Real-Time Mental Arithmetic Task Recognition From EEG Signals

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***Abstract*—Electroencephalography (EEG)-based monitoring the state of the user's brain functioning and giving her/him the visual/audio/tactile feedback is called neurofeedback technique, and it could allow the user to train the corresponding brain functions. It could provide an alternative way of treatment for some psychological disorders such as attention deficit hyperactivity disorder (ADHD), where concentration function deficit exists, autism spectrum disorder (ASD), or dyscalculia where the difficulty in learning and comprehending the arithmetic exists. In this paper, a novel method for multifractal analysis of EEG signals named generalized Higuchi fractal dimension spectrum (GHFDS) was proposed and applied in mental arithmetic task recognition from EEG signals. Other features such as power spectrum density (PSD), autoregressive model (AR), and statistical features were analyzed as well. The usage of the proposed fractal dimension spectrum of EEG signal in combination with other features improved the mental arithmetic task recognition accuracy in both multi-channel and one-channel subject-dependent algorithms up to 97.87% and 84.15% correspondingly. Based on the channel ranking, four channels were chosen which gave the accuracy up to 97.11%. Reliable real-time neurofeedback system could be implemented based on the algorithms proposed in this paper.**

***Index Terms*—Brain state, electroencephalography (EEG), fractal dimension, mental arithmetic task, neurofeedback.**

I. INTRODUCTION

MODERN electroencephalography (EEG) devices provide us a convenient way to monitor human brain activities in real-time as recently, EEG devices became wireless and portable. EEG devices like Emotiv [1], could be used easily in real-time applications as EEG data are transmitted through the Bluetooth, and such device could be setup within minutes. The convenience of the EEG technology has boosted further development of EEG-based applications such as brain–computer interfaces (BCIs) [2]–[6], neurofeedback systems [7]–[9], and brain function training [10]–[12] and performance training systems [13].

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Neurofeedback games could be used for training of different brain functions. Mental arithmetic task recognition from EEG in real-time could be useful for patients with psychological disorders like dyscalculia where the difficulty in learning and comprehending the arithmetic exists [14], attention deficit hyperactivity disorder (ADHD) [15], and autism spectrum disorders (ASD) [9] where attention deficit problem exists. It is also feasible to build a neurofeedback system based on mental arithmetic task recognition algorithm for healthy adults to improve their working performance. Similar approach could be used for the concentration training of drivers or nuclear facility operators as well.

In previous works, mental arithmetic task recognition and training systems were mainly based on EEG power spectrum density (PSD) calculation [16]–[18]. For example, in [16], decrease at lower beta band within the left parietal cortex was associated to a sign of retrieval of arithmetic facts from long term memory. In another work [17], significant changes in alpha band and beta band were reported when the subject was doing the mental arithmetic task. Besides PSD features, autoregressive model (AR) coefficients were also successfully applied for mental arithmetic task classification in [19].

Although, the power spectrum based features of EEG signals were well applied in EEG related researches like arithmetic recognition, those linear features may not characterize nonlinearity of brain activities. Nonlinear analysis of EEG signals could afford more information from different aspects [20]. In our work, fractal dimension models are used to quantify the complexity of EEG signals to represent the dynamic properties of brain activities. Nonlinear FD features have been proven effective in EEG studies [21]–[24]. Compared to the linear PSD features, fractal dimension features could perform better in EEG-based applications such as emotion recognition [25], neurofeedback [26], [27].

In this work, we designed and implemented an experiment on induction of mental arithmetic task and relaxed states. We proposed generalized Higuchi fractal dimension spectrum (GHFDS) to analyze the multifractality of EEG signals and applied it in the mental arithmetic tasks recognition. AR features [19], statistical features, PSD features, and GHFDS features were extracted to analyze the recorded EEG data. The features and its combinations were analyzed. It was shown that using the GHFDS features in combination with other features could enhance the mental arithmetic task classification rate. The possibility of reducing the number of channels used in the mental arithmetic task classification was discussed.

TABLE I
MENTAL TASKS CLASSIFICATION ACCURACY FOR ALL SUBJECTS
(32 PRINCIPAL COMPONENTS WERE USED)

Subject	Gender	Efficiency	Accuracy	Std
1	Female	30	100%	0
2	Male	16	91.89%	11.59
3	Female	22	100%	0
4	Male	24	98.42%	3.16
5	Male	23	97.89%	4.21
6	Male	20	97.78%	4.44
7	Male	24	98.04%	2.41
8	Male	28	98.22%	3.56
9	Female	17	100%	0
10	Male	54	89.13%	7.10

II. METHOD

A. Mental Arithmetic Task Experiment

Mental arithmetic tasks experiment was organized for 10 subjects aged from 22 to 30. In order to minimize the impact of the subjects' intelligence level, postgraduate students and research staff were chosen as participants of the experiment. Two mental tasks for relax and arithmetic operation were arranged respectively following the standard procedures [16], [20]. Each subject had two sessions. Each session had either relax or mental arithmetic task. Each session lasted 2 min. In the relax task, subjects were asked to open their eyes and try to be relaxed. There was no mental arithmetic task to fulfill in this session. Subjects were required to breathe deeply and focus on their breath. In the mental arithmetic task, subjects were required to complete arithmetic calculations as quick as possible. Totally, 100 three-digits addition problems, (for example, $752 + 464$) were printed and given to each subject to make sure it is enough for the 2 min session. The subjects did not need to write down the answers to avoid additional movements of their head and body. The number of arithmetic problems solved by each subject in 2 min is listed in Table I as the "efficiency" column. During each session, EEG signals were recorded for further processing and classification.

EEG signals from 14-channels were recorded by Emotiv device with 128 Hz sampling frequency and 16-bit A/D resolution. The Emotiv device can be set up quickly and it is suitable for real-time applications [6], [13]. The electrodes were placed according to the extended 10–20 international system [28]. The 14 positions were AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4. All positions and contacts of the Emotiv electrodes were examined carefully before recording to make sure that locations of the EEG sources are correct. EEG signals were transmitted to computer with Bluetooth and were recorded with Emotiv TestBench software.

The overall EEG processing procedure for mental arithmetic task classification is shown in Fig. 1. The same procedure was used in mental tasks classification in [19]. The EEG data recorded in each session was divided into five nonoverlapping trials in order to provide block wise partitioning of the data. First, artifacts were removed with 2–42 Hz 324-order equiripple FIR band-pass filter and notch filter as it was recommended by Emotiv device designer and in [29]. Both filters were designed with Matlab signal processing toolbox. Raw EEG signals were normalized to zero mean and variance one. Normalized EEG signals were divided into 4-s segments with the overlapping of 3 s (as shown in Fig. 2). In each trial, 21 segments could be extracted. The first and the last segments in each trial were dropped out to avoid overlapping between different trials. The remaining 19 segments were used in the classification. Segments contains ocular artifacts detected with a fixed-weight leakage normalized stochastic least mean fourth algorithm [30] are ignored. Totally 95 segments could be extracted at most for one session. Features were extracted, and PCA method was used to construct the feature space. One out of five trials is used for establishing the classifiers' parameters. Four-fold cross validation was used for remaining four trials of the recorded EEG signals.

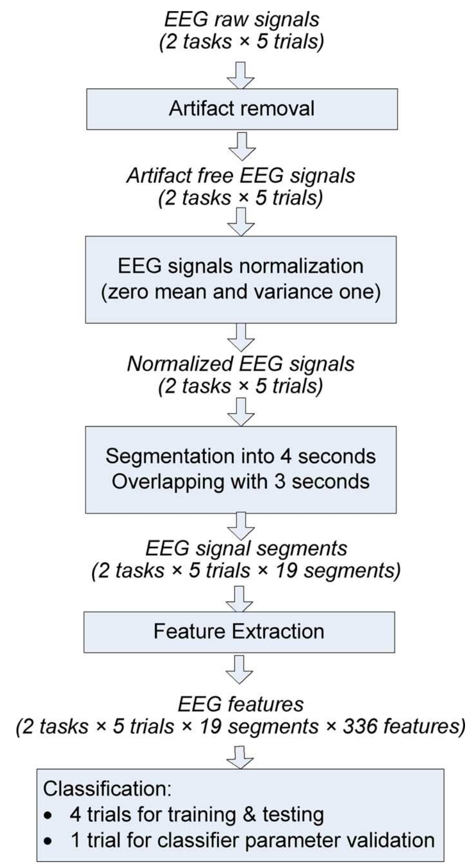


Fig. 1. Flow diagram shows the overall procedure for metal tasks classification using raw EEG signals.

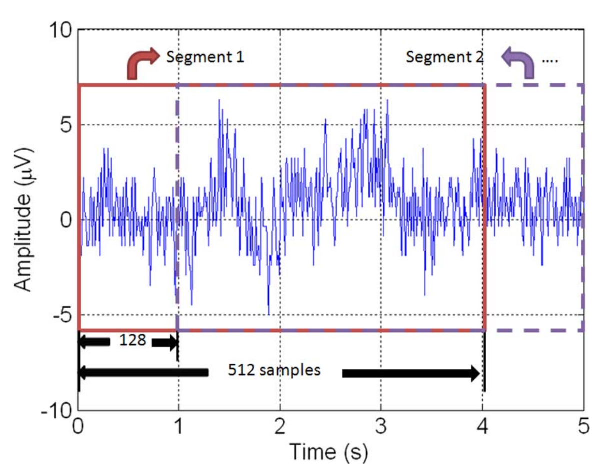


Fig. 2. EEG signals were divided into 4-s segments with the overlapping of 3 s.

B. Feature Extraction

In the feature extraction step, EEG frequency band power, six order AR model coefficients, statistical features, and fractal dimension features were extracted.

EEG frequency band powers were widely used in EEG analysis. Powers over δ band (2–4 Hz), θ band (4–8 Hz), α band (8–12 Hz), β_1 band (12–18 Hz), β_2 band (18–30 Hz), and γ band (>30 Hz) were estimated with periodogram method [16]. AR model was also successfully applied in EEG based mental tasks classification [19] and other EEG applications [31]. Six-order AR model was applied in this experiment and six coefficients were estimated as features. Statistical features were well adopted in EEG based emotion recognition [32], [33]. In this work, six statistical features were extracted, i.e., means of the raw signal, standard deviations of the raw signal, means of the absolute value of the first and second difference of the raw signal, means of the absolute value of the first and second difference of the normalized signal.

Fractal dimension value is a standard quantification of self-similarity of an object [34]. There is a well-known method for estimating fractal dimension value of time series, i.e., Higuchi method. In Higuchi method [35], the time series is first divided into different subsequences according to the delay-time embedding technique [36] as shown in (1). N is the number of samples in the signal

$$\begin{aligned} X_k^1 &: x(1), x(1+k), \ldots, x\left(1 + \left\lfloor \frac{N-1}{k} \right\rfloor k\right) \\ X_k^2 &: x(2), x(2+k), \ldots, x\left(2 + \left\lfloor \frac{N-2}{k} \right\rfloor k\right) \\ X_k^k &: x(k), x(k+k), \ldots, x\left(k + \left\lfloor \frac{N-k}{k} \right\rfloor k\right). \end{aligned} \tag{1}$$

The average length $L(k)$ of the time series is calculated by

$$L_k(m) = \frac{1}{k}\left[\left(\sum_{i=1}^{\lfloor \frac{N-m}{k} \rfloor} |x(m+ik) - x(m+(i-1)k)|\right) \times \frac{N-1}{\lfloor \frac{N-m}{k} \rfloor k}\right]$$

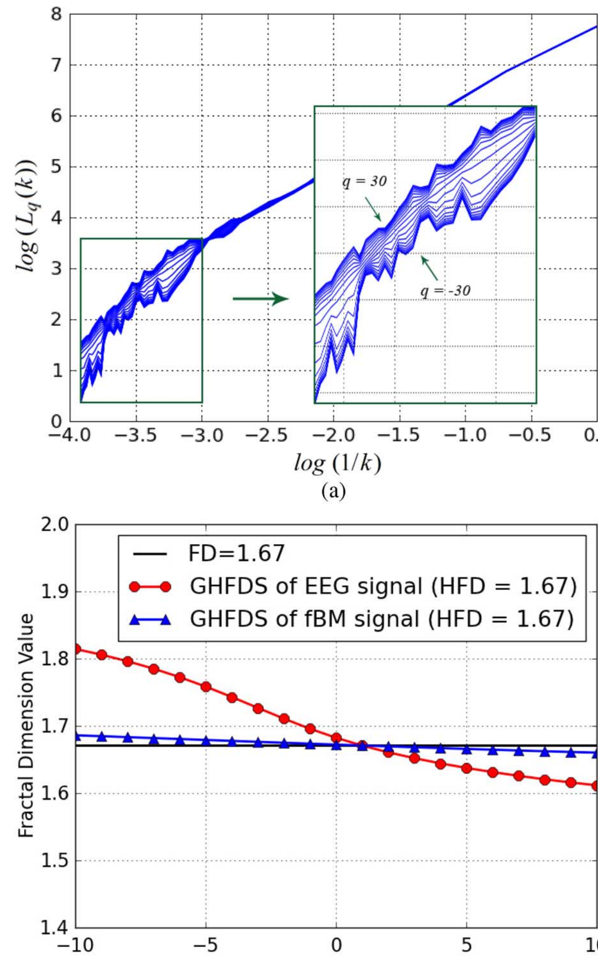
$$L(k) = \frac{1}{k}\sum_{m=1}^{k} L_k(m). \tag{2}$$

The relationship between $L(k)$ and k is shown in

$$L(k) \propto k^{-\mathrm{HFD}}. \tag{3}$$

Higuchi fractal dimension (HFD) has recently become a commonly used tool in fractal dimension analysis of biomedical signals. Biological systems exhibit a complex behavior which cannot be characterized with single fractal dimension value [37]. In our work, in order to quantify the multifractality of EEG signals, Higuchi method was generalized to the form of fractal dimension spectrum (named GHFDS) by indentifying the scaling of the qth-order moments where the power-law depends on the average subsequence length. The original Higuchi method is using the first moment as $q = 1$.

In our new GHFDS method, time-series is divided into several subsequences in the same way as in Higuchi method in (1).



(a)
(b)

Fig. 3. (a) Proportional relationship between $L(k, q)$ and FDS_q for EEG signal. (b) GHFDS of mono-fractal signal (fBM signal) and multi-fractal signal (EEG signal), and CFDS of fBM signal.

In the average length calculation step, the order parameter q is introduced. The average length for the order q is calculated by

$$L_q(k) = \left(\frac{1}{k}\sum_{m=1}^{k} [L_k(m)]^q\right)^{\frac{1}{q}}, \quad q \in R, q \neq 0 \tag{4}$$

$$L_0(k) = \exp\left(\frac{1}{k}\sum_{m=1}^{k} \log [L_k(m)]\right). \tag{5}$$

The relationship between $L_q(k)$ and k is shown in

$$L_q(k) \propto k^{-FDS_q}. \tag{6}$$

Fractal dimension methods could be tested on mono-fractal signals such as fractional Brownian motion (fBM) signal [38] or Weierstrass signals [39] where theoretical fractal dimension values are known in advance and have the same fractal dimension values if different orders are used. The mono-fractal fBM signal with FD $= 1.67$ was generated and used for the testing. The GHFDS values of the fractional Brownian motion signal and multi-fractal signal (EEG signal) were calculated by the proposed generalized fractal dimension method described by (4) and (5). In Fig. 3(a), the proportional relationship between $L_q(k)$ and FDS_q for EEG signal is shown. The slopes are different when the order parameter q changes from -30 to 30 that correspond to theoretical prediction. In Fig. 3(b), the fBM signal and EEG signal have the same fractal dimension value of order 1 (FD $= 1.67$). The blue line is the calculated fractal spectrum GHFDS of the fBM signal where the red line is the calculated fractal spectrum GHFDS of EEG signal (multi-fractal signal). Compared to the generalized correlation fractal dimension spectrum (CFDS) [40], our GHFDS method could obtain flatter spectrum for mono-fractal fBM signal which ideally has to be a constant. The time complexity of GHFDS $(O(n))$ is also smaller than that of CFDS $(O(n^2))$.

In our experiment, six GHFDS values for $q = 0, \ldots, 5$, which could quantify the scaling effects of the larger fluctuation [41], were extracted to represent the multifractality of EEG signals.

C. Principal Component Analysis

Principal component analysis (PCA) is a quantitative method for reducing the redundant information among all the observations. Some extracted features are strongly correlated to other features, e.g., within statistical features there are features depending on each other. PCA models can extract significant components from the original data by mapping the data to the principal component (PC) space [42]. The PCA model can be represented as follows:

$$X = TP^T + E \tag{7}$$

where X is the original data matrix. Each row of X represents one observed sample. T is the scores matrix which represents coordinates in PC space. P is the loadings matrix which reveals the relations between the original space and PC space.

In general, higher-order PCs represent the noisy. With appropriate PC selection strategy, reduced scores matrix (T) could be used as new features. Loadings matrix (P) could be used for transforming new data into PC space.

D. Classification

Support vector machines (SVMs) [43] were used for mental arithmetic task classification.

SVMs are learning systems which are used in high feature dimension classification. The aim of support vector machine is to devise a computationally efficient way to calculate optimal separating hyperplanes. The distance from hyperplanes to the nearest sample point in each class is maximized. SVM with radial basis function (RBF) as kernel was applied in mental tasks classification. The dual form of the optimization problem is shown in

$$\begin{aligned} &\text{maximize} \sum_{i=1}^{m} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{m} y_i y_j \alpha_i \alpha_j K(\overrightarrow{x_i}, \overrightarrow{x_j}) \\ &s.t. \sum_{i=1}^{m} \alpha_i = 0, \quad 0 \le \alpha_i \le C \ for\ i = 1, 2, \ldots m. \end{aligned} \tag{8}$$

The RBF kernel function is shown in

$$K(\overrightarrow{x_i}, \overrightarrow{x_j}) = \phi(\overrightarrow{x_i}) \cdot \phi(\overrightarrow{x_j}) = \exp\left(-\gamma \left|\left|\overrightarrow{x_i} - \overrightarrow{x_j}\right|\right|^2\right) \tag{9}$$

$\overrightarrow{x_i}$ and $\overrightarrow{x_j}$ are feature vectors.

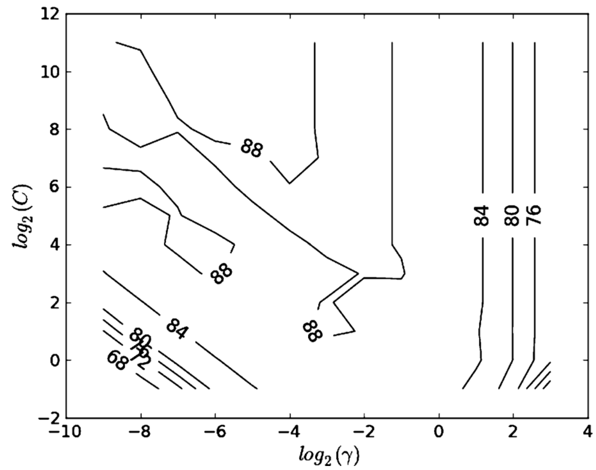


Fig. 4. Contours of validation accuracy for SVMs' parameters (C, γ).

The parameter γ in the kernel function and soft margin parameter C were selected carefully on validation dataset with grid-searching procedure [44].

All the classification results presented in this paper were obtained on NEC PC platform with windows xp, matlab, quad Q9400 2.66-Hz processor, and 4G RAM. LIBSVM [45] package was used as SVMs implementation.

III. Results

A. Classifier Parameter Selection

For SVMs with RBF kernel, two parameters (C and γ) are required to be optimized. Grid-searching technique is used for choosing the best (C, γ) pair in $(\mathrm{C} - \gamma)$ plane on validation dataset. The parameters for all SVMs are assumed to be the same. In Fig. 4, the validation accuracy is demonstrated with contour lines in $(\mathrm{C} - \gamma)$ plane. The $(\mathrm{C}, \gamma) = (2^4, 2^{-5})$ is chosen due to the SVMs with this parameter pair can achieve the best validation accuracy 89.0%.

For each segment of EEG data, totally 336 features were extracted. PCA method was used to reduce the dimension of the feature space when all features were used. The principal component loadings matrix (P) was calculated using the training dataset, and then, it was applied to the testing dataset to extract the principal component coordinates. The number of PC components used in the experiment is discussed according to the classification success rate. Fig. 5. shows the boxplots for mental arithmetic task classification accuracy based on different number of principal components. The mean accuracy is marked as the star symbol. Mean accuracy and standard deviation are also displayed below each boxplot. The classification accuracy based on features without PCA is also shown in this boxplot. If the largest 32 principal components are used, the average classification accuracy is 97.14%, which is almost the same as when all features are used (97.87%). In our algorithm, 32 principal components were selected.

The mean accuracy of the mental arithmetic task classification for each subject was evaluated using four-fold cross validation. The results are shown in Table I. The "efficiency" column records the average number of math addition problems they

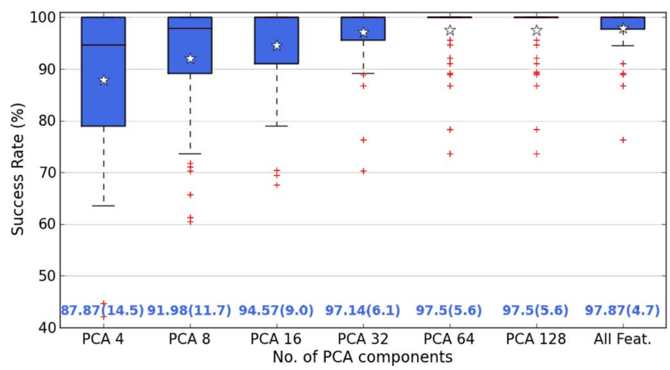


Fig. 5. Boxplot for mental tasks classification accuracy. Different number of PCA components was used in the experiment. The performance of the classifier increases when more PCA components are used. Last (on the right) boxplot represents the classification accuracy when all features are used. When more than 32 components are adopted, the performance of the classifier stays the same.

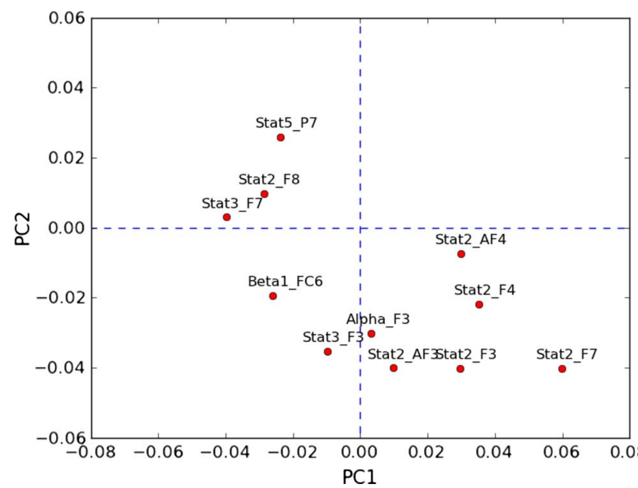


Fig. 6. PCA loadings plot for PC1 and PC2. The features of which the loadings distance to the origin (0, 0) is larger than 0.03 are shown in the loadings plot. The features are labeled with the feature type and channel number. "Stat" stands for the statistical feature. "Beta1" and "Alpha" are PSD features.

solved during the "arithmetic" session. Subject 2 has the lowest efficiency during the math test, and Subject 10 has the highest efficiency. However, Subject 10 explained that he did not do the calculation with care. It could be a possible reason that the classification rate of both Subject 2 and Subject 10 are worse than that of the other eight subjects.

B. Feature Comparison

In our experiment, totally four groups of features were extracted for mental arithmetic task classification. Within these features, EEG frequency band powers represent the power distribution in frequency domain. These features are commonly used for EEG analysis in neurofeedback systems. AR features are parameters in linear prediction model which reveal the relations between current sample and previous samples. Six statistical features are common quantifications used in statistics that represent the mean, standard deviation, and gradients. Higuchi fractal dimension spectrum is used to quantify the complexity and multifractality of the EEG epoch.

First, we analyze the loadings plot in PCA to compare different features. In Fig. 6, the loadings plot for PC1 and PC2 is shown. In this figure, the average loadings matrix is analyzed. The features of which the loadings distance to the origin (0, 0) is larger than 0.03 are shown in the loadings plot. The features are labeled with feature type and channel number. From the loadings plot, in general, statistical features have the most significant influence to PC1 and PC2. However, using only two components cannot get high classification accuracy, and the loadings values for all features are relatively small and closed to each other. The other features may also be important for arithmetic mental task classification.

We also conducted a comparison between different types of features by measuring the classification accuracy based on these feature groups individually. The features comparison result is shown in Fig. 7. In each test, all channels were used. Mean accuracy of the mental arithmetic task classification for 10 subjects is listed. Statistical features obtained the best mean classification accuracy 90.33%. AR model coefficients and GHFDS got 83.96% and 80.57% mean accuracy respectively which were lower than that of statistical features but significantly higher than that of power features (67.07%). Combing all features together enhanced the classification accuracy significantly up to 97.87%.

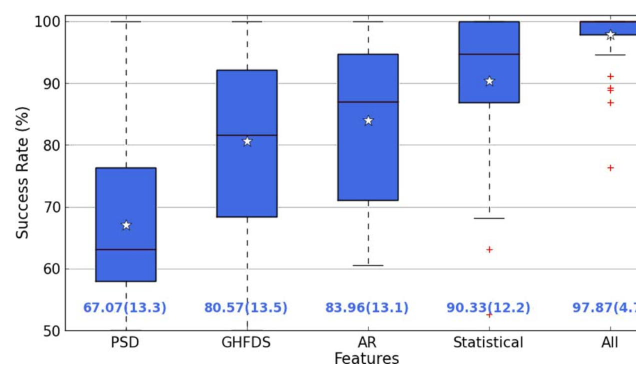


Fig. 7. Boxplot for mental tasks classification accuracy based on different features. Last (on the right) boxplot represents the classification accuracy when all features are used.

C. Reduce Number of Channels

One of the aims of our work is to build a portable real-time EEG based mental training neurofeedback system. Minimizing the number of EEG channels used in mental tasks classification algorithms would make the system more mobile and easier to setup and maintain.

First, we ranked all 14 channels based on the mental arithmetic task classification accuracy by using all features extracted for each channel. Table II shows the rank of all channels according to the mental arithmetic task classification accuracy. Features from the channel F8 achieved the best classification mean accuracy equal to 84.15%. This result is consistent with the real-time FD value observations shown in Fig. 9 where the scaled Higuchi FD values in frontal lobe are significantly different when the subject is processing arithmetic operations: the subject has the lowest HFD in the relaxed session compared to the highest HFD in the mental arithmetic session.

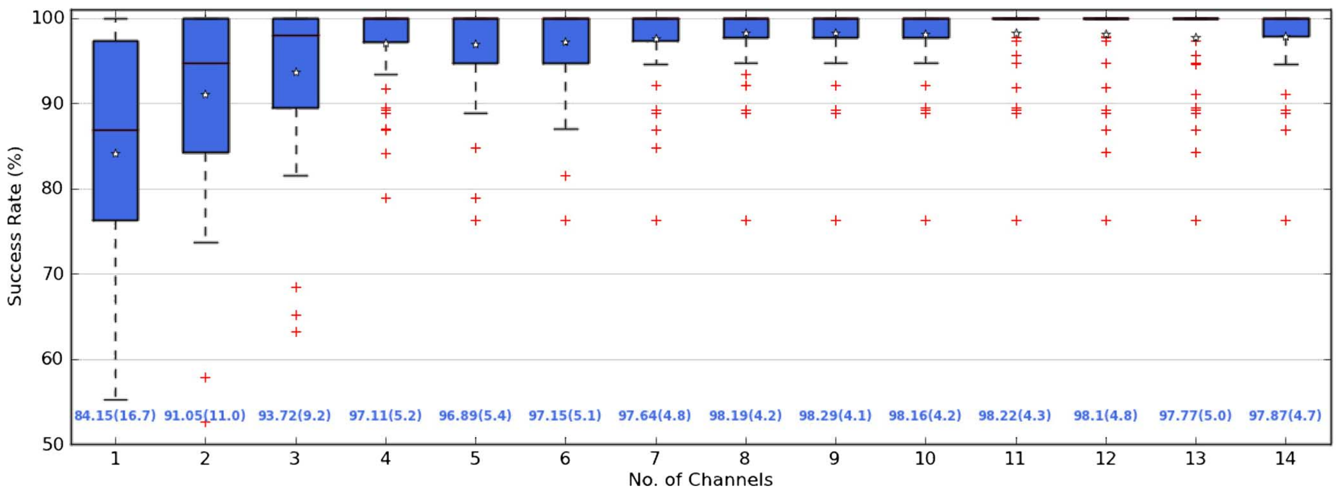


Fig. 8. Boxplot for mental tasks classification accuracy. Different number of channels is used in this experiment. These channels are selected according to the channels rank table in each step.

TABLE II
RANK OF CHANNELS FOR MENTAL TASKS CLASSIFICATION

Channels (10-10 System)	Mean Accuracy	Std
F8	84.15%	11.94
F3	82.15%	16.70
O2	79.46%	15.82
AF3	78.42%	18.09
AF4	77.38%	14.78
F4	76.72%	21.97
P8	76.33%	20.54
O1	75.57%	20.72
FC5	75.56%	18.04
P7	75.41%	18.77
FC6	71.86%	21.31
F7	70.76%	22.30
T7	70.45%	21.23
T8	69.42%	18.78

Then, channels were selected according to the channel accuracy rank shown in the Table II. For example, when four channels were used in the algorithm, the following channels located at F8, F3, O2, AF3 are selected. The features from the selected channels were used in mental arithmetic task classification. The comparison of mean classification accuracy was conducted when different number of channels for all features (without PCA) was used. As it is shown in Fig. 8, the mean classification accuracy increases when the number of channels used in the experiment increased. However, if more than four channels are selected, the accuracy would not be significantly improved. Finally, for the mental arithmetic task recognition algorithm, four channels located at F8, F3, AF3, O2 were chosen as it gave 97.11% accuracy.

D. *Time Complexity of Feature Extraction Methods*

As our final objective is to build a real-time mental arithmetic task recognition system, the time spent on the feature extraction step should be reasonable. The algorithms for extracting PSD features, AR features, Statistical features, and GHFDS features have time complexity O(nlog(n)), O(n), O(n), and $\mathrm{O}(\mathrm{n}\log^2(\mathrm{n}))$, respectively. Then, time complexity of extracting all features for one segment of the signal is $\mathrm{O}(\mathrm{n}\log^2(\mathrm{n}))$. Extracting all features from one EEG channel under MATLAB R2010a on a desktop with Core 2 Quad CPU Q9400 @ 2.66 GHz and 3.25 GB RAM could be completed within 400 ms. The feature extraction algorithms could be used in real-time mental arithmetic task recognition systems with four EEG channels. If all 14 EEG channels are used, a suitable parallel computing framework, for example, framework MapReduce [47] could be applied. Applying parallel computing frameworks on clusters would help accelerate the feature extraction process.

IV. DISCUSSION

In Section III, four groups of features were extracted from 14 EEG channels, and the classification accuracy was analyzed. Classification parameters were selected by grid-searching in $(\mathrm{C}-\gamma)$ plane. 32 PCA components were used to reduce the dimension of the feature space when all features were applied. In such case, the applicable classification accuracy could be maintained. In this work, the proposed algorithms are subject-dependent ones. We trained a specific SVM model for each subject. When all features and all channels were used, PCA method was applied to reduce the number of features.

GHFDS method was proposed for EEG data analysis, and it was applied for mental arithmetic task classification. FD values could quantify the complexity of the EEG signals. The complexity of EEG signal recorded in frontal lobe is higher when subject is performing the mental arithmetic operations than that of EEG signal recorded when the subject is relaxed as it was seen from Fig. 9. This observation is consistent with the experiment results that the F8 channel is the best channel for mental arithmetic task classification.

Neurofeedback systems based on mental arithmetic task classification algorithms could be used for treating dyscalculia, ADHD, concentration training and performance enhancing with content of games. The features commonly used in neurofeedback games are EEG frequency band powers [16]–[18]. In [16] and [17], the correlation between PSD features and mental arithmetic tasks was reported. In [18], classification of

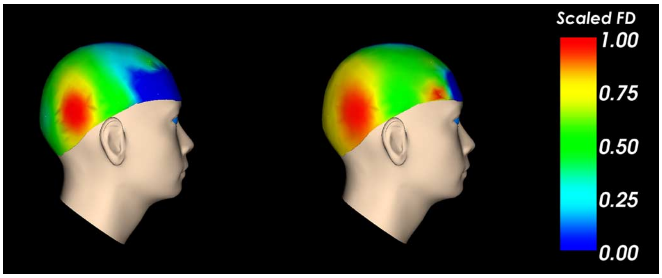


Fig. 9. Real-time Higuchi FD value comparison for two mental tasks. The left color map shows the scaled Higuchi FD value of the subject' brain when he is relaxed. The right color map shows the scaled Higuchi FD value of the subject's brain when he is doing arithmetic operation.

mental arithmetic tasks with different difficulty levels was implemented. EEG frequency band powers were used as features. 83% classification accuracy was reported for two brain states: the state of performing the most difficult mental arithmetic task and the relaxation state using 16 channels. In Fig. 7, it was shown that mental arithmetic task classification accuracy could be enhanced when other features were used together with EEG frequency band powers. Here, accuracy of two brain states recognition (mental arithmetic task and relaxation state) improved from 67.07% with PSD features to 97.87% with all features including PSD, GHFDS, AR, and statistical features using 14 channels. In [19], AR features were used for five types of mental tasks recognition with six EEG channels. In our experiment, combination of AR features with PSD, GHFDS, and statistical features gave better performance in mental arithmetic task recognition than just using AR features. The classification accuracy for two mental states recognition was enhanced by 13.91% (from 83.96% with AR features to 97.87% with all features).

Using less EEG channels in real-time EEG-based applications is another option for reducing the cost in feature extraction process. Systems could also be set up much easier and faster. Meanwhile, with an algorithm based on more EEG channels, applications accuracy could be compromised if any channels were found not activated. Thus, systems based on less EEG channels could be more robust. The tradeoff between reducing number of EEG channels and maintaining the classification accuracy encouraged us to conduct a channel ranking analysis described in Section III-C. Using only four channels which have the highest ranking as it was shown in Table II could maintain good mental arithmetic task classification accuracy.

Emotiv device with 14 channels was selected as the equipment for the experiment. This device can be easily set up without any professional help within short time and can be used for different real-time EEG-based applications. When using the Emotiv device in research, connections of the EEG electrodes should be checked carefully before recording the data. EEG signals are filtered by high order band-pass filter as it was suggested by [29], [46]. Removing ocular artifacts in real-time is still the challenging task. Currently, we are discarding the EEG segments containing the ocular artifacts detected with the fixed-weight leakage normalized stochastic least mean fourth algorithm. Further efforts could be made to correct the EEG signals recorded with eye movement and blinking artifacts.

The proposed algorithms are subject-dependent and need a training session last for 2 min for a new user. Subject-independent algorithms for real-time mental arithmetic task recognition could be studied in the future work to reduce the set up time cost introduced by the training session. In the subject-independent algorithms, SVM models would be trained by larger EEG database and classified by different parameters (age, gender, etc.) first. The user is required to input several parameters, like gender and age. A suitable SVM model with similar parameters would be selected for real-time mental arithmetic task classification.

V. Conclusions

In this paper, we first designed and implemented the EEG based arithmetic mental task experiment with Emotiv device for 10 subjects. After preprocessing the data, four groups of features, i.e., statistical features, AR model coefficients, PSD features, GHFDS features were extracted for the mental arithmetic task classification. Grid-searching technique was used for selecting SVM parameters. First, we proposed mental arithmetic task classification algorithm based on 14 channels. Four groups of features were extracted and 32 PCA components were selected. The mean classification accuracy of 97.14% was achieved. Among all four groups of features, algorithms based on statistical features had the best accuracy compared to other three groups. Using all four groups of features enhanced the accuracy up to 97.87%. One channel located at F8 gave the best mean accuracy equal to 84.15% using all features. Four channels located at F8, F3, O2, AF3 gave the mean classification accuracy 97.11% using all features. The possibility of applying the proposed four-channel mental arithmetic task classification algorithm in neurofeedback systems was also discussed. High accuracy of the mental arithmetic task classification algorithm could enhance the efficiency of neurofeedback systems.

References

[1] K. Stytsenko *et al.*, "Evaluation of consumer EEG device Emotiv EPOC," presented at the MEi:CogSci Conf., Ljubljana, Slovenia, 2011.

[2] B. Rebsamen *et al.*, "Controlling a wheelchair indoors using thought," *IEEE Intell. Syst.*, vol. 22, no. 2, pp. 18–24, Mar. 2007.

[3] R. Krepki *et al.*, "Berlin brain-computer interface—The HCI communication channel for discovery," *Int. J. Human Comput. Studies*, vol. 65, pp. 460–477, 2007.

[4] O. Bai *et al.*, "A high performance sensorimotor beta rhythm-based brain-computer interface associated with human natural motor behavior," *J. Neural Eng.*, vol. 5, pp. 24–35, 2008.

[5] A. Lécuyer *et al.*, "Brain-computer interfaces, virtual reality, and videogames," *Computer*, vol. 41, pp. 66–72, 2008.

[6] K. Stamps and Y. Hamam, "Towards inexpensive BCI control for wheelchair navigation in the enabled environment—A hardware survey," in *Proc. 2010 Int. Conf. Brain Informat.*, Toronto, ON, Canada, 2010, pp. 336–345.

[7] T. Fuchs *et al.*, "Neurofeedback treatment for attention-deficit/hyperactivity disorder in children: A comparison with methylphenidate," *Appl. Psychophysiol. Biofeedback*, vol. 28, pp. 1–12, 2003.

[8] T. M. Sokhadze *et al.*, "EEG biofeedback as a treatment for substance use disorders: Review, rating of efficacy, and recommendations for further research," *Appl. Psychophysiol. Biofeedback*, vol. 33, pp. 1–28, 2008.

[9] L. Thompson *et al.*, "Neurofeedback outcomes in clients with Asperger's syndrome," *Appl. Psychophysiol. Biofeedback*, vol. 35, pp. 63–81, 2010.

[10] D. Vernon *et al.*, "The effect of training distinct neurofeedback protocols on aspects of cognitive performance," *Int. J. Psychophysiol.*, vol. 47, pp. 75–85, 2003.

[11] S. Hanslmayr *et al.*, “Increasing individual upper alpha power by neurofeedback improves cognitive performance in human subjects,” *Appl. Psychophysiol. Biofeedback*, vol. 30, pp. 1–10, 2005.

[12] H. Heinrich *et al.*, “Annotation: Neurofeedback—Train your brain to train behaviour,” *J. Child Psychol. Psychiatry Allied Disciplines*, vol. 48, pp. 3–16, 2007.

[13] G. N. Ranky and S. Adamovich, “Analysis of a commercial EEG device for the control of a robot arm,” in *Proc. Bioeng. Conf.*, 2010, pp. 1–2.

[14] J. Tajar and S. Sharifi, “Dyscalculia: Learning disabilites in mathematice and treatment with teaching remedial method Iranian children 6 years old,” *Aust. J. Basic Appl. Sci.*, vol. 5, pp. 891–896, 2011.

[15] J. F. Lubar *et al.*, “Evaluation of the effectiveness of EEG neurofeedback training for ADHD in a clinical setting as measured by changes in T.O.V.A. scores, behavioral ratings, and WISC-R performance,” *Biofeedback Self-Regulation*, vol. 20, pp. 83–99, 1995.

[16] T. Harmony *et al.*, “Do specific EEG frequencies indicate different processes during mental calculation?,” *Neurosci. Lett.*, vol. 266, pp. 25–28, 1999.

[17] T. Inouye *et al.*, “The 3-dimensional representation of EEG distance by use of Shannon-Gelfand-Yaglom information measure during mental arithmetic,” *Brain Topogr.*, vol. 8, pp. 379–384, 1996.

[18] B. Rebsamen *et al.*, “Evaluation of cognitive workload from EEG during a mental arithmetic task,” in *Proc. Human Factors Ergonom. Soc.*, 2011, pp. 1342–1345.

[19] N. Y. Liang *et al.*, “Classification of mental tasks from EEG signals using extreme learning machine,” *Int. J. Neural Syst.*, vol. 16, pp. 29–38, 2006.

[20] S. Micheloyannis *et al.*, “Usefulness of non-linear EEG analysis,” *Acta Neurologica Scand.*, vol. 97, pp. 13–19, 1998.

[21] X. Wang *et al.*, “Research on the relation of EEG signal chaos characteristics with high-level intelligence activity of human brain,” *Nonlinear Biomed. Phys.*, vol. 4, 2010.

[22] P. Ramanand *et al.*, “Complexity quantification of dense array EEG using sample entropy analysis,” *J. Integrative Neurosci.*, vol. 3, pp. 343–358, 2004.

[23] H. Yang *et al.*, “Correlation dimensions of EEG changes during mental tasks,” in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol.*, 2004, pp. 616–619.

[24] B. Weiss *et al.*, “Comparison of fractal and power spectral EEG features: Effects of topography and sleep stages,” *Brain Res. Bull.*, vol. 84, pp. 359–375, 2011.

[25] Y. Liu *et al.*, “Real-time EEG-based human emotion recognition and visualization,” in *Proc. 2010 Int. Conf. Cyberworlds*, Singapore, 2010, pp. 262–269.

[26] A. Bashashati *et al.*, “Fractal dimension-based EEG biofeedback system,” in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol.*, 2003, pp. 2220–2223.

[27] Q. Wang *et al.*, “Fractal dimension based neurofeedback in serious games,” *Vis. Comput.*, vol. 27, pp. 299–309, 2011.

[28] R. W. Homan *et al.*, “Cerebral location of international 10-20 system electrode placement,” *Electroencephalogr. Clin. Neurophysiol.*, vol. 66, pp. 376–382, 1987.

[29] E. W. Anderson *et al.*, “A User Study of Visualization Effectiveness Using EEG and Cognitive Load,” in *Proc. EuroVis*, Bergen, Norway, 2011, pp. 791–800.

[30] P. Celka *et al.*, “Preprocessing and time-frequency analysis of newborn EEG seizures,” *IEEE Eng. Med. Biol. Mag.*, vol. 20, no. 5, pp. 30–39, Sep./Oct. 2001.

[31] J. Pardey *et al.*, “A review of parametric modelling techniques for EEG analysis,” *Med. Eng. Phys.*, vol. 18, pp. 2–11, 1996.

[32] R. W. Picard *et al.*, “Toward machine emotional intelligence: Analysis of affective physiological state,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 23, no. 10, pp. 1175–1191, Oct. 2001.

[33] K. Takahashi, “Remarks on emotion recognition from multi-modal biopotential signals,” in *Proc. IEEE Int. Conf. Ind. Technol.*, 2004, pp. 1138–1143.

[34] H. Kantz and T. Schreiber, *Nonlinear Time Series Analysis*, 2nd ed. Cambridge, U.K.: Cambridge Univ. Press, 2004.

[35] T. Higuchi, “Approach to an irregular time series on the basis of the fractal theory,” *Physica D: Nonlinear Phenomena*, vol. 31, pp. 277–283, 1988.

[36] W. Van De Water and P. Schram, “Generalized dimensions from near-neighbor information,” *Phys. Rev. A*, vol. 37, pp. 3118–3125, 1988.

[37] P. L. Curto-Risso *et al.*, “Monofractal and multifractal analysis of simulated heat release fluctuations in a spark ignition heat engine,” *Physica A: Stat. Mechan. Appl.*, vol. 389, pp. 5662–5670, 2010.

[38] P. Abry and F. Sellan, “The wavelet-based synthesis for fractional Brownian motion proposed by F. Sellan and Y. Meyer: Remarks and fast implementation,” *Appl. Comput. Harmonic Anal.*, vol. 3, pp. 377–383, 1996.

[39] A. Burykin *et al.*, “Generating signals with multiscale time irreversibility: The asymmetric Weierstrass function,” *Complexity*, vol. 16, pp. 29–38, 2011.

[40] K. Pawelzik and H. G. Schuster, “Generalized dimensions and entropies from a measured time series,” *Phys. Rev. A*, vol. 35, pp. 481–484, 1987.

[41] J. W. Kantelhardt *et al.*, “Multifractal detrended fluctuation analysis of nonstationary time series,” *Physica A: Stat. Mechan. Appl.*, vol. 316, pp. 87–114, 2002.

[42] K. H. Esbensen, *Multivariate Data Analysis in Practice*, 5th ed. Oslo, Norway: CAMO, 2002.

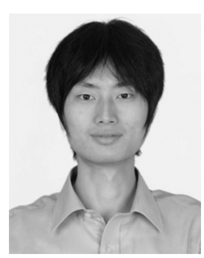
[43] C. J. C. Burges, “A tutorial on support vector machines for pattern recognition,” *Data Mining Knowledge Discovery*, vol. 2, pp. 121–167, 1998.

[44] C. W. Hsu and C. J. Lin, “A comparison of methods for multiclass support vector machines,” *IEEE Trans. Neural Netw.*, vol. 13, no. 2, pp. 415–425, Mar. 2002.

[45] C. C. Chang and C. J. Lin, “LIBSVM: A Library for support vector machines,” *ACM Trans. Intell. Syst. Technol.*, vol. 2, pp. 27:1–27:27, 2011.

[46] J. Dean and S. Ghemawat, “MapReduce: Simplified data processing on large clusters,” *Commun. ACM*, vol. 51, pp. 107–113, 2008.

[47] P. Bobrov *et al.*, “Brain-computer interface based on generation of visual images,” *PLoS ONE*, vol. 6, 2011.



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