Mental Workload Classification and Measurement Using Functional Near-Infrared Spectroscopy (fNIRS)

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Abstract The objective is to use functional near-infrared spectroscopy (fNIRS) to classify and measure mental workload in n-back tasks. Prefrontal cortex (PFC) responses were monitored with fNIRS while 18 subjects completed n-back tasks, performance and NASA-TLX scales were also recorded. It was found that there was significant difference in performance, subjective scores, and fNIRS data under different difficulty tasks; dorsolateral prefrontal cortex (DLPFC) is more sensitive to fNIRS in PFC; using support vector machine (SVM) could realize accurate classification of 4 mental workload levels; SVM decision values could assess and predict mental workload effectively.

Key words spectroscopy; functional near-infrared spectroscopy; hemodynamics; mental workload

OCIS codes 300.6340; 260.3060; 170.0110

基于功能性近红外光谱的脑力负荷评估

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摘要 实验目的是在 *N*-back 任务中利用功能性近红外光谱(fNIRS)进行脑力负荷的分级和测量研究。对 18 名被试者进行了图片 *N*-back 工作记忆任务,利用 fNIRS 采集了被试者大脑皮层前额叶的血氧变化,同时记录了绩效与主观问卷数据。结果发现不同难度任务下绩效结果、主观问卷结果及 fNIRS 参数均有显著差异;背外侧前额叶区(DLPFC)对 fNIRS 的响应比较敏感;利用支持向量机(SVM)可以较为准确地识别 4 个难度 *N*-back 任务的脑力负荷; SVM 判决值的一种变换形式能够作为评估和预测脑力负荷的指标。

关键词 光谱学;功能性近红外光谱;血液动力学;脑力负荷

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1 Introduction

Mental workload is operators' physiological and psychological need induced during one or more tasks[1]. Hart and Staveland[2] thought mental workload was not an inherent characteristic, and mental workload would be produced

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when task demands, work environment, operator's skills, behavior and perception interacted. Mental workload is multidimensional, its factors can be summarized in three aspects as human, task and environment, and individual's ability, motivation, strategy, mood and status will affect its level (Fig. 1)[3-4].

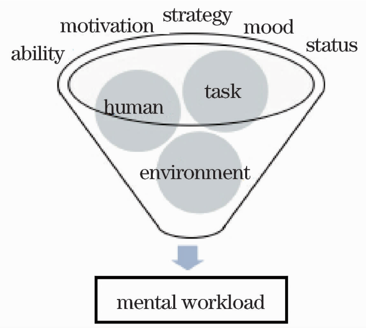

Fig. 1 Influence factors of mental workload

With the rapid development of science and technology, particularly the wide application of computer and automation technology, the systematization and automation of modern human-machine system has been greatly improved. The division role of human and machine is very different from before, the physical work load has been greatly reduced, but the mental workload is increasingly higher[5].

Mental workload is a key factor in many complex and control systems, especially in some situations where performance failures can result in catastrophic losses and casualties (e. g. airplane piloting, spacecraft rendezvous and docking, air traffic control). In particular, excessively high or low mental workload can make operators lose critical information or out of the loop (OOTL)[6]. So accurate assessment and prediction of mental workload is essential in human-machine systems, which can help prevent error or failure through reasonable intervention by decline of prediction performance.

Mental workload is a multidimensional concept, it should be measured through multiple aspects. Yet people cannot directly evaluate the mental workload, and the common indirect measurement includes subjective rating scale, behavior performance and physiological parameter methods. Among these basic methods of mental workload measurement, physiological methods are the most promising for field application. Psychophysiological and neurophysiological measurement is usually used to represent the mental workload in special tasks because they can offer objective, continuous and real-time monitoring that does not interfere the operators' mental workload[7-8].

There are various psychophysiological and neurophysiological methods that can be used to study the mental workload, including electrophysiological signal in central nervous system (CNS) or peripheral nervous system (PNS), and hemodynamic indicators (Fig. 2). Electrophysiological information of CNS function such as electroencephalography (EEG) and event-related potential (ERP) has been confirmed for accurate measurement of mental workload. As task difficulty increases, the EEG signal's power in beta bandwidth and the activity of theta bandwidth will increase, and the activity in alpha bandwidth will be suppressed. The related electrophysiological method of PNS for mental workload measurement includes electrocardiogram (ECG), electromyogram (EOG), respiratory wave (RW), pulse wave (PW), galvanic skin response (GSR), *etc*. Researchers found that the level of mental workload tasks was associated with such features as heart rate (HR), heart rate variety (HRV) of ECG, blink frequency and cycle of EOG. Besides the electrophysiological parameters, hemodynamic methods such as functional near-infrared spectroscopy (fNIRS)[9] and functional magnetic resonance imaging (fMRI) are new and effective ways to study human cognitive activity. The concentration change of fNIRS hemodynamic parameter and blood oxygenation level dependent (BOLD) activation map of fMRI has been confirmed with significant difference among tasks of different difficulty[10-11].

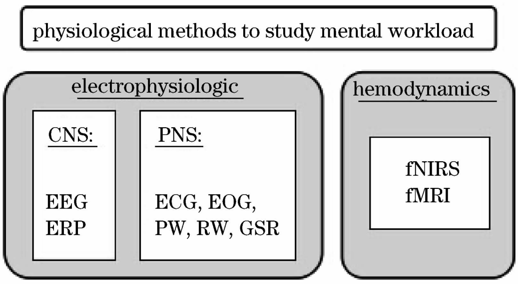

Fig. 2 Physiological methods to study mental workload

In this study, we utilized an optical method fNIRS, an appropriate candidate to measure mental workload in field condition, to measure the hemodynamic parameters. fNIRS is a newly developed technology that utilizes light from 700 nm to 900 nm to monitor the state oxygenation of biological tissues[11-12]. fNIRS is highly portable, safe, relatively cheap, user-friendly, noninvasive, near-zero cost and with rapid application time. Most biological tissues are relatively transparent to light within the wavelength range, so relatively little scattering of photons occurs when the light is introduced to tissues. It makes fNIRS very suitable for tissue imaging. Using the modified Beer-Lambert law and fNIRS measurement conducted at two different wavelengths within the near infrared light range at two adjacent moments, the relative change in concentrations of HbO and Hb can be obtained. The physiological parameters in the cortex are closely related with human oxidation and metabolism, they can be used for the detection of cognitive activities and mental workload[13-14].

The prefrontal cortex (PFC) has been identified to be sensitive to working memory related tasks. Smith *et al*. validated that the PFC is relevant to memory tasks using PET, and Cohen *et al*. also confirmed it by fMRI. Owen *et al*.[15] confirmed the importance and efficiency of PFC for n-back task. Hoshi *et al*.[16] showed patio temporal change of working memory tasks in the PFC based on fNIRS signal average, and Herff *et al*.[17] analyzed it using single trial analysis. Their results confirmed that fNIRS was ideally suited for measurement of PFC. In our research, we will study the fNIRS signal of PFC during n-back tasks.

In recent years, lots of studies in neuroscience have used fNIRS to explore the mechanism of brain function. Ayaz *et al*.[18] confirmed that fNIRS could be used for evaluating mental workload of n-back standard tasks and complex air traffic tasks (ATC) under field conditions. They also showed that fNIRS could evaluate the operators' expertise progress during complex UAV driving tasks. Justin *et al*.[19] conducted a research on UAV operator training assessment and interface development. Preliminary results of pilots showed that the fNIRS features were sensitive to mental workload in visual search and vigilance tasks.

Although various researches have been organized using fNIRS signal in PFC, there are still lots of issues to be studied. Researches before mainly utilized the amplitude of fNIRS oxygen data in PFC to confirm which channels or areas are more relevant regions in PFC. They have not realized high accuracy classification and not confirmed the least channels needed to reach special classification accuracy. Yet an index of fNIRS which can stand for the degree of mental workload has not been found. So the objective of the present study is to explore the most sensitive channels and areas in PFC, try to realize high classification accuracy and study the relationship between channel number and classification accuracy, and try to find an index of fNIRS for evaluating mental workload.

2 Methods

2.1 Participants

In this study, we recorded 12 healthy subjects (4 females) with a mean age of 24 years, and all of them were right-handed. All participants had normal or corrected to normal vision, and did not have any mental diseases. They were informed prior to the experiment and signed the written consent form. To avoid training effect, all of the selected subjects had never taken part in an n-back task before.

2.2 Experiment design

The n-back working memory task is a commonly used experimental paradigm in cognitive neuroscience field. In the task, participants have to continuously remember the last n of a series of rapidly flashing stimulus. The stimulus can be letters, spatial orientation graphs or pictures, which are presented to them on a screen. Our task requires subjects to press the left arrow key when a picture is the same as the n^{th} picture before the current stimulus, and right arrow key for the different picture. The n-back paradigm used here was completed using E-prime 2.0 by the authors. And the behavior performance data including respond time (RT) and accuracy (ACC) were calculated automatically by the software. We recorded subjects' fNIRS data during the whole test and asked them to fill out NASA-TLX[20] subjective scales.

We used an Oxymon Mk III produced by Artinis Medical Systems to record fNIRS signals. The two wavelengths used in this system are 765 nm and 856 nm, and the concentration changes of HbO, Hb and tHb were got by it[21-22]. We attached 4 light transmitters and 4 light receivers to the forehead, placed them at a distance of 3.5 cm, and made a layout of 10 channels of fNIRS signal (Fig. 3).

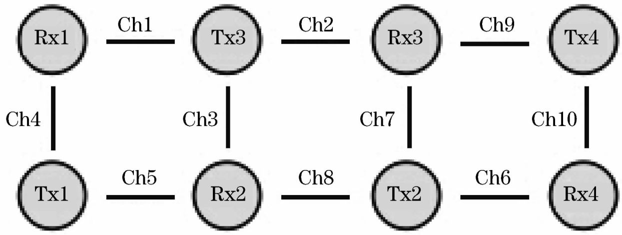

Fig. 3　Layout of PFC fNIRS channels

We investigated 9 trails of task in our study, including 0-, 1-, 2-, 3-back tasks and rest intervals. 4 trails of 0～3-back training tasks were conducted in turn firstly, then 5 trails of 0～3-back formal tasks and the contrast rest interval were carried out randomly. More specifically, every task trail was composed of task instruction, picture presentation, black screen during key reaction and recovery rest. Every picture was displayed for 500 ms, and 1500 ms of black screen was left to response. There were 150 pictures presented in each task trail, and every trail took 5 min. There was 2 min of recovery rest time after the end of every task trail to ensure the oxygenation data return to baseline. The contrast rest interval was 5 min without any task. The entire experiment time was 38 min. During the entire experiment, hemodynamics of the PFC was recorded continuously at a sample rate of 250 Hz.

2.3 Artifacts removal

Although the physiological parameter method of fNIRS has the real-time and objective advantages, there still exist some artifacts due to experimental error, instrument error and physiological interference. The physiological noise comes from the spontaneous low frequency oscillation of measured tissues, which is mainly caused by heartbeat, respiration and blood pressure pulsation. The moving artifacts are some spikes caused by the optodes' position dislocation or movement.

We used the method of IIR low-pass filter, wavelet decomposition and reconstruction[23-24], and correlation-based signal improvement (CBSI)[25-26] methods to deal with the artifacts. An elliptical IIR low-pass filter of 0.5 Hz cutoff frequency was used to attenuate heart beat influence. Then we utilized 3 degree wavelet decomposition and reconstruction to remove Gauss noise and device interference. Finally, the method of CBSI was used to remove the interference of movement.

2.4 Feature extraction and data processing

We analyzed the behavior performance results and NASA-TLX subjective scales by using ANOVA statistical method. Then we focused on the analysis of physiological fNIRS data. For each optode, we intercepted the fNIRS data of different difficulty levels and rest interval. Then we conducted a down sampling of 10 Hz with the data, and calculated the average value of every 2 seconds data.

First of all, we processed fNIRS data using the above artifacts removal means.

Secondly we explored the most sensitive regions to n-back tasks in PFC. We used these average value as extracted features to test and verify the fNIRS classification result of mental workload. The classification algorithm we used here is support vector machine (SVM). We can obtain a series of accuracy by using the fNIRS data of each channel, and we used it to sort the channels as a representation of sensitivity. The channel sensitivity can be regarded as a method of sensitive cortex region verification in n-back task.

Then we counted the ordinary amplitude change of fNIRS data and utilized SVM classifier to classify the different difficulty level tasks based on all the 10 channels' data features. After all the channel feature statistical data of all participants is obtained, we adopted a method of support vector machine-recursive feature elimination (SVM-REF) for channel screening. Using this method we could obtain the least number of channels to realize certain classification accuracy.

Lastly, we attempted to use transformation of SVM classification decision value to represent the degree of mental workload. We designed the training samples' standard decision value of rest, 0-back, 1-back, 2-back and 3-back as 0, 25, 50, 75 and 100, and estimated the test samples. We also tried to use only 0-back and 3-back tasks' fNIRS data as training sample to test all the 0～3-back tasks.

3 Results

3.1 Behavior performance

To confirm that the participants perceived the different n-back tasks as different, we analyzed the behavior performance of accuracy and response time when a subject pressed the key. As shown in Fig. 4, the one-way ANOVA results showed significant difference between the 4 n-back levels in the ACC [$F(1, 12)=8.32$, $p<0.05$] and RT [$F(1,12)=26.35$, $p<0.05$]. The ACC decreased from 97.8% on average for 0-back condition to 93.7% for 1-back, to 91.8% for 2-back, and to 86.8% for 3-back condition. And the RT increased from 520.2 ms on average for 0-back condition to 581.9 ms for 1-back, to 635.1 ms for 2-back, and to 684.3 ms for 3-back condition. This clearly proves that the 4 n-back tasks have significantly different difficulty levels.

3.2 Subjective rating

In order to improve the credibility of the NASA-TLX subjective scales, we used the way of dialogue to fill out the scales. The ANOVA conducted on the subjective rating data revealed significant effect of task difficulty, $F(1,12)=54.3$, $p<0.05$, indicating higher subjective scale with higher task difficulty. As shown in Fig. 5, the NASA-TLX scales increased from 13.7 on average for 0-back condition to 17.6 for 1-back, to 29.4 for 2-back, and to 40.7 for 3-back condition. This shows the different levels of workload induced by the 4 n-back tasks again.

3.3 fNIRS data

We used IIR low-pass filter, wavelet decomposition and reconstruction, and correlation-based signal improvement (CBSI) methods to deal with the artifacts. The artifacts removal result of each step can be seen in Fig. 6, and we can see that most of the physiological, movement or device artifacts occur after the three steps.

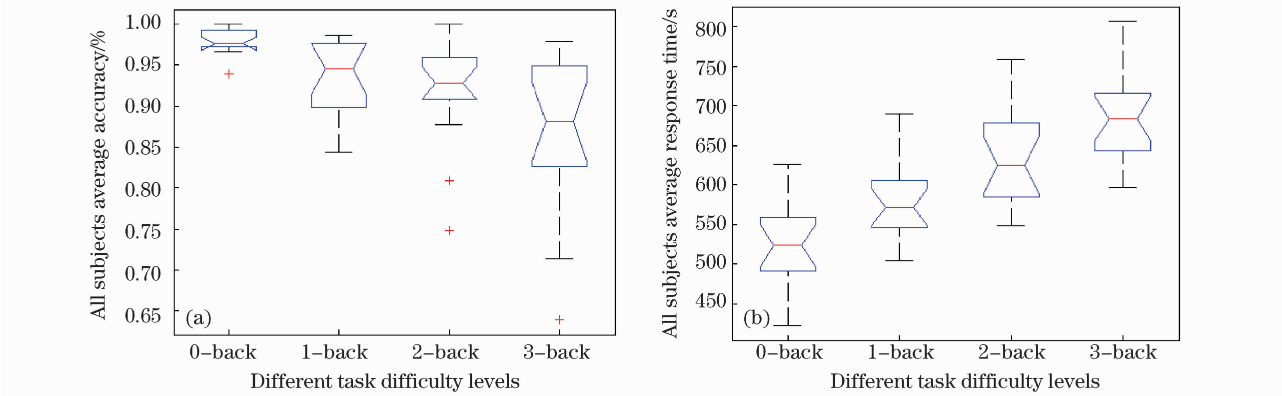

Fig. 4 Behavior performance under different difficulty tasks. (a) Accuracy; (b) response time

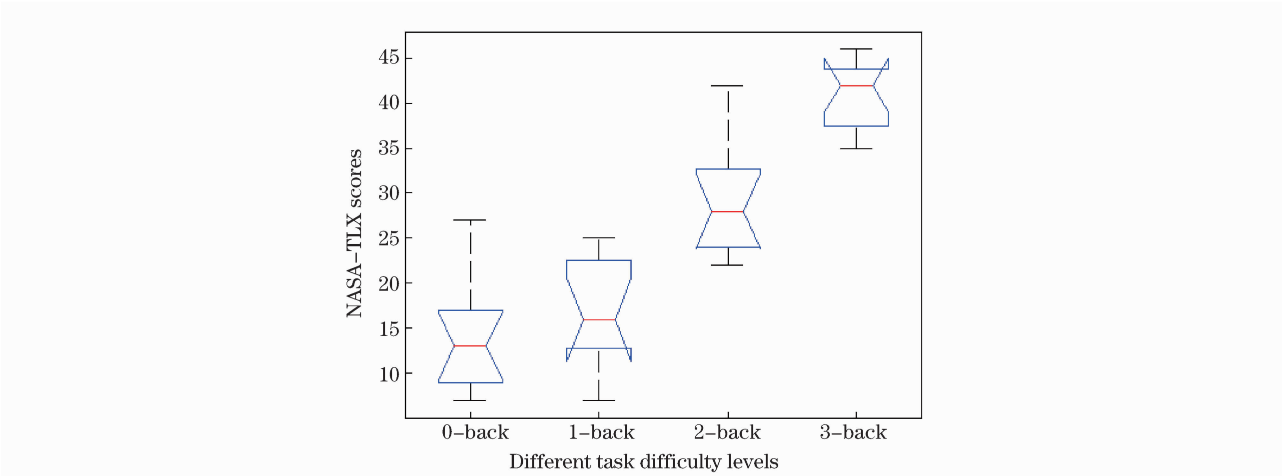

Fig. 5 Subjective rating under different difficulty tasks

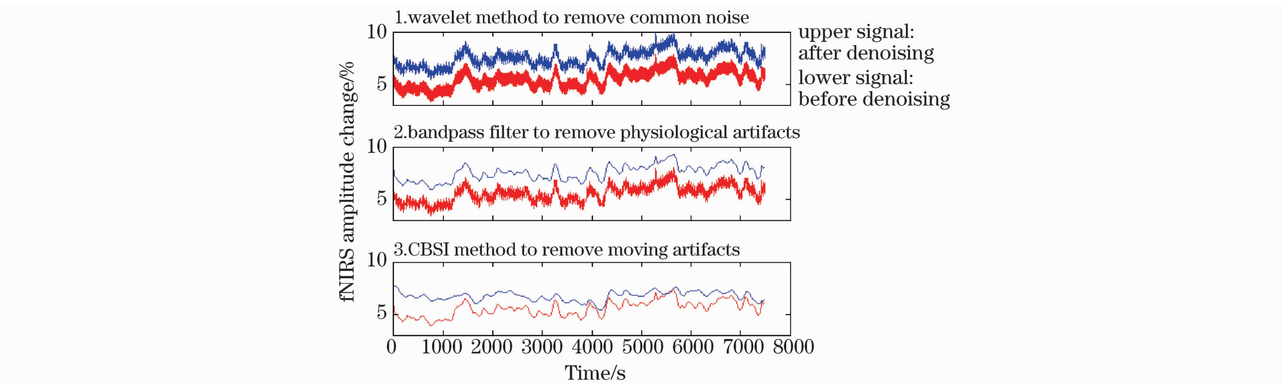

Fig. 6 Artifacts removal results

As introduced before, we used each channel's classification accuracy sum of three features (HbO, Hb, tHb) of all subjects to describe the channels' sensitivity. Table 1 shows the result of sum value, which suggests that the 1^{st}, 5^{th}, 9^{th} and 10^{th} channels are the most sensitive channels and they exist in the region of DLPFC (Fig. 7).

To understand if the hemodynamic data for the four n-back tasks yield any difference, the primary effect of task difficulty with HbO $F(1,12)=13.5$, $p<0.05$ and tHb $F(1,12)=30.1$, $p<0.05$ was observed on optode 1. The level of HbO and tHb shows increase under conditions of 0～2-back tasks as the task difficulty increases, but deceases when the task changes from 2-back to 3-back (Fig. 8). Although the effect is significant only on several optodes, the similar tendency of variation can be seen on all optodes in left and right DLPFC.

Table 1 Channel sensitivity scores

CH	1	2	3	4	5
Value	17.722	16.648	16.043	16.753	19.586
CH	6	7	8	9	10
Value	16.386	15.462	15.927	17.124	17.923

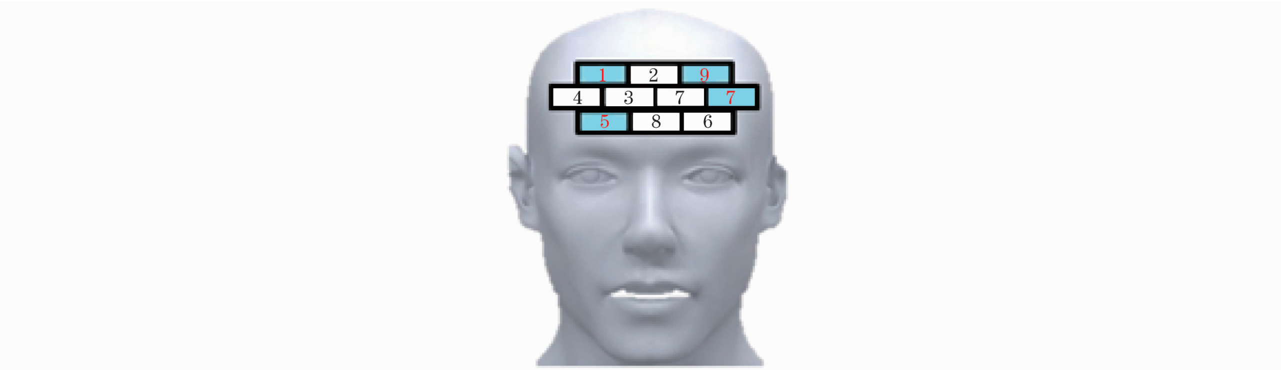

Fig. 7 Sensitive channels obtained by fNIRS

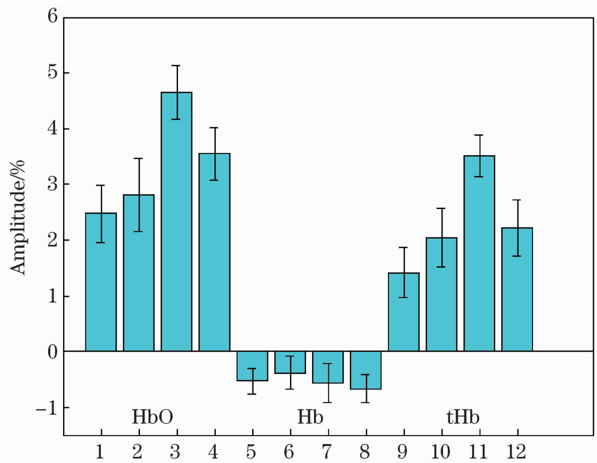

Fig. 8 Amplitude change of fNIRS data

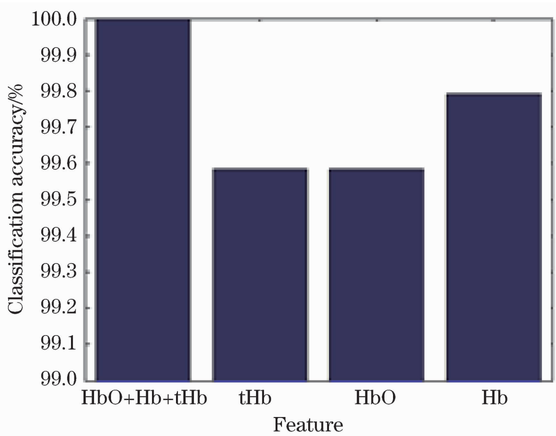

Fig. 9 Classification accuracy

The results above have demonstrated difference and change mechanism of oxygenation data under 4 conditions, and then we used SVM classifier to class oxygenation data under the 4 conditions. We only concerned the fNIRS data from the same group tasks, and data from cross-time and cross-task will be studied later. We utilized 1^{st}～5^{th} channels of the fNIRS data from 0～3-back tasks as training samples of SVM classifier, and used the remaining fNIRS data as the test samples. Fig. 9 shows the classification accuracy of four difficulty level tasks using all 10 channels' fNIRS features, and the feature composed of HbO, Hb and tHb shows the best result. The classification accuracy reaches 99% using individual feature of HbO, Hb or tHb in all the 10 channels and composite features of them. Fig. 10 shows the channel screening result using SVM-REF method. The result proves that the number of channels influences the classification significantly. Using the feature of one channel, we could only get classification accuracy lower than 80%. The classification accuracy is improved obviously as the number of channels for classification features increases. When the number of channels reaches 4 or more, the accuracy will exceed 95% no matter individual or composite features are used.

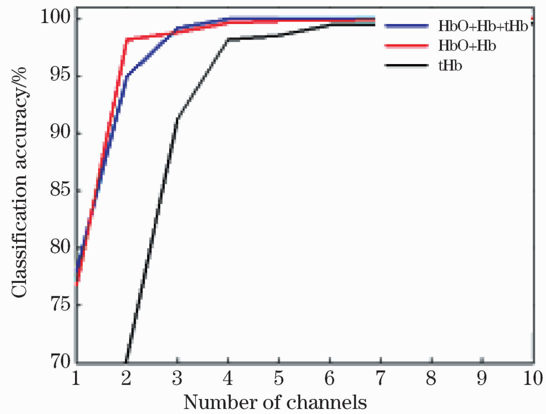

Fig. 10 Channel screening result

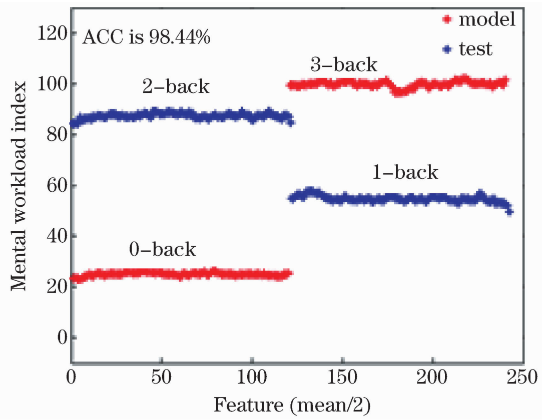

Fig. 11 Mental workload index

Finally we used transformation of SVM decision value as the mental workload index, and realized assessment of 0～3-back task mental workload under the condition of 4, 3 or even 2 kinds of tasks' fNIRS data as training samples. We designed the training samples' standard decision values of rest, 0-back, 1-back, 2-back and 3-back as 0, 25, 50, 75 and 100, and estimated the test samples. As shown in Fig. 11, we used 0-back and 3-back task data as training samples (marked with red dots) to measure the 1-back and 2-back tasks. The designed mental workload indexes of 0-back and 3-back are about 25 and 100. We can see mental workload index result of the tested samples of 1-back and 2-back tasks, the index is 50～60 for 1-back task and 80～90 for 2-back task, which is consistent with the expected results.

4 Discussion and conclusion

The objective of this study is to examine the impact of mental workload on neurophysiological measurement of hemodynamic response in PFC during n-back tasks. From the methodological point of view, fNIRS data was compared with behavior performance and NASA-TLX subjective scales. An experimental n-back task was designed to produce mental workload of memory working.

The analysis of behavior performance showed significant difference in ACC and RT of different difficulty level n-back tasks, and the NASA-TLX scale showed the same significant difference in total scores. As the difficulty level increases, the ACC showed clear decrease while the RT and subjective scale score showed apparent elevation simultaneously. The behavior performance and subjective scale results prove that our laboratory task is sufficiently engaged to induce different levels of mental workload.

We focused on the fNIRS data in PFC. Firstly, through a series of filters including IIR low-pass, wavelet decomposition and reconstruction, and CBSI methods, we got clean fNIRS signal. Using fNIRS data on PFC of 12 subjects, we were able to calculate the sensitivity index of each channel. As expected, DLPFC was the most sensitive region of fNIRS in PFC to mental workload, which was proved by the rank of channel sensitivity. Then we analyzed the fNIRS data amplitude of channel 1, which is among the DLPFC. The result is partly akin to Herff's studies, indicating that more difficult n-back task induces higher HbO and tHb changes. In addition, we found that the HbO and tHb change in amplitude might decline when task difficulty was over a certain degree. Though we did not find effect of mental workload on PFC, our results revealed significant difference between tasks, such as change in oxygenation level of optode 1. The results can describe the oxygenation change with mental workload in PFC.

Finally we used SVM method to classify four difficulty level n-back tasks, and we got 99% classification accuracy when using features of all the 10 channels as SVM features. With the help of SVM-REF, we confirmed that the classification accuracy was higher as the number of channels used as SVM features increased, and the least channel number was 4 to realize the accuracy higher than 90%. We also realized mental workload measurement using the SVM decision values as description index. We can use fNIRS of two end difficulty level tasks to forecast the other tasks.

In conclusion, we proved the validity and scientificity of fNIRS to measure mental workload, tested the sensitivity cortex regions, and realized mental workload classification of 4 difficulty levels and measurement in n-back tasks. In the following work, we are planning to try more new noise removal methods and fNIRS features. We may also carry out tests to combine the fNIRS with more physiological parameters, such as EEG, ECG *etc.* and try some verification test cross tasks or subjects.

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