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Are you afraid of heights and suitable for working at height?

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ABSTRACT

Fear of highs is one of the most common phobias all around world. It could affect people's life, work and health. Standing on high-altitude can lead to fear, anxiety or even panic to some people. In this paper, EEG method is creatively combined with VR technology to assess the severity of fear of heights. By doing time-frequency analysis, we found that alpha band (8–13 Hz) and high beta (20–30 Hz) are sensitive to fear of heights and frontal and parietotemporal areas are the regions of interests for fear of heights. Then using cross mutual information we built up a functional brain networks of every subject. And we extracted EEG features from the brain networks. Statistical analysis was performed to select the features based on significance of difference. Finally, we implemented classification. The performance of classifiers (the average accuracy could reach 94.44%) based on the proposed method was compared to the performance of classifiers based on the traditional physiological features. As a result, the proposed method was verified to be reliable and superior on estimating the severity of fear of heights. In addition, the system was tested on elderly people and came out with good performance. It turns out that the proposed system has good generalization capability and adaptability.

1. Introduction

Fear of heights (acrophobia) could affect people's life, work and even health, such as elevator maintenance personnel working at heights, senior people with poor ability of balance and ordinary people living and working in high-rise buildings, especially in today's world as more and more high-rise buildings are built. [1–8]. The lifetime prevalence of fear of heights is up to 28%. Fear of highs is one of the most common phobias all around world [9].

There are many speculations about the causes of fear of heights, including the conflict between vision and the somatosensory and vestibular systems; the cognitive bias that explain body sensations and so on. However, researchers generally recognized that visual effects at high altitudes are the core reason [1,10]. Standing at high altitudes, the boundaries of objects are unclear. Our brain has less information so that we feel not safe, especially for people with acrophobia. Since fear of heights is mainly stimulated by visual effects, virtual reality (VR) technology has become a new direction for analyzing fear of heights. With the rapid development of science and technology, researchers started using VR technology to analysis fear of heights, and even established virtual reality exposure therapy (VRET) [11–17].

VR technology has many benefits. First of all, for participants, especially those who are concerned about heights, VR is safer than real situation. Subjects do not have to be exposed to dangerous high altitudes. Meanwhile, laboratory experiments could protect the confidentiality of subjects and prevent possible public embarrassment. Besides, VR technology makes it easier to change experiments settings.

On the other hand, there are many researches using electroencephalography (EEG) to analyze the posture control of fall-risk [18–22]. At the same time, correlation between EEG and emotion feelings has been extensively studied [23–29]. However, few researches have focused on EEG and fear of heights. This paper creatively combines VR technology and EEG to assess the severity of fear of heights.

Traditionally, researchers used subjective fear measure (multiple questionnaires) and basic physiological measurements, such as heart rate (HR), skin conductance level (SCL) and salivary cortisol, to assess the fear ratings [11,30]. However, according to Diemer, Lohkamp, Muhlberger and Zwanzger [11], basic physiological measurements could not reflect the real fear of heights. Their experiments showed that when subjects with acrophobia (got high subjective fear rating) and healthy subjects (no subjective fear) were exposed to the same VR height challenge, they both experienced increase in heart rate and SCL.

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Same as conventional physiological measurements described above, EEG as a neurophysiological method is also an objective method. Researches on EEG and emotions are hot, and EEG is confirmed to reflect subjective feelings. Among those researches, many of them pointed out that frontal EEG asymmetry could be used as evidence of the associations between brain electrical activity and observed emotion-related behaviors, especially at F3/F4 medial frontal scalp locations [31–34]. Diaz and Bell [31] proposed that task right frontal EEG asymmetry could predict fear behaviors.

The purpose of this study was to figure out the connection between fear of heights and EEG, with the help of VR technology. As shown in Fig. 1, we wanted to use features extracted from EEG signals to assess the severity of fear of heights. In another word, we wanted to use EEG, an objective method, to assess a psychological concept. In addition, as former researches pointed out that traditional physiological measurements may not reflect the real fear of heights. We compared the results of both methods to verify the reliability of our proposed method. Our work could be helpful with the therapy of fear of heights, the selection of elevator maintenance personnel, and so on.

The rest of the paper is organized as follows. Experiments and methodologies we used are introduced in Section 2. Section 3 shows the results we found and we discussed the reliability of the proposed method in Section 4. Finally, the paper is concluded in the last section.

2. Material and methods

2.1. Experiments

76 healthy subjects (34 females and 42 males, mean age: 25.3 ± 2.7 years) were recruited in this study. They all had normal or corrected to normal eyesight, without any neurological disease history. According to their subjective evaluation, 22 of them are not fear, 33 of them are a little fear, and 21 of them are very fear.

The EEG was recorded with a 37-channels Ag/AgCl scalp electrodes Neuroscan system at a rate of 1000 Hz with 24 bit resolution. 30 electrodes are located according to the standard 10–20 placement system. Four electro-oculograms (EOGs) were recorded in order to discard ocular artifacts. Respectively, two horizontal EOGs were placed at both outer canthi, while two vertical EOGs were placed above and below the left eye. A mid-forehead electrode served as ground. The impedances of all electrodes were below 5kOhms. The recording was referenced to two linked mastoid electrodes.

With the help of the RESP module (as shown in Fig. 1, the blue module and the respiration strap worn on the subject's chest) of the Biofeedback2000^{x-pert}, we collected the amplitude and frequency of the thoracic respiration of all subjects. And we recorded the skin temperature, pulse rate (the number of heart beats per minute (bpm)) and the skin conductance level (SCL) by the MULTI module of Biofeedback2000^{x-pert} (as shown in Fig. 1, the yellow module worn on the subject's left hand).

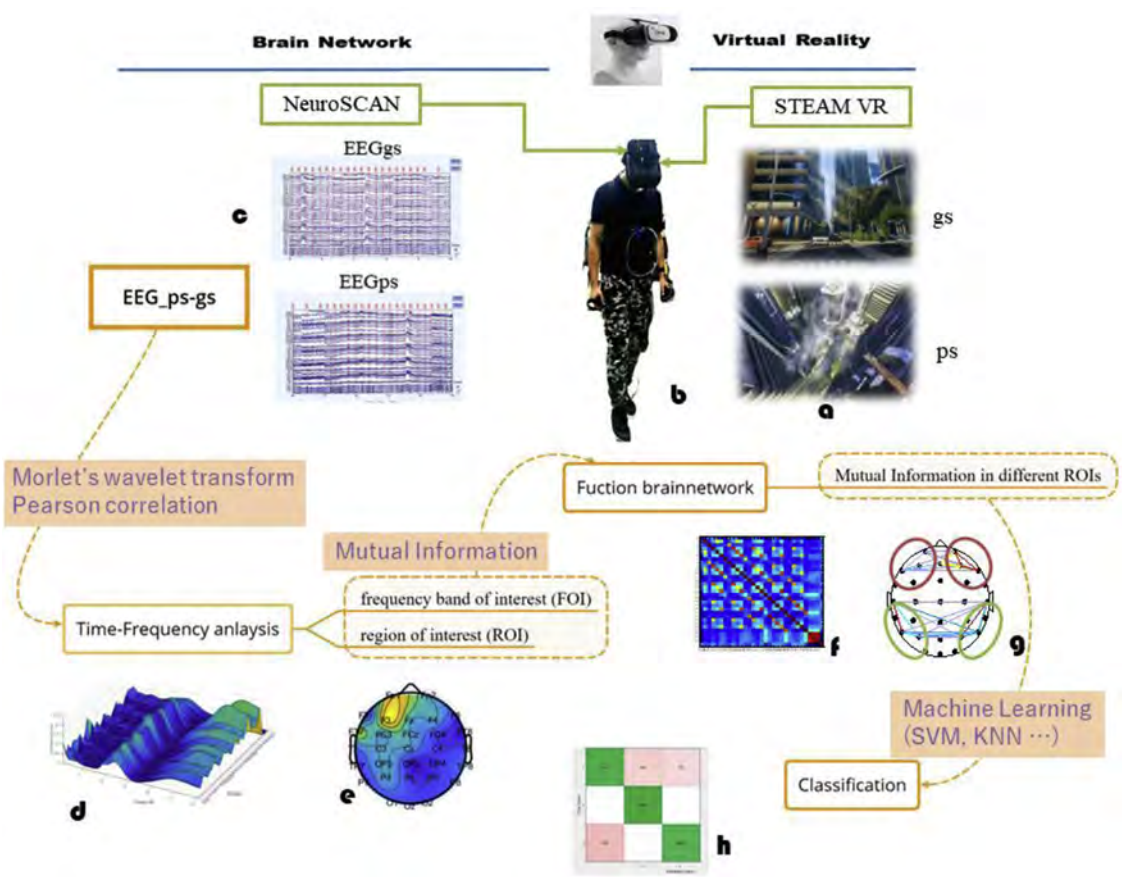

Fig. 1. The framework of this paper. The virtual scene shots of different modes are shown in (a), where 'gs' stands for ground standing and 'ps' stands for plank standing; (b) shows the devices that were used in our experiments, involving NeuroSCAN for EEG recording, STEAM VR for VR stimulating and Biofeedback 2000^{x-pert} for basic physiological data collection; the EEG_{ps} minus EEG_{gs} of each subject was used in further analyses; based on wavelet transform and Pearson correlation, we did time-frequency analysis, and the frequency bands of interest (FOIs) and regions of interest (ROIs) were found for fear of heights illustrated in (d) and (e), respectively; the cross mutual information of each pair of channels in *FOIs* were calculated and constructed in an adjacent matrix per subject as (f); from (f) to (g), we extracted features from the adjacent matrix; finally we did classification by multiple classifiers and the results were compared with traditional physiological methods.

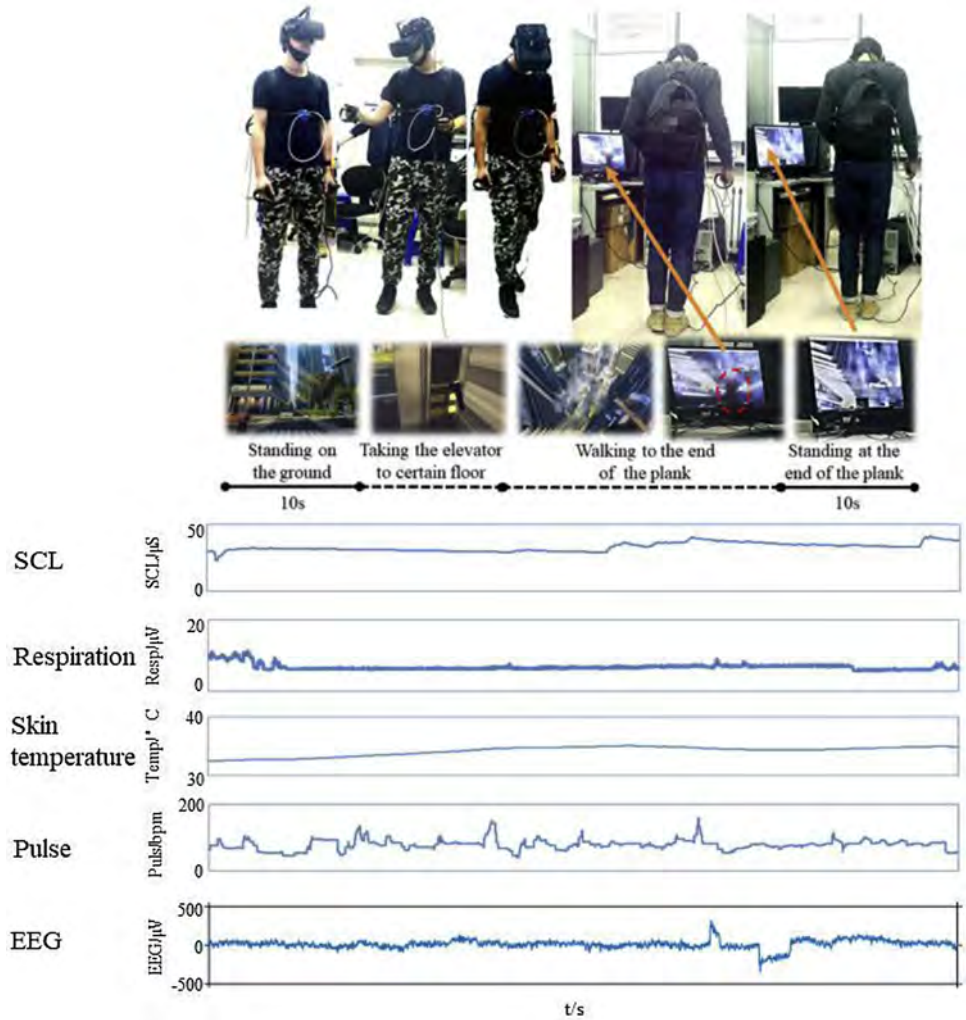

Fig. 2. The flowchart of the experiments. The experiments contain standing on the ground, taking the elevator to the height, walking to the end of the plank and standing at the end of the plank, where the time of standing on the ground and standing at the end of the plank were certain at 10 s, and the time of walking on the plank was different between subjects. Basic physiological features (SCL, respiration, skin temperature and pulse) and EEG data were collected.

With the help of a virtual reality game called Richie's Plank Experience on Steam [35], subjects had to walk on a thin plank which was about 160 m high above the ground. The width of the plank was 0.15 m and the length of the plank was 2.5 m. As shown in Fig. 2, firstly each subject was asked to stand on the ground for about 10 s, and then take the elevator to the plank on a certain story. Subjects had to walk to the end of the plank and stand at the edge for about 10 s. We collected both the basic physiological features (SCL, respiration, skin temperature and pulse) and EEG data when subject stood on the ground, and stood at the end of the plank, respectively.

2.2. Time-frequency analysis

In order to find out the frequency band of interest, we used Morlet wavelet approach to transform EEG data into time-frequency domain. Morlet wavelet is widely used in time-frequency analysis of EEG [6,36,37]. Then we calculated the Pearson correlation coefficient between EEG data at each frequency and the fear value data in time domain. We searched for connection between EEG data (EEGps subtract EEGgs) and fear of height. First of all, the size of EEGps and EEGgs in time domain need to be same, here is 10 s (10,000 sample points).

Each signal was analyzed in TF domain by convolution with complex Gaussian Morlet's wavelets [38] around its central frequency f_0 as:

$$w(t, f_0) = A \cdot \exp(-t^2/2\sigma_t^2) exp(2i\pi f_0 t) \quad (1)$$

where the normalization factor $A = \left(\sigma_t\sqrt{\pi}\right)^{-1/2}$, time domain standard (SD) $\sigma_t = 1/2\pi\sigma_f$, frequency domain SD $\sigma_f = f_0/7$ (a wavelet family is characterized by a constant ratio f_0/σ_f should be greater than 5 (Grossmann et al., 1990)). The investigated f_0 ranges from 0.5 to30 Hz in 0.5 Hz step. As a result, we can get every subject's TF power map of all the channels in different conditions.

2.3. Mutual information and functional brain network

Furthermore, we wanted to figure out the *ROI*s which could reflect the fear of heights. After we got the time-frequency maps of each channel, we averaged the EEG data of the alpha band and high beta band. The TF map (10,000 × 60) of each channel was averaged across the selected *FOI* to produce 1 × 10,000 power curves. The averaged power signal in time domain of a certain channel (x) was then used to compute the cross mutual information (CMI) with the fear value (y). As a result, we can find out which channel has high *MI* with the fear value, and that's the *ROI*s.

The cross mutual information $MI(x, y)$ is a measure of the mutual dependence between two random variables x and y [6],

$$MI(x, y) = H(x) + H(y) - H(x, y) \tag{2}$$

where $H(x) = -\sum_{x} p(x) log_2 p(x)$ is the entropy of a random variable x. In information theory, entropy is the measure of the amount of information that is missing before reception. $p(x)$ is the probability density function (pdf) of x. $H(x, y) = -\sum_{x,y} p(x, y) log_2 p(x, y)$ is the joint entropy, and $p(x, y)$ is the joint pdf between x and y.

Moreover, let x be one of the channels EEG_i and y be another EEG_j, $MI(EEG_i, EEG_j)$ could represent the mutual dependence between channel i and j. And finally, a 30×30 adjacent matrix could be got, which is the basic of building a FBN. The adjacent matrix is a triangle symmetric matrix, and all the numbers on diagonal of the matrix are one, which represent self-to-self dependence. And then several statistical methods were used to analysis the adjacent matrixes, and features for assessing fear of heights were extracted.

2.4. Classifiers

Supervised machine learning methods were used to identify the severity of fear of heights of subjects. To build the classifiers, we firstly extracted features using functional brain network. Within the *ROI*s and *FOI*s we found, the averaged *MI* indexes in certain regions were calculated as features. Then after statistical analysis, we chose those who came up with significant difference as final inputs of the classifiers.

Once the input matrix was formed, we moved to classification stage. In this stage multiple classification algorithms were utilized, including Quadratic SVM, medium Gaussian SVM, Cubic SVM, Quadratic Discriminant, fine KNN, weighted KNN, subspace KNN and so on. A MATLAB™ toolbox for Classification and Learner was used to implement all these classification works.

And then we compared these classifiers for ending up with the best performances. The percentage of accuracy was used to estimate the classifier performance, where 10-fold cross-validation was used to reduce the differences introduced by the different sample partitions.

Besides, to verify the priority of our proposed method, we compared the classification performance of EEG features with that of traditional physiological features.

3. Results

3.1. Frequency bands of interest and regions of interest

The result shows in Fig. 3, where the x axis represents the frequency band, the y axis represents the EEG recorded channels and the z axis represents the correlation coefficients between EEG and fear values changing over time at certain frequency. It shows that

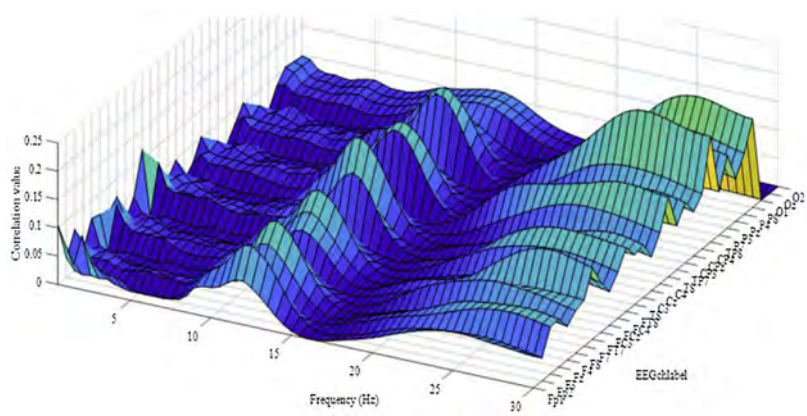

Fig. 3. Correlation coefficients of the frequency of each channel. The x axis stands for frequency band, y axis stands for 30 EEG channels and z axis stands for the correlation coefficients.

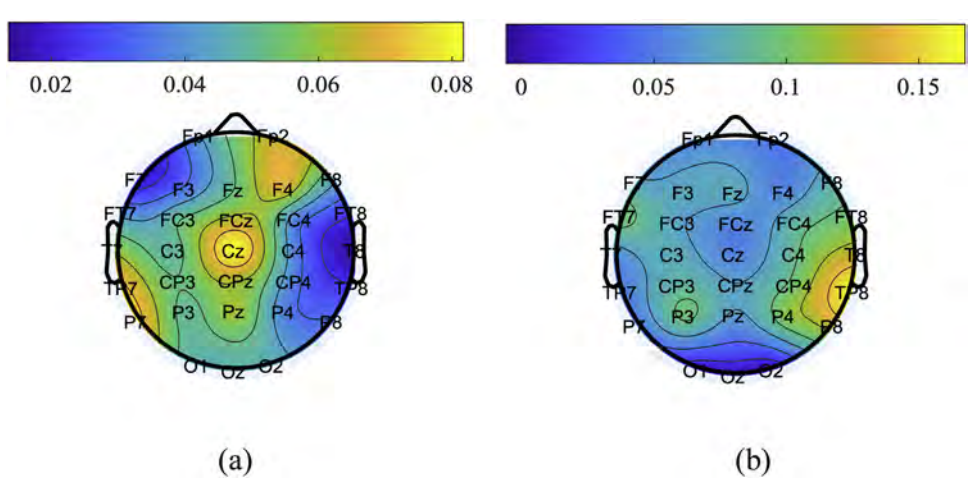

Fig. 4. Cross mutual information of frequency bands of interest in topoplot. In detail, (a) is for alpha band and (b) is for high beta band. The strength of the CMI is indicated with a color scale, from blue (CMI = 0) to red (CMI = 1).

alpha band (8–13 Hz) and high beta band (20–30 Hz) are the *FOI*s for fear of height.

Doing CMI between the averaged power signals of each channel in selected frequency band and fear values changing over time, Fig. 4(a) for alpha band and (b) for high beta band were got. The color bar shows the value of *MI*. From Fig. 4, we can see alpha band has higher correlation than high beta band. And it can be seen that frontal area (especially the left frontal area), left central area and right parietotemporal area are the *ROI*s for alpha band; frontal area (especially the left frontal area), central area and parietotemporal area are the *ROI*s for high beta band.

In the experiments of this paper, fear of heights could cause arousal fear and anxiety. According to previous researches, fear could lead to frontal EEG asymmetry. Moreover, high anxiety (both clinical and nonclinical) is associated with hyperarousal, which includes increased muscle tension, agitation, and the somatic symptoms of panic. And it is predicted to cause more intense right parietotemporal activity in alpha band. This is consistent with our findings.

In addition, researches on postural control of fall-risk point out that central area is considered to be associated with balance maintain. In this paper we focus on the effect of fear of heights on EEG, instead of fall-risk on EEG. So the frontal area and parietotemporal are selected as the *ROI*s.

3.2. Analysis of the functional brain network

According to the ROIs found above, we divided the whole recorded channels into four cortical regions: left frontal area (LF), right frontal area (RF), left parietotemporal area (LPT) and right parietotemporal area (RPT), as shown in Table 1. Inter-connections and intra-connections were calculated as the extracted features. In detail, inter-connection of LF (I_{LF}), inter-connection of RF (I_{RF}), intra-connection between LF and RF ($I_{LF\text{-}RF}$), inter-connection of LPT (I_{LPT}), inter-connection of RPT (I_{RPT}) and connection between LF and RF ($I_{LPT\text{-}RPT}$) are involved.

Table 1
The definition of the selected regions.

Label	Cortical location	Channels
LF	Left frontal area	Fp1,F3,F7
RF	Right frontal area	Fp2,F4,F8
LPT	Left parietotemporal area	T7, P7, P3
RPT	Right parietotemporal area	T8, P8, P4

Suppose there are three electrodes (x1, y1, z1) in a cortical region R1 and three other electrodes (x2, y2, z2) in cortical region R2, inside distances (like I_{R1}) and distances among the different regions (like $I_{R1\text{-}R2}$) are used to calculated inter-connection and intra-connection, respectively.

$$I_{R1} = d_{x1y1} + d_{x1z1} + d_{y1z1} \tag{3}$$

$$I_{R1-R2} = d_{x1x2} + d_{y1x2} + d_{z1x2} + d_{x1y2} + d_{y1y2} + d_{z1y2} + d_{x1z2} + d_{y1z2} + d_{z1z2} \tag{4}$$

where $d_{x,y}$ is the Euclidean distance of the edge of node x and node y. If the elements in adjacent matrix are the strength of connection, then $d_{x,y} = w_{x,y}$. Here in this paper $d_{x,y} = MI_{x,y}$.

The I_{LF}, I_{RF}, $I_{LF\text{-}RF}$, I_{LPT}, I_{RPT} and $I_{LPT\text{-}RPT}$ of alpha and high beta band are considered as twelve features for assessing fear of heights.

The outputs are shown in Fig. 5, where three subjects were compared one from 'not fear' group, one from 'a little fear group' and one from 'much fear' group. From it we can see the connectivity is increased as the severity of fear increases, especially at the right hemisphere.

We calculated the 6 EEG features we mentioned above in both *FOI*s, as shown in the box diagrams Figs. 6 and 7.

3.3. Statistics analysis for feature selection

To avoid overfitting, we did one-way ANOVA for all twelve EEG features to do feature selection. The *F* scores and *p* values are shown

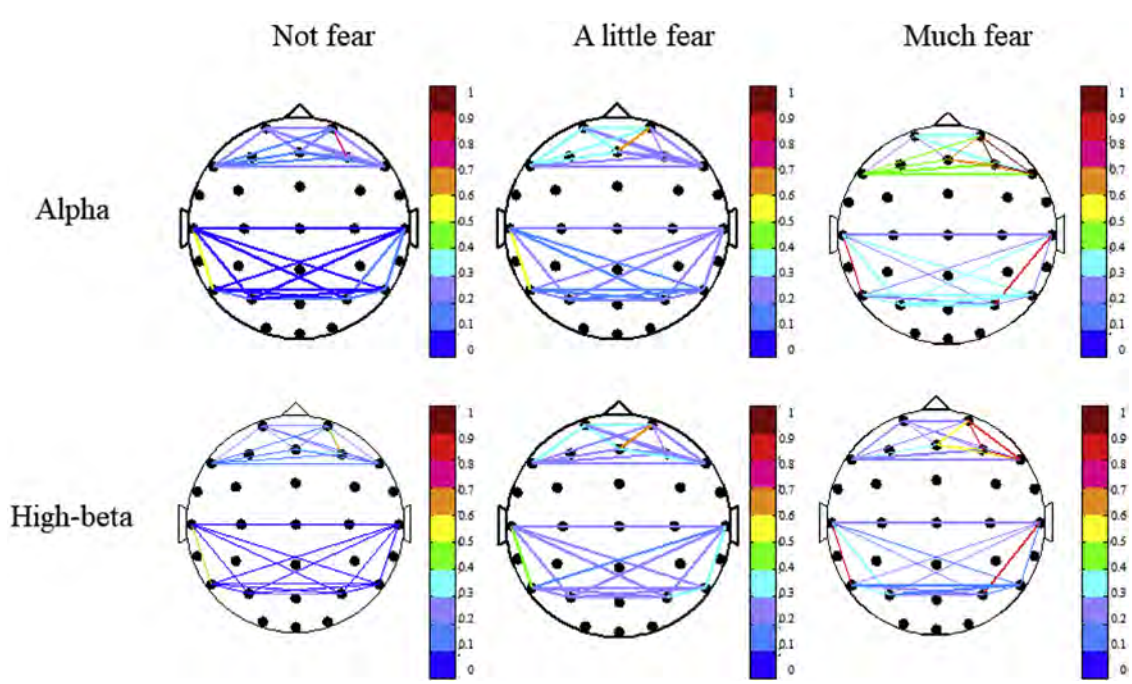

Fig. 5. The outputs of FBN of three subjects in three groups respectively. Only concerned about the *ROI*s (bilateral frontal areas, bilateral parietotemporal areas and their inter-connection areas).The strength of the CMI is indicated with a discrete color scale, from blue (CMI = 0) to red (CMI = 1). From it we can see the connectivity is increased when the severity of fear increases, especially at the right hemisphere.

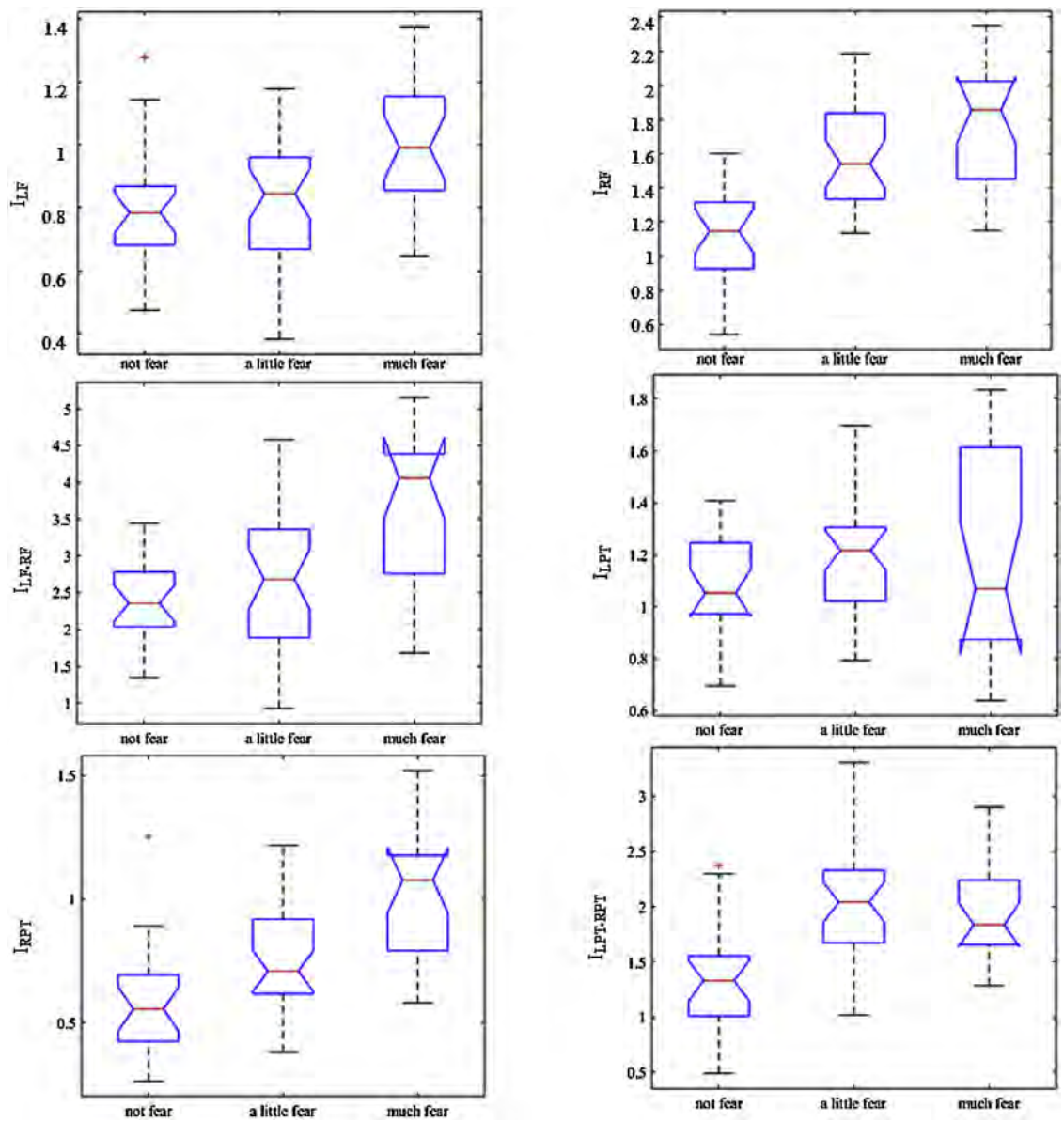

Fig. 6. The box plots for EEG features in alpha band. It shows the variations in samples of a statistical population, including interquartile range, mid-hinge, range, mid-range and tri-mean. The outliers are plotted as individual points.

Table 2
The *F* score of parameters for each *ROI*.

F score of different parameters	Alpha band	High beta band
I_{LF}	$F_{(2,75)}=6.48$	$F_{(2,75)}=4.92$
I_{RF}	$F_{(2,75)}=27.81$	$F_{(2,75)}=15.79$
$I_{LF\text{-}RF}$	$F_{(2,75)}=12.86$	$F_{(2,75)}=12.07$
I_{LPT}	$F_{(2,75)}=1.64$	$F_{(2,75)}=0.28$
I_{RPT}	$F_{(2,75)}=17.15$	$F_{(2,75)}=10.43$
$I_{LPT\text{-}RPT}$	$F_{(2,75)}=14.69$	$F_{(2,75)}=1.82$

Table 3
The *p* value of parameters for each *ROI*.

p value of different parameters	Alpha band	High beta band
I_{LF}	$p^{*}=0.0026<0.01$	$p^{*}=0.0099<0.01$
I_{RF}	$p^{**}=1.05e^{-9}$«0.01	$p^{**}=2.00e^{-6}$«0.01
$I_{LF\text{-}RF}$	$p^{**}=1.64e^{-5}$«0.01	$p^{**}=2.95e^{-5}$«0.01
I_{LPT}	$p=0.2016>0.01$	$p=0.7592>0.01$
I_{RPT}	$p^{**}=7.83e^{-7}$«0.01	p^{**}=0.0001«0.01
$I_{LPT\text{-}RPT}$	p^{**}=4.36e^{-6}«0.01	p=0.1697>0.01

Note: * represents significant different, p<0.01; ** represents highly significant different, p<0.001.

in Tables 2 and 3. *F* score could reflect the difference between within-class and between-class. Sequential forward selection (SFS) then is carried out by ranking all the features. Finally 9 features are selected out, including I_{LF}, I_{RF}, $I_{LF\text{-}RF}$, I_{RPT} and $I_{LPT\text{-}RPT}$ of alpha band and I_{LF}, I_{RF}, $I_{LF\text{-}RF}$ and I_{RPT} of high beta band. I_{LPT} in both FOIs show no significant difference. And for $I_{LPT\text{-}RPT}$ in high beta band, there is no significant difference between each two of the three groups.

We could find out that frontal area, especially right frontal and intra-frontal area in both *FOIs* are more sensitive to fear of heights. Besides, right parietotemporal area is another import region for fear of heights analysis, especially in alpha band (because it could distinguish three groups). As for left parietotemporal area, it only gets significant in alpha band.

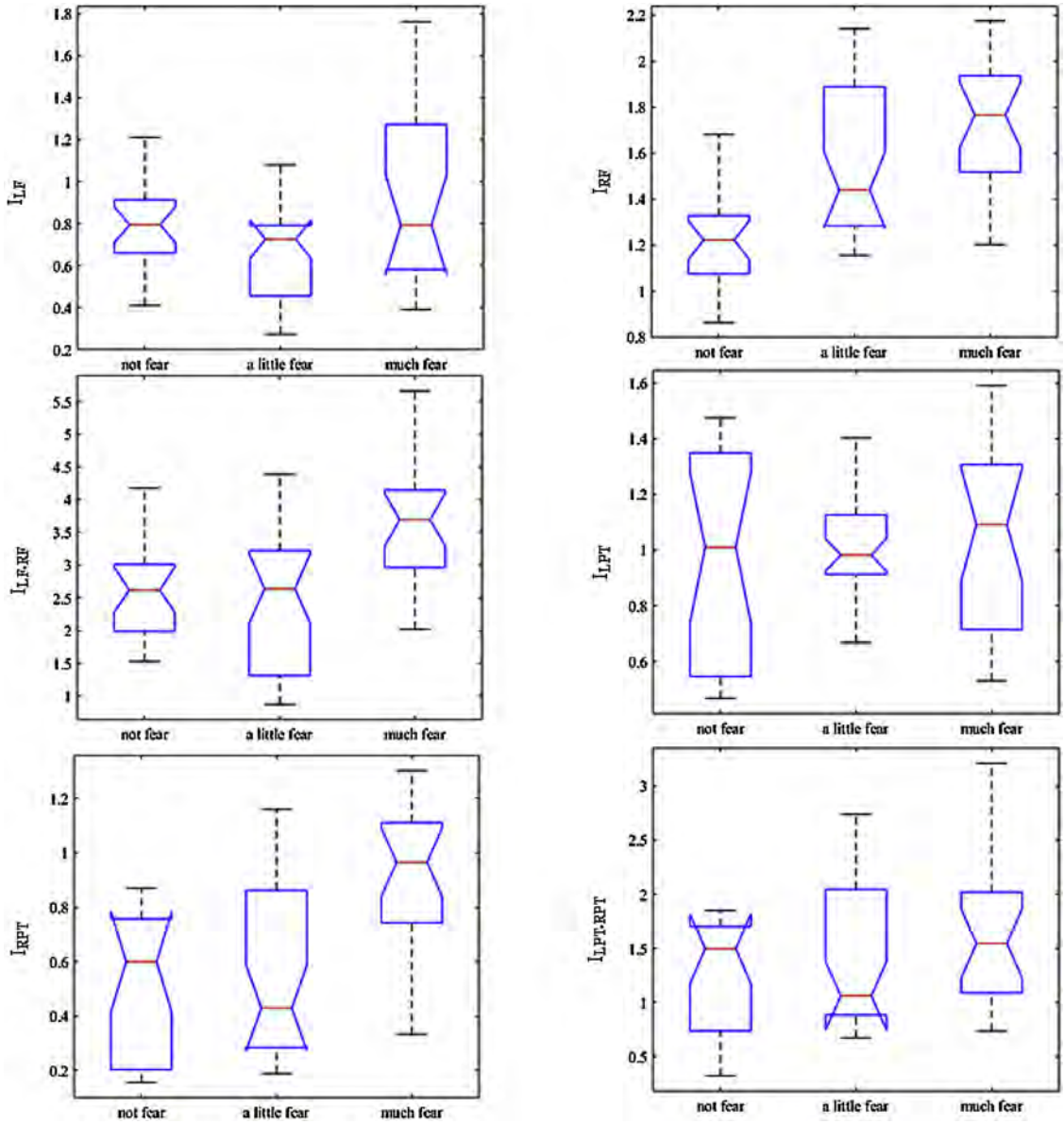

Fig. 7. The box plots for EEG features in high beta band. It shows the variations in samples of a statistical population, including interquartile range, mid-hinge, range, mid-range and tri-mean. The outliers are plotted as individual points.

3.4. Classification results

The classification results of 10-fold cross validation are shown in Table 4 in form of mean value ± standard deviation (SD). It can be seen that the accuracy of estimating severity of fear of heights based on the FBN features we found is high. Especially for Cubic SVM method, the average accuracy could reach 94.44%. For three-class classification this could be considered as a good performance. Besides, it could see that SVM methods perform better than KNN methods. The KNN and SVM methods are mature classification algorithms. KNN method uses local information for prediction and it is more suitable for crossed or overlapping samples. While, SVM is based on statistical learning theory and it has good generalization ability for small sample size condition. Since our dataset is a bit small, we guessed that it is why the SVM methods might perform better.

Table 4
The Classification Outputs.

Classification method	Accuracy (mean ± SD %)	
	9 features of FBN	Traditional physiological features
Cubic SVM	94.44±0.58	76.12±1.21
Medium Gaussian SVM	91.84±0.58	61.56±1.58
Quadratic SVM	93.32±0.78	79.46±1.51
Quadratic Discriminant	93.92±0.71	60.18±1.74
Fine KNN	92.88±0.71	65.52±1.46
Weighted KNN	92.62±1.16	74.72±1.63
Subspace KNN	89.74±2.17	60.09±0.69

Table 5
The confusion matrix of a test on elder people based on Cubic SVM.

True class	*Predicted class*		
	Not fear	*A little fear*	*Much fear*
Not fear	1	0	0
A little fear	0	3	1
Much fear	0	1	4

4. Discussions

4.1. Comparison with traditional physiological methods

Moreover, to examine and verify that features extracted from functional brain network are suitable for assessing the degree of acrophobia, we did classification based on the traditional methods and did comparison [30]. As what we introduced in Introduction section, we extracted the basic physiological features. In detail, the physiological features included the difference of the breathing frequency and amplitude, the skin temperature and the SCL. We subtracted control interval states (stand on the ground) from challenge interval states (stand at the edge of the plank). And for SCL and skin temperature, we did log-transformed. However, because of the artifacts and measurement failures, we removed several of them which were not available.

And the classification results are shown in Table 4. The classification outputs of traditional features are generally smaller than the outputs of FBN features. For instance, the accuracy of Quadratic Discriminant for FBN is $93.92 \pm 0.71\%$, while for traditional physiological methods it is only $60.18 \pm 1.74\%$. So we could say that the proposed EEG method is much better than traditional physiological methods on estimating the severity of fear of heights. Thus, our method is verified to be useful and superior.

4.2. Verification on elder people

To test the generalization capability and adaptability of our proposed estimating system, we found some elderly people including not fear (1 subject), a little fear (4 subjects) and much fear (5 subjects) groups, and asked them to try on our proposed system. And based on our proposed system, the severities of acrophobia of these elder people were estimated at an accuracy of 80%. The output confusion matrix is shown as Table 5. In detail, one 'much fear' subject was misidentified as 'a little fear' and one 'a little fear subject' was misidentified as 'much fear'. Basically, this could show that the generalization of our proposed method is good.

4.3. VR technology in fear of heights researches

Although VR technology has widely been used in today's researches, it could date back to the Second World War, when the flight simulator was developed [10]. Besides military development, the American army started to use VR to treat fear of flying and fear of heights, because they found that the emotional and physical symptoms in VR seemed to be phobic behaviors (real fear) [39]. Cleworth, Horslen and Carpenter [40] compared the effects of real and virtual heights and verified that VR could be applied to the study of fear and anxiety induced by standing on elevated surfaces. They pointed out that standing at simulated heights has been associated with changes in physiological arousal, anxiety, and perceptions of height, which are similar to those recorded under real height conditions. More significant fear and anxiety may occur when subjects are standing at the edge of an elevated surface [20,41].

5. Conclusion

This paper using VR technology established a vivid virtual environment where subjects were asked to exposure at a high altitude. The EEG signal were recorded when the subjects was standing on the ground and at the edge of a plank about 160 m high above the ground. With the help of EEG method, the FOIs and ROIs of fear of heights are found out – alpha and high beta bands are the FOIs, the frontal and parietotemporal areas are the ROIs. Furthermore, the features of FBN method are extracted. Statistical analysis was done with these features. With these selected features and labels, we trained the classifiers. By comparing to traditional physiological features, EEG based features were verified to be more reliable and accurate as for fear of heights assessment. By testing on elder people, our proposed assessment system was proved to be with good generalization capability and adaptability.

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