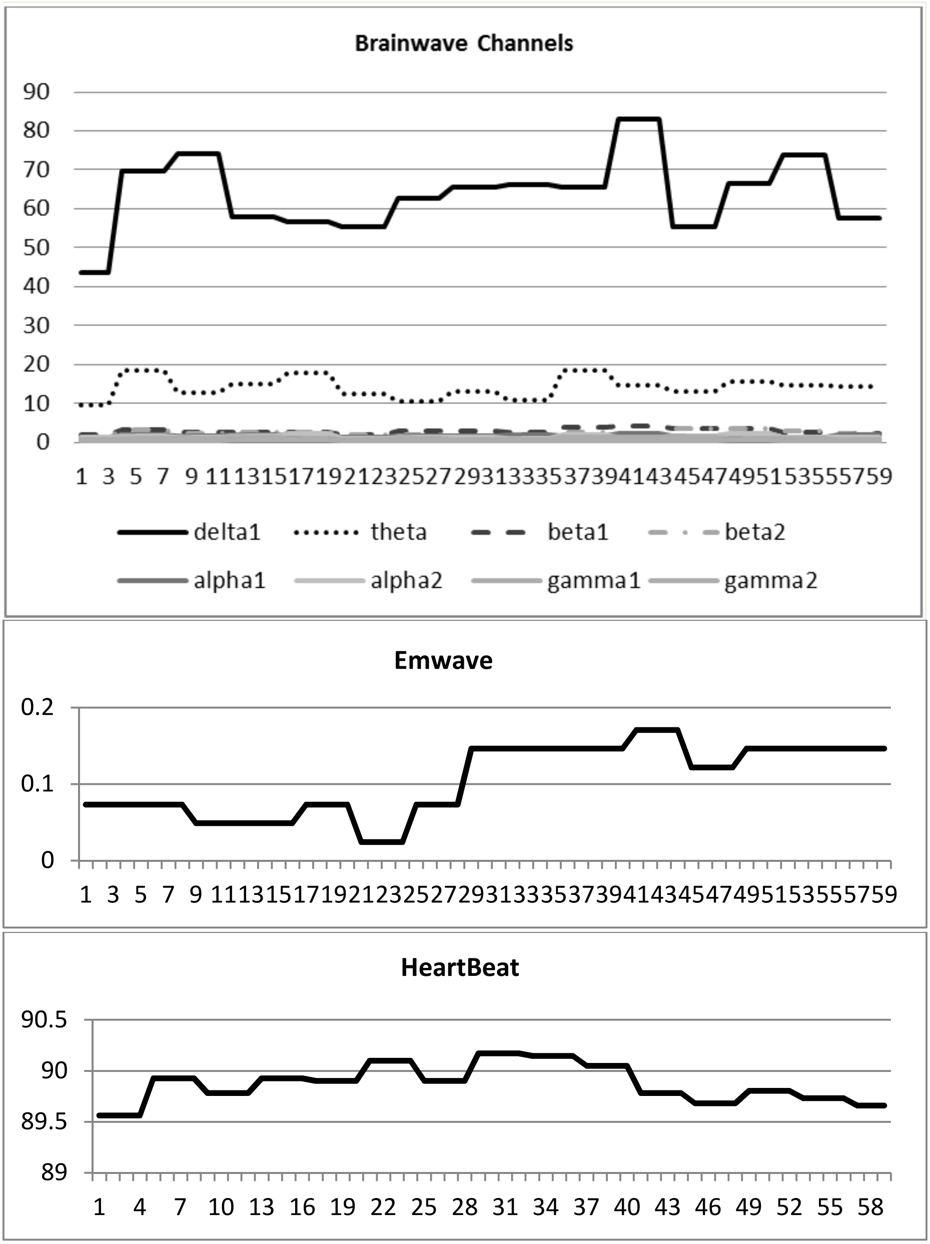

Fig. 1. (*continued*)

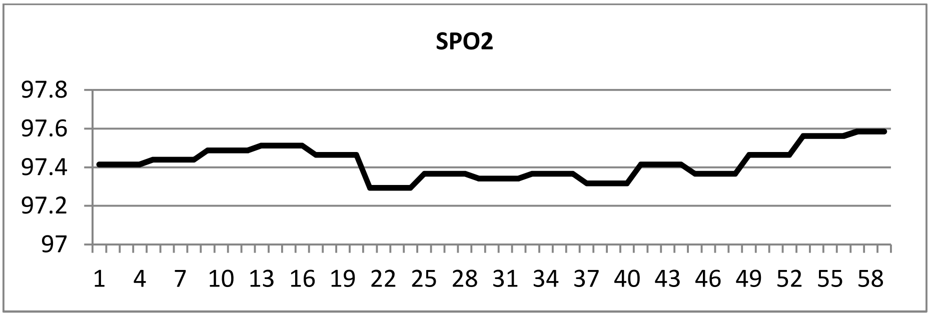

Fig. 1. (*continued*)

4.1 Classification Accuracy

This study uses C-support vector machine that cost set to 1 and degree set to 3 with radial basis function kernel via 10-folds validation method. The results are summarized as shown in Table 2. Among six types of SVM models, Model 2 has the best SVM classification accuracy (98.31%). The model 1 to model 3 used the averaged value of original physiological signal values. The model 4 to model 6 (difference model) used the difference value of original physiological values via equation 2. Generally speaking, the averaged value models have better performance than the difference models.

The model 4-6 used difference model that used the formula as below:

$$\Delta f\left(x_t\right) = f\left(x_{t+1}\right) - f\left(x_t\right) \tag{2}$$

where X denotes the physiological signal variables, and t denotes the time in second.

Table 2. Classification results of SVM (C-SVM) among six models (10 folds)

	Original Value Model			Difference Value Model		
	Model1	Model2	Model3	Model4	Model5	Model6
	5s	10s	30s	5s	10s	30s
Accuracy	96.61%	**98.31%**	94.92%	91.53%	83.05%	42.37%
TP Rate	0.966	0.983	0.949	0.915	0.831	0.424
FP Rate	0.366	0.083	0.050	0.915	0.831	0.583
Precision	0.967	0.983	0.950	0.838	0.690	0.404
Recall	0.966	0.983	0.949	0.915	0.831	0.424
F-Measure	0.962	0.983	0.949	0.875	0.754	0.397

5 Conclusion and Suggestion

This study investigated the window size effect on SVM in emotion recognition via our developed emotion norm database in our previous study [2]. We compared two models—one is original value model (model 1 to model 3) that averaged the original physiological signal values, and the other one is difference value models (model 4 to model 6) that used difference values of physiological signal values. In order to understand the optimal time-interval for emotion recognition, three different time-interval sizes (5 seconds, 10 seconds, and 30 seconds) are selected in this study for SVM model. The results showed that the original value models have better performance than difference value models. Among all models, the model 3 that used 30 seconds as emotion time-interval has the best performance. The implications for researchers reveal that the participant's emotion was triggered in the first 30 seconds. The limitation of this study is the sample size. We only selected IAPS 5480 as the tested dataset. This study suggested that future research can use more different IAPS photo data to test the external validity. .

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