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Using Support Vector Regression to Estimate Valence Level from EEG

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***Abstract*—Emotion recognition is an integral part of affective computing. An affective brain-computer-interface (BCI) can benefit the user in a number of applications. In most existing studies, EEG (electroencephalograph)-based emotion recognition is explored in a classificatory manner. In this manner, human emotions are discretized by a set of emotion labels. However, human emotions are more of a continuous phenomenon than discrete. A regressive approach is more suited for continuous emotion recognition. Few studies have looked into a regressive approach. In this study, we investigate a portfolio of EEG features including fractal dimension, statistics and band power. Support vector regression (SVR) is employed in this study to estimate subject's valence level by means of different features under two evaluation schemes. In the first scheme, a SVR is constructed with full training resources, whereas in the second scheme, a SVR only receives minimal training resources. MAE (mean absolute error) averages of 0.74 and 1.45 can be achieved under the first and the second scheme, respectively, by fractal feature. The advantages of a regressive approach over classificatory approach lie in continuous emotion recognition and the possibility to reduce training resources to minimal level.**

Keyword*—*EEG; affective BCI; valence estimation; SVR

I. Introduction

Human emotion conveys important information during inter-personal interaction. In human-computer interaction, there is a trend to incorporate user's affective input into system design. The so-called "affective computing" is the computing that relates to, arises from or influences emotion [1]. Emotion recognition is an integral part of affective computing. Based on the recognized user's emotion, the interaction session could be made more adaptive to user's feeling. For example, a game can adaptively decrease the difficulty level if the user feels frustrated, or increase the level when the user feels the opposite. A music player can adaptively select music to play in consonance with the user's feeling.

Computerized emotion recognition can be achieved by different methodologies. The first attempt dates back to 1972 by Williams et al [2]. They proposed to identify human emotions based on speaker's speech signal. Other methods include text-based [3] and facial recognition-based [4] etc. EEG (electroencephalograph)-based emotion recognition started to gain more attention in the latest decade when new, portable and wireless EEG technology was introduced, which has paved the way for the application of EEG to extend from clinical use for patients to entertainment use for healthy users. It has proven that EEG carries emotion information and can be used as a source to identify human emotion [5]. Comparing with the speech-based, face-based and text-based methods, EEG-based emotion recognition does not require explicit inputs from users during the interaction session. Furthermore, EEG measures the spontaneous brain activity and has the potential to assess the truly felt emotion from within.

Human emotion can be modelled by a 3-dimensional valence-arousal-dominance space [6]. Under such model, an emotion can be assessed from each of the three dimensions. The valence dimension indicates the pleasantness level, from most unpleasant to most pleasant. The arousal dimension is associated with the excitation level, from most inactivated to most aroused. The dominance dimension refers to the submissiveness-dominance nature of an emotion. For example, when a person feels pleasant (high in valence), activated (high in arousal) and in dominating situation (high in dominance), he/she is having a happy emotion. Alternatively, we can use a (*v, a, d*)-tuple to denote such emotion. Suppose each dimension ranges from 1 to 9, a happy emotion can be denoted as, for instance, (8.2, 8.7, 7.6). Therefore, there are generally two approaches to emotion recognition. One approach is classification, which employs a classifier to classify emotion into different categories such as happy, sad, fear, angry etc. The other approach is regression which, based on the numerical notation, estimates the numerical value on each dimension.

In previous studies, EEG-based emotion recognition was mostly done in a classificatory manner. Ishino and Hagiwara [7] employed alpha, beta, gamma power and neural network to classify four emotions (joy, anger, sorrow, relaxation) and achieved accuracy from 54.50 % to 67.70 %. Lin et al [8] adopted Support Vector Machine (SVM) to discriminate four emotions (joy, anger, sadness, pleasure) using difference of power between symmetric electrodes as feature. The reported accuracy was 90.72 %. Wang et al. [9] used log power feature and explored several different classifiers to classify four emotions (joy, relax, sad, fear). Best accuracy of 66.51 % was achieved by SVM. Petrantonakis and Hadjileontiadis proposed to use higher order crossings (HOC) as features and SVM to differentiate six emotions (happiness, surprise, anger, fear, disgust, sadness). Murugappan [10] used statistical features from different frequency bands and KNN to identify five emotions (happy, surprise, fear, disgust, neutral).

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The classificatory approach has been extensively studied, whereas very few studies have investigated the regressive approach. The regressive approach has several merits over classificatory approach. In classificatory approach, the emotions can only be categorized into pre-defined emotion labels. The classifier is unable to generate emotion labels beyond those that are used to train it. Human emotions are discretized under this approach. Although it is intuitive to use descriptive emotion labels to refer to emotions, it may be misinterpreted in some cultural context. Some emotion labels are not cross-lingual, e.g., Polish does not have an exact equivalent word for "disgust" [11]. Moreover, human emotions are more of a continuous phenomenon instead of discrete states. These problems can be avoided in the regressive approach. First and foremost, continuous emotion recognition is possible under the numerical notation: the regressor outputs continuous, real values instead of discrete words. The regressive approach may also have the potential to minimize training resources when it is crucial to do so.

Soleymani et al. [11] did a pilot study in regression-based emotion recognition using power spectrum density feature extracted from EEG. Uzun et al. [12] employed Support Vector Regression (SVR) and Hilbert Huang transform to estimate three emotion primitives. In this study, we adopt the regressive approach and focus on estimating the valence ratings—the first principal component [14] that counts for the most variance in ratings of emotional experience—from EEG signals, under controlled arousal/dominance condition. Valence perception has been associated with the lateral brain pattern [15][16], which results in asymmetric activities between left and right hemispheres. Positive emotions (high valence) generally trigger greater left hemispheric activities, whereas negative emotions (low valence) stimulate the right hemisphere more. Some studies [17][18], however, report that such lateral pattern is subject-dependent and some subjects may exhibit the reversed pattern: greater left hemispheric activities correspond to positive emotion perception, and greater right hemispheric activities are associated with negative emotion. We measure such asymmetry by difference of feature parameters between left and right hemispheres. We investigate and compare several different features against each other. We also investigate the possibility to minimize training resources under the regressive approach, which, to the best of our knowledge, has not been investigated in current literature.

The rest of the paper is organized as such: Section II describes the experiment methods in this study; Section III presents the experiment results with discussions; Section IV concludes the paper.

II. Methods

A. Dataset

The DEAP dataset [1] by Koelstra et al. [13] was used in this study. The dataset contains multimodal physiological data from 32 subjects under emotion elicitation experiment. Physiological signals were recorded at a 512 Hz sampling rate and down-sampled to 128 Hz. Data in DEAP include 32-channel EEG, 4-channel EOG (electrooculogram), 4-channel EMG (electromyogram), respiration, plethysmograph and temperature. Subjects were required to report their truly felt emotions in accordance with the valence-arousal-dominance emotion model on a 1-9 scale after exposure to each affective stimulus (one-minute long music video). Each subject was exposed to totally 40 different stimuli, resulting in 40 one-minute long EEG trials.

Since we focus on estimating valence dimension, the other two variables, arousal and dominance, are kept under control when valence changes. We consider rating = 5 as a delimiter when controlling the arousal and dominance variables. Arousal larger than 5 is considered high arousal (HA) and less than 5 low arousal (LA), and similarly for the dominance variable. Considering that discrimination between two valence ratings may not be meaningful when the two ratings are too close to each other (e.g. 2.34 and 2.36), we further partition the valence ratings into four sub-zones and focus on estimating valence ratings in four levels. The available nine subjects meeting the abovementioned selection criteria are listed in Table I. The Arousal/Dominance column refers to the controlled arousal/dominance condition. The available EEG trial IDs in DEAP are listed the table under each valence level. The #Comb column refers to the total number of combination of trials from four levels. Particularly, subject 5 satisfies the trial selection criteria under two arousal/dominance conditions: HAHD and LALD. Both conditions are considered and investigated for subject 5. For the rest subjects, only one arousal/dominance condition is satisfied.

B. Feature Extraction

In this study, we investigate a portfolio of different EEG features including fractal dimension (FD) [19], band power features and six statistical features (STAT) introduced in [20]. Band powers include theta band (4-8 Hz), alpha band (8-12 Hz) and beta band (12-30Hz). Statistical features consist of 1) mean; 2) standard deviation; 3) mean of absolute values of first order differences; 4) mean of absolute values of first order differences from z-scored (zero-mean and unit-variance) EEG signals; 5) mean of absolute values of second order differences; 6) mean of absolute values of second order differences from z-scored EEG signals.

The fractal dimension features are computed by Higuchi algorithm as was used in [19]. Power features are extracted by Fast Fourier Transform. Statistic features are computed as in [20]. All feature parameters are extracted in a sliding window fashion from each channel. The width of the sliding window is set to 512 but window step size varies from 32 to 512, yielding different overlapping rates (93.75 %, 87.50 %, 75.00 %, 50.00 % and 0.00 %). Then, in order to measure the asymmetric activities between left and right hemispheres, the difference of feature parameters between left hemisphere and right hemisphere are computed by

$$\Delta F_{l-r} = F_l - F_r, \forall l \in LH, \forall r \in RH \, , \qquad (1)$$

where F_l and F_r denote the feature parameter extracted from channel l and r, ΔF_{l-r} the difference of feature values between channel pair l-r, LH the left hemisphere channel set comprising 14 channels ({FP1, AF3, F3, F7, FC5, FC1, C3, T7, CP5, CP1, P3, P7, PO3, O1}) and RH the right hemisphere channel set consisting of 14 channels

[1] http://www.eecs.qmul.ac.uk/mmv/datasets/deap/

TABLE I. SUBJECT SELECTION FROM DEAP DATASET. AROUSAL/DOMINANCE CORRESPONDS TO THE CONTROLLED AROUSAL DOMINANCE CONDITION. THE THIRD TO SIXTH COLUMN LIST THE TRIAL ID IN DEAP UNDER EACH VALENCE LEVEL. THE LAST COLUMN SHOWS THE NUMBER OF COMBINATION OF TRIALS FROM DIFFERENT VALENCE LEVELS.

Subject	**Arousal/Dominance**	**Trial ID in DEAP**				**#Comb**
		Level 1 $(v<2)$	***Level 2*** $(2<v<4)$	***Level 3*** $(6<v<8)$	***Level 4*** $(v>8)$	
5	HAHD	23,37	30	31,34,40	2,4,11	18
5	LALD	32	28	1,9,12,14,17,20,26,27	18,19	16
7	HALD	24	16	2,4,6,11,14	20	5
8	HALD	31,36	40	13	12	2
10	HAHD	35	2,34,39	1,4,5,6,9,19	11	18
13	HALD	23,31,35,37,38,39	30	11,18,20,28	13	24
14	HALD	21, 30	23,24,29,33,34,35,37,38	20	1	16
24	HAHD	21	7	1,2,4,5,9,11,19,27	3,14,18	24
25	HAHD	10,32,33,37,38,39	2,18,23,35	3,7,13,15,19,20	1,8,9,11,12,14,22	1008
28	HAHD	35,38	32	1,2,5,10,19,27,31,33,40	3,4,6,7,20	90

({FP2, AF4, F4, F8, FC6, FC2, C4, T8, CP6, CP2, P4, P8, PO4, O2}). The differencing operation yields 196 ΔFs over 196 channel pairs. The ΔFs are concatenated to form a feature vector ΔF^k_{l-r} , where k indicates the kind of feature and hence can be any of FD, 1-6 STAT, theta, alpha and beta power.

C. Linear Correlation

To see how ΔF correlates with subject's valence ratings v, the Pearson correlation coefficient is analyzed for each kind of feature per channel pair. In this analysis, ΔFs computed using non-overlapping sliding window from trials under the same arousal dominance condition are concatenated to form a vector Φ. Subject's valence ratings from all trials under the same arousal dominance condition are concatenated to form a vector Ψ. Linear correlation between Φ and Ψ is given by

$$r(\Phi,\Psi)=\frac{\mathrm{cov}(\Phi,\Psi)}{\sigma_\Phi\sigma_\Psi}, \tag{2}$$

where $\mathrm{cov}(\cdot)$ is the covariance operator and σ denotes the standard deviation.

D. Regression

The Support Vector Regression (SVR) with Radial Basis Function (RBF) kernel implemented in LIBSVM [21] is adopted in this study. The goal of a regressor is to perform real-value mapping f, such that $f(\Delta F^k_{l-r})\rightarrow v$, where ΔF^k_{l-r} is the feature parameters of kind k and v is the valence rating by the subject. It is worth noting that v is continuous, hence continuous rather than discrete emotion recognition is possible under regressive approach.

After feature extraction, half of the data are randomly drown to form a training set, and the other half will be used as a test set. The training set will be used to tune the SVR parameters C and γ in a grid-search manner. The test set will be used to evaluate the regression performance in a leave-one-out fashion. The regression performance is measured by mean absolute error (MAE)

$$MAE=\frac{1}{N}\sum_i^N\left|\hat{v}_i-v_i\right|, \tag{3}$$

where $\hat{v}_i$ is the estimated valence rating of the ith sample given by the regressor, and v_i the true valence rating given by the subject.

As can be seen in Table I, the numbers of available trials for different valence levels are not balanced. To avoid unbalanced comparison and to focus on estimating four valence levels, we repeatedly draw one trial from each of the four levels until all possible trial combinations have been exhausted. The regression performance is evaluated on and averaged over the test sets of all trial combinations. The numbers of trial combinations are listed in the last column in Table I.

We conduct two kinds of evaluations. In the first kind, the regressor is trained with and tested on four levels' resources. In the second kind, the regressor is trained with two level's resources (min valence level and max valence level), but tested on four levels' resources. The purpose of the second kind of evaluation is to investigate whether it is possible to minimize training resources. Considering that the acquisition of EEG training data is laborious, and the calibration process maybe tedious for some subjects, it is helpful to minimize training resources so that the subject can start to use the brain-computer interface as fast as possible.

III. RESULTS AND DISCUSSIONS

The linear correlation between subject's valence ratings and different features from the best channel pair are presented in Table II. To compensate for multiple comparisons, the 0.05 alpha level is divided by a factor of 196. Only when the p value is smaller than 2.55e-04 is it considered significant (marked by *). The results in Table II show that FD, 3rd and 5th STAT and beta power have significant linear relationship with valence ratings. Thus, the features may be used as an indicator to reveal the subject's valence level. The results also support the lateral phenomenon related to valence perception, though the lateral pattern varies among different features and subjects.

The subject's valence level is estimated by SVR using different kinds of feature in two schemes. In the first scheme, the regressor is constructed with training resources from four valence levels, and tested on four valence levels, in a leave-one-out manner based on the exhaustion of all level combinations. To take advantage of the linear relationship, in the second scheme, the regressor is trained with only two levels' resources (max and min levels), but tested on four levels' resources, in the same

TABLE II. LINEAR CORRELATION COEFFICIENT BETWEEN SUBJECT'S VALENCE RATINGS AND DIFFERENT FEATURE. ASTERISK INDICATES SIGNIFICANCE.

Subject	Arousal/Dominance	FD	STAT						Power		
			1st	*2nd*	*3rd*	*4th*	*5th*	*6th*	*theta*	*Alpha*	*Beta*
5	HAHD	-0.42*	0.29	0.36*	0.49*	-0.48*	0.48*	-0.49*	0.28	0.31	-0.36*
5	LALD	-0.29*	-0.11	-0.27	-0.31*	-0.24	-0.32*	-0.26	-0.14	-0.27	-0.33*
7	HALD	0.45*	0.27	-0.68*	-0.72*	0.48*	-0.73*	0.48*	-0.47*	-0.40*	-0.66*
8	HALD	0.54*	-0.19	0.46*	0.52*	0.51*	0.51*	0.51*	-0.28	0.45*	0.53*
10	HAHD	0.55*	-0.12	-0.53*	-0.77*	0.51*	-0.76*	0.51*	-0.20	-0.24	-0.70*
13	HALD	-0.54*	-0.16	0.34*	0.59*	-0.53*	0.57*	-0.52*	0.21	0.25	-0.47*
14	HALD	0.28	0.26	-0.27	-0.61*	0.37*	-0.57*	0.35*	0.18	0.27	0.44*
24	HAHD	-0.28*	0.18	-0.14	-0.31*	-0.26	-0.32*	-0.22	-0.09	-0.18	-0.21
25	HAHD	-0.17	0.11	-0.18	-0.29*	-0.17	-0.26*	-0.17	-0.15	0.14	0.23*
28	HAHD	0.23	0.12	0.28*	0.37*	0.23	-0.37*	0.25*	0.23	0.23	0.31*

cross-validation manner as the first scheme. In both schemes, the final MAE is averaged over 5000 bootstrap-sampled MAEs per subject. Reported in Table III are the final MAE averaged over all subjects, and the boxplots of MAE averages are shown in Fig. 1 for different features. In Table III, FD feature achieves the minimal MAE in comparison with other features in both evaluation schemes. The MAE also tends to decrease when the step size shrinks. The minimal MAE averages of 0.74 and 1.45 are obtained by FD feature for the first and the second schemes, respectively. In the STAT portfolio, the 3rd STAT performs the best under 50.00 % window overlapping, but is inferior to the 4th STAT when window overlapping exceeds 50.00 %. The combination of all STAT features is not found to improve the performance. In the power feature portfolio, similarly, a combination of theta, alpha and beta does not lead to improved performance. The best power feature is from beta band. In all features, performance of the second evaluation scheme at step size 32 is comparable to that of the first scheme at step size 128.

In Fig. 1, the upper and the lower portion show the boxplots of the first and the second evaluation scheme, respectively. It can clearly be seen that FD has the minimal MAE average in all cases. However, the boxes for the 4th and 6th STAT are more compact, indicating smaller variance. The tendency that MAE decreases when window overlapping increases is mostly noticeable for FD, the 4th and 6th STAT.

To compare the two evaluation schemes, we further analyze the 95.00 % bootstrap confidence interval of MAE averages in both evaluation schemes for FD feature, using the BCA (Bias-Corrected and Accelerated) method [22]. The boxplots in Fig. 2 show the lower and upper bounds of the 95.00 % confidence intervals for both schemes under different window overlapping. The blue boxes represent the first evaluation scheme—training with full resources, whereas the beige boxes represent the second evaluation scheme—training with minimal resources. As we can see from Fig. 2, when the sliding window does not overlap, the confidence intervals under two evaluation schemes have substantial overlapping. This may indicate that the performance does not significantly differ. However, when window overlapping increases, confidence interval overlapping shrinks. No confidence interval overlapping exists when sliding window overlaps above 87.50 %. The performance of the two schemes differs significantly at this level. Both schemes yield improved results when sliding window overlapping increases. However, it is not clear whether the improvement is due to dependency introduced by overlapping window.

IV. CONCLUSION

Human emotion recognition is an integral part of affective computing. EEG-based emotion recognition attempts to identify human emotion by means of spontaneous brain signals, thus has the potential to assess the truly felt emotion from within the subject. An affective brain-computer interface can benefit the user in a number of applications, including but not limited to entertainment. Previously, EEG-based emotion recognition was explored extensively in a classificatory manner. The use of descriptive emotion label is intuitive but suffers from a few drawbacks. In this manner, emotions are discretized by a set of pre-defined emotion labels, whereas human emotions are more of a continuous phenomenon. In this work, we explore to estimate subject's valence level in a continuous way by means of a regressive approach. Valence level has been associated with the pleasantness level under the valence-arousal-dominance emotion model. A portfolio of EEG features including FD, STAT and band powers is investigated. FD, 3rd and 5th STAT and beta power are found to significantly correlate with valence level. We adopt a SVR to estimate subject's valence level from the EEG signals in two evaluation schemes. In the first evaluation, the SVR is constructed with training resources from four valence levels, and tested on four valence levels. In the second evaluation, the SVR is trained with only the minimal number of resources—the max and min valence level—and tested on four levels. Confidence interval analysis shows that the performance of the two evaluation schemes do not differ significantly when the sliding window are non-overlapping. Both schemes yield improved results when sliding window overlapping increase. MAE averages of 0.74 and 1.45 can be achieved under the first and the second evaluation scheme, respectively, by FD feature. It is possible to minimize training resources if it is crucial to do so, at a fair amount of performance trade-off for ease of training. A smaller step size setting may be advisable when one wants to minimize training resources. The merits of a regressive approach over a classificatory approach lie in continuous emotion recognition, and the possibility to reduce EEG training resources to minimal level.

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TABLE III. MAE AVERAGE OVER ALL SUBJECTS UNDER DIFFERENT EVALUATION SCHEMES, DIFFERENT FEATURES AND DIFFERENT OVERLAPPING WINDOW SETTINGS.

Step size (Overlapping)	Evaluation Scheme	FD	STAT								Power			
			1st	*2nd*	*3rd*	*4th*	*5th*	*6th*	*STAT Combined*	*theta*	*alpha*	*beta*	*Power combined*
512 (0.00 %)	1st	**2.27**	2.71	2.58	**2.27**	2.47	2.32	2.52	2.43	2.72	2.69	**2.42**	2.70
	2nd	**2.41**	2.75	2.71	**2.50**	2.58	2.53	2.61	2.63	2.76	2.75	**2.59**	2.75
256 (50.00 %)	1st	**1.83**	2.72	2.39	**1.97**	1.99	2.03	2.06	2.11	2.60	2.56	**2.15**	2.53
	2nd	**2.09**	2.75	2.55	**2.21**	2.22	2.26	2.28	2.35	2.74	2.71	**2.31**	2.69
128 (75.00 %)	1st	**1.40**	2.74	2.28	1.75	**1.57**	1.84	1.66	1.91	2.54	2.43	**2.00**	2.42
	2nd	**1.83**	2.76	2.50	2.09	**1.91**	2.14	1.98	2.19	2.71	2.64	**2.22**	2.63
64 (87.50 %)	1st	**1.02**	2.72	2.14	1.54	**1.16**	1.63	1.25	1.70	2.46	2.28	**1.84**	2.27
	2nd	**1.60**	2.75	2.42	1.91	**1.68**	1.99	1.72	2.03	2.66	2.54	**2.14**	2.51
32 (93.75 %)	1st	**0.74**	2.72	2.00	1.34	**0.84**	1.44	0.90	1.47	2.38	2.11	**1.70**	2.10
	2nd	**1.45**	2.75	2.30	1.75	**1.52**	1.83	1.55	1.86	2.60	2.42	**2.06**	2.40

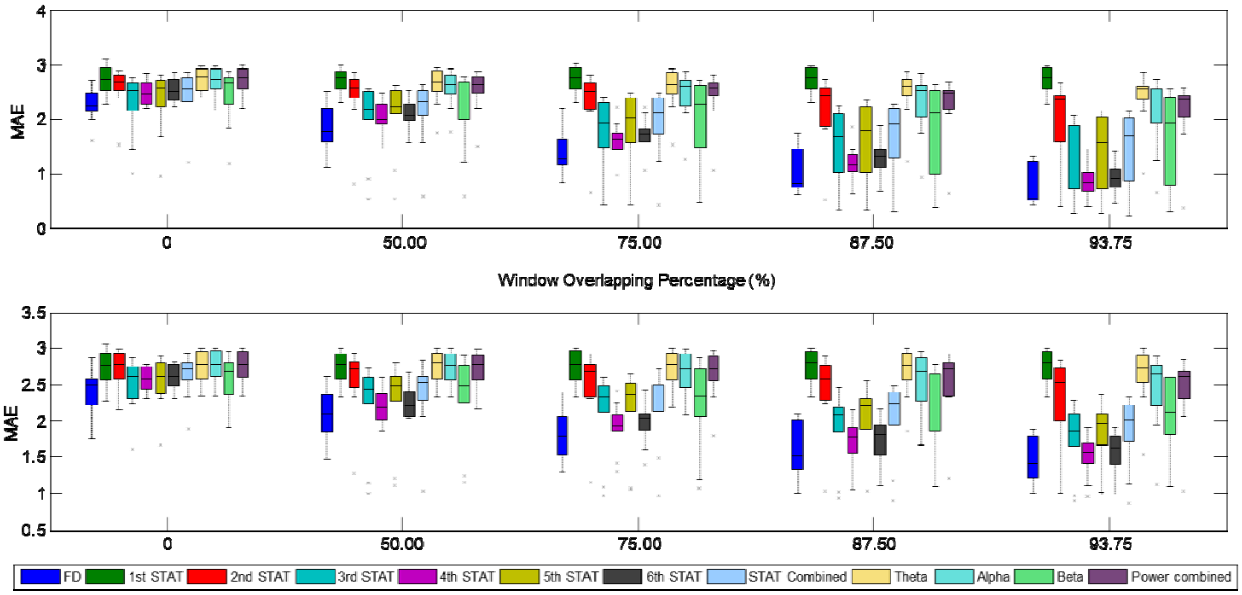

Figure 1. Boxplots showing distribution of MAE averages over all subjects. Upper: 1st evaluation scheme—train with full resources. Lower: 2nd evaluation scheme—train with minimal resources.

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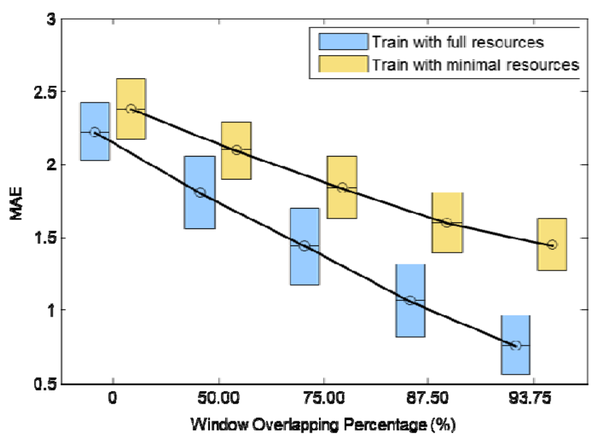

Figure 2. Boxplot showing 95.00% confidence intervals of MAE by FD feature under different overlapping window settings and two evaluation schemes: 1st scheme—train with full resources; 2nd scheme—train with minimal resources.

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