Evaluating Nonlinear Variability of Mental Fatigue Behavioral Indices during Long-Term Attentive Task

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This study investigates the behavioral indices of attention. A simple repetitive attentive task that resulted in mental fatigue was used consecutively in four trials. In the first step, reaction time and error responses were recorded to evaluate differences among trials. During the task, subjects showed different responses to stimulations. In the second part, to recognize the strategies, multiple clustering methods such as k-means and fuzzy c-means were performed in which behavioral indices and nonlinear features were used. In the last section, mental behavior was identified as a result of the chaotic properties of variations in reaction time. Therefore, the Lyapunov exponent of reaction times was evaluated. Results revealed that behavioral indices could distinguish attention from the occurrence of mental fatigue in trials. In addition, the three strategies used by subjects during the test protocol were assessed. Finally, variation of indices extracted from nonlinear analysis, that is, decrease in degree of chaotic behavior determined the transition from attention to mental fatigue. © 2012 Wiley Periodicals, Inc. Complexity 17: 7–16, 2012

Key Words: attention; mental fatigue; complexity; nonlinear analysis; return map; Lyapunov exponent; reaction time

1. INTRODUCTION

There are many investigations of behavioral and mental effects on performance. Although much research has been conducted to identify attention and fatigue, many of the regulatory processes that determine human behavior under mental fatigue remain unknown. People usually explain how they feel and how their behavior changes when mental fatigue occurs, for example, attention...
deficiency and less flexibility, but no one can exactly explain what physiologically happens during mental fatigue [1].

Attention is the selective concentration and allocation of processing resources on a task to the exclusion of other tasks [2]. Attention is also described as the sustained focus of cognitive resources on prioritized information while filtering extraneous irrelevant information. According to this definition, attention as a very basic function involves other cognitive functions like ability of focus, vigilance, selection, and responding simultaneously that make it the basis of clinical models [3] in evaluation of attention. In a long-term attentive task, most of these functions contribute to a subject’s generation of response.

One common medical definition of fatigue is “the state of weariness following a period of exertion, mental or physical, characterized by a decreased capacity for work and reduced efficiency to respond to stimuli” [4], so mental fatigue is recognized by a reduction of mental performance. This kind of fatigue can result from mental factors such as stress, sleeplessness, depression, illness, or disrupting repetitive tasks. Feelings of mental fatigue are significantly related to neural responses during a fatiguing cognitive task [5]. However, there is no universally accepted definition of fatigue and the operational definition is consistent with widely accepted measures of fatigue when measured as a feeling state [6]. Transition from an alert state to a fatigue state happens during a process in which brain activity is the interchange of the cortex activation and deactivation in specific areas which represents certain patterns that could be detected by electroencephalography (EEG) and functional magnetic resonance imaging [7].

Several psychological assessments can be performed to determine a subject’s cognitive strength [8]. In all of these tests, usually subjects’ performances are evaluated by comparing indices with normal population. In psychological assessments of attention, usually indices like reaction time (RT) with omission, commission, and false alarm errors are used [9, 10]. Moreover, many other studies have been performed to model brain activity during mental fatigue based on time and frequency features extracted from EEG signals [11–17]. In these studies, clustering methods were used to indicate brain states during fatiguing processes [18].

The primary purpose of this study was to determine the variation of behavioral indices during a long-term attentive task based on statistical analysis. The perception of mental fatigue was induced using a simple long-term cognitive task that involved attention and executive function. As expected, there were significant differences among trials of test during fatiguing process. In addition, RT, as an indicator of fatigue, was focused on to determine different response strategies in subjects. It was hypothesized that during fatiguing tasks, intensity of mental fatigue feelings would vary among subjects and the responding strategies would take only few clusters.

Another hypothesis concerned the systemic behavior of human during transition from attention to mental fatigue. It was expected that human behavior as a chaotic system [19, 20] would change during this transition and that is the reduction of the degree of chaos when mental fatigue occurs. Complexity variability of physiological responses has been studied in various investigations to represent dynamics of the biological system [21–24]. The main purpose of this article is to show the variation in attention by analyzing the return map of RTs and Lyapunov exponent extracted from them.

In this study, we performed a simple mental fatiguing task to evaluate the behavioral indices variation in transition from attention to mental fatigue. Then, we clustered different strategies used by subjects in response to stimulation. We realized that nonlinear analysis of behavioral indices such as return map and Lyapunov exponent could determine mental behaviors.

2. DATA AND METHODS

The participants were 20 volunteer bachelor students of biomedical engineering who were 18–22 years old. They were all accustomed to operating a computer keyboard and were not on any medication with a sufficient rest before the test.

In this study, we used a continuous performance task algorithm named “Sustained Attention Dots” from Amsterdam Neuropsychological Tasks developed by de Sonneville [25, 26]. To ensure that mental fatigue can occur, this algorithm was modified to include four trials of 600 patterns. Each pattern consisting of three, four, or five white dots presented on a black computer screen. Equal numbers from each kind of pattern were randomly distributed during each trial. These patterns had random configurations to prevent fixed pattern application and dependence of responses on memory (Figure 1).

Subjects had to respond differently depending on the odd or even number of dots in each pattern presented. Presentation of dot patterns was balanced (i.e., 4-dot patterns were presented an equal number of times as 3-dot or 5-dot patterns). Each pattern was displayed for up to 8 s or until the subject pressed a keyboard button. The interval between each response and the next pattern stimulus was fixed at 250 ms.

Before starting the experimental task, the process was explained to each subject to ensure that the instructions had been understood. Then the subjects, one at a time, performed the first trial of patterns, which took approximately 10–15 min according to their rate of response. After that, subjects were asked to self-rate how fatigued they felt on a scale of 0–10, where 10 meant insufferable to continue. Afterward, the second trial of patterns was presented to each subject. This process continued until...
the end of the task by presenting all 2400 patterns in four trials without any rest.

2.1. Behavioral Indices
To evaluate the attention state of subjects during mental assessments, statistical analysis of behavioral indices is most commonly used [27, 28]. In continuous performance tests, these indices usually involve different kinds of error responses to two types of stimulations, and response time is considered an indicator of reaction speed. Error indices are defined based on response types to stimulation; commission error indicates the incorrect responses to target stimulations, while the false alarm shows the incorrect responses to nontarget stimulations. Missed responses for both kinds of stimulations are also calculated [29–32].

In addition, based on signal detection theory, two criteria were used: sensitivity index for the subjects’ detection ability to distinguish target stimulations from nontarget ones and response criterion index to evaluate responding strategies [30, 31]. All extracted behavioral indices were transformed to a score that could be used to compare the behavior of subjects to that of a normal population. According to McGee et al. [33] and Molteni et al. [34], a weighed sum of indices generates the score. In this study, different error indices, RT, and sensitivity index was used to assess mental fatigue.

2.2. Clustering Response’s Strategies
Although the trend of responses in all subjects showed a transition from attention to mental fatigue, their reactions differed from each other during the test. Means of indices used to compare trials indicated different classes of response strategy. To determine whether there were any classes of similar strategies, various algorithms were used to cluster around subjects based on behavioral measures. This clustering was performed in two ways to distinguish subjects.

All extracted behavioral indices for each subject were used to generate feature vectors for four trials, and \( k \)-means [35, 36] and fuzzy c-means (FCM) [37] methods were used to cluster around subjects. This method of clustering was based on feature vectors containing means of the indices during the entire testing period.

2.3. RTs’ Time-Series Analysis
The return map represents the relation between a given point in a time series plotted on the \( x \) axis and the next point in the time series plotted on the \( y \) axis. The return map of RTs was obtained by plotting \( RT_n+1 \) against \( RT_n \). Analysis of the data points \( (RT_n, RT_{n+1}) \) on the map was performed by evaluating the coverage region variation. When the return map is confined to a region of the map, symptoms of chaos can be observed [38]. To quantify variation in return map coverage region a circle with the highest concentration of dots in all return maps was selected, and the ratio of dots outside the circle to dots inside it was considered a map feature. An increase of this feature means an extended coverage region in the return map and a lower concentration of dots in the specific region.

Another way of quantifying subjects’ chaotic behavior during the task is computing the Lyapunov exponent from the time series of RTs. When the sequence of RTs’ differences is calculated, it is assumed to increase exponentially, at least on the average. This parameter as defined by Sprott [39] and Hai-Feng [40] can be calculated in several ways. As it is shown in formula (1), \( \lambda \) is defined as the Lyapunov exponent, if it is positive, the behavior is chaotic [38].

\[
\lambda = \frac{1}{n} \ln \frac{d_n}{d_0} \quad \text{where} \quad d_n = |x_{j+n} - x_{i+n}|
\]

In (1), \( x_i \) is the sample of series at the time \( i \) and \( x_j \) is close to sample \( x_i \). To avoid having anomalously small values for \( \lambda \), \( x_j \) should not follow \( x_i \) too closely in time sequence. In this study, autocorrelation function was used to consider various proposed criteria for choosing a minimum time separation. In addition, while the value of \( \lambda \) may usually depends on the value of \( x_i \) being chosen as an initial value, this dependency has been eliminated by using an average value of \( \lambda \) over a large number of initial values. This invariant was used to distinguish different states of behavior during the mental fatigue task.
3. RESULTS

3.1. Behavioral Indices Extracted from the Four Trials

To evaluate subjects’ reaction during the task and their varied responses to the three kinds of stimulations, four features (the percentage of commission, false alarm error, RT, and sensitivity index) were extracted. For the best observation of subjects’ performances, these error indices and RT were calculated in the following situations:

- calculation of overall error percentage in each trial;
- separate calculation of the percentage of each kind of error (commission and false alarm) in each trial;
- division of each trial into 10 parts consisting of 60 stimulations and then calculation of the percentage of each kind of error (commission and false alarm) in each 10th;
- separate calculation of mean and standard deviation of RT in each trial for all stimulations;
- calculation of mean and standard deviation of RT in each trial for each kind of stimulation pattern;
- division of each trial into 10 parts consisting of 60 stimulations and then calculation of mean and standard deviation of RT in each 10th.

In addition, to compare them sensitivity index as the relation of correct responses to target stimulation with respect to incorrect responses to nontarget stimulation for each trial was calculated. In Table 1, mean variation of error indices, RT, and sensitivity index for all subjects in each trial are sequentially displayed. From the variation trend of indices such as the increasing of overall error (from 2.83% to 4.17%) and the reduction of RT (from 917 to 808 ms) and the sensitivity index (from 3.93 to 3.65), it can be observed that from trial 1 to trial 4 the amount of attention decreased.

To better show the variation and to identify in details how indices changed in each trial, a 10-part division was used. Therefore, the mean of commission errors, false alarm errors, and RT of all stimulations were calculated in each 10th of trials for all subjects. The variations are displayed in Figure 2 and reveal that in each trial indices did not change uniformly.

To compare different trials, it should be determined whether significant differences exist on a dependent variable over two or more measures in time. As most statistical hypotheses are based on normal distribution of variables, the Kolmogorov-Smirnov test was used to assure this among all subjects. The results for all extracted variables showed that p-value for this nonparametric test was more than 0.05, and so there was no significant difference between distributions of variables.

A repeated measure of analysis of variance (ANOVA) was used to compare trials. Like the t-test, the ANOVA calculates the ratio of the actual differences to the differences expected by chance alone. This ratio is called the F-ratio, and it can be compared to an F-distribution. Statistical package for the social sciences 17 was used to do statistical analysis. The results of one-way ANOVA for each of the indices are represented in Table 2. The p-value for all these measures except for the false alarm showed a significant difference across trials.

In Table 3, each trial is compared with other trials to determine the points in time at which a significant change in the dependent variables occurs. At α = 0.05 level, if a p-value is less than 0.05, two compared trials differ significantly; however, this often is not as important as identifying a “trend” in the data.

3.2. Response Strategies Clustering

To compare subjects in responding to stimulations and to show if any similar strategy was used, different types of clustering methods were performed. In the first step, feature vectors of behavioral indices were generated for each subject. Static vectors contained the percentage of commission error, false alarm error, mean RTs, and sensitivity index of the four trials. The clustering method used for these features was k-means; and FCM where different numbers of clusters were examined to reach the best performance in distinguishing response strategies.
Results of both k-means; and FCM with different types of distance functions showed that selected strategies could be divided into three clusters as follows:

- Response strategy in the first group indicated that subjects’ mental fatigue increased as trials continued. In this group, the decrease of RT and sensitivity index during trials and the increase of errors in answers were concurrently observed.
- In the second group, as trials increased the sensitivity index decreased except for the fourth trial. The same trait was also observed for the RT index mean.
- In the third group, subjects alternatively showed symptoms of attentiveness and fatigue.

### 3.3. Return Map of RTs’ Time Series

In this study, the return map was constructed based on RTs to display the relationship between two consecutive points in the time series. To evaluate variation of RTs during trials, a separate map was generated for each trial and the ratio of the dots outside a specific circle to those inside was calculated. For the best possible observation of variation of RTs during trials and per different stimulations.

### TABLE 2

<table>
<thead>
<tr>
<th>Measure</th>
<th>Type III Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Commission error</td>
<td>106.212</td>
<td>3</td>
<td>35.404</td>
<td>7.110</td>
<td>0.000</td>
</tr>
<tr>
<td>False alarm error</td>
<td>4.882</td>
<td></td>
<td>2.249</td>
<td>2.198</td>
<td>0.120</td>
</tr>
<tr>
<td>Mean of RT</td>
<td>153,088.900</td>
<td>2.171</td>
<td>120,655.833</td>
<td>5.133</td>
<td>0.026</td>
</tr>
<tr>
<td>Sensitivity index</td>
<td>1.655</td>
<td>3</td>
<td>0.552</td>
<td>5.718</td>
<td>0.002</td>
</tr>
</tbody>
</table>
(3, 4, and 5 dots), return maps were separately extracted for each case which is illustrated in Figure 3 as an example for a subject. In the first row, a return map for each trial is sequentially drawn based on data points \((RT_n, RT_{n+1})\) per all kinds of stimulations. The other three rows indicate a return map for each kind of pattern in the four trials. The mean variation of the ratio parameter, \(\rho\), for all subjects during the four trials is displayed in Table 4. Variation of this parameter when calculated in all patterns reduced sequentially. This means the occupied region by dots in the return map shrank in consecutive trials. For each kind of pattern (3, 4 and 5 dots), the computed parameter in the fourth trial is lower than the first trial but the variation trend is different in other trials.

**TABLE 3**

Result of One-Way Repeated Measure of ANOVA for Four Measures

<table>
<thead>
<tr>
<th>Index</th>
<th>Paired Trials</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1 &amp; 2</td>
</tr>
<tr>
<td>Commission error</td>
<td>0.0159</td>
</tr>
<tr>
<td>Mean RT</td>
<td>0.0370</td>
</tr>
<tr>
<td>Sensitivity index</td>
<td>0.8933</td>
</tr>
</tbody>
</table>

**FIGURE 3**

Sample of RTs’ return maps for a subject in each trial and for different stimulation patterns.
3.4. Lyapunov Exponent Results from RTs

In the definition of the Lyapunov exponent for the time-series data, exponential rate of separation of the two trajectories is assumed. Evaluating the validity of this assumption is possible by plotting the natural logarithm of the RTs’ differences $d_n$ as a function of the index $n$. Exponential divergence leads to a nearly straight-line arrangement of points, where the slope can be used as a Lyapunov exponent. In practice, the least square straight-line fitting to the data was used to determine the feature.

Similarly, variation of the Lyapunov exponent was evaluated during mental fatigue tasks among all subjects. To this end, the mean and standard deviation of this feature were extracted for each trial for all patterns separately and as a whole (Table 5). The results indicated that Lyapunov exponent was always greater than zero that means behavior of the system is always chaotic but the reduction of the parameter from the first to the last trial (0.65–0.56) displays a change toward less chaotic behavior.

Comparing trials based on $\rho$ and $\lambda$ parameters using the repeated measure of ANOVA and $t$-test showed significant differences in the first and last trails.

4. DISCUSSION

4.1. Behavioral Indices

Several psychological assessments of attention have been conducted to demonstrate variations in attention indices, including RT, commission error, and false alarm in numerous fatiguing processes [9, 10]. In this study, as illustrated in Table 3, participants’ performance during a mental fatigue task was assessed by evaluating behavioral indices using statistical analysis. Commission error and mean RTs distinguished the first trial from all others among all participants ($p < 0.05$). The sensitivity index indicated significant differences between the first two trials and the remaining ones. The first outcome from these variations was the general difference in all participants’ behavior in trial 1 compared to that in trials 3 and 4. Table 1 illustrates an increasing flow of commission error as well as a decrease in RT and sensitivity index in subsequent trials. Therefore, the results confirm fatigability of the task, as all participants mentioned it during the test. Table 1 shows the mean variation of indices for each trial that required at least 12 min to complete.

Each trial was divided into 10 parts to focus on the details of indices’ variation during the trial. As Figure 2 demonstrates, consistent behavior is not evident in the indices during each trial, and many changes occur. On average, at the beginning of each trial, participants tried to focus their attention, which resulted in fewer errors and longer RT than during the rest of the test. In addition, although the average of trial errors increased as the task continued, errors varied in each trial, indicating that attention changed in each trial regardless of other trials. Thus, to accurately determine the attention state, behavioral indices that can highlight these changes in a short time

<table>
<thead>
<tr>
<th>Index</th>
<th>Trial 1</th>
<th>Trial 2</th>
<th>Trial 3</th>
<th>Trial 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rho$ for all patterns</td>
<td>0.694 ± 0.238</td>
<td>0.360 ± 0.106</td>
<td>0.349 ± 0.101</td>
<td>0.310 ± 0.128</td>
</tr>
<tr>
<td>$\rho$ for 3-dot patterns</td>
<td>0.343 ± 0.181</td>
<td>0.207 ± 0.110</td>
<td>0.204 ± 0.131</td>
<td>0.189 ± 0.113</td>
</tr>
<tr>
<td>$\rho$ for 4-dot patterns</td>
<td>0.850 ± 0.393</td>
<td>0.401 ± 0.233</td>
<td>0.337 ± 0.179</td>
<td>0.375 ± 0.250</td>
</tr>
<tr>
<td>$\rho$ for 5-dot patterns</td>
<td>1.276 ± 0.396</td>
<td>0.558 ± 0.242</td>
<td>0.712 ± 0.227</td>
<td>0.499 ± 0.265</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Index</th>
<th>Trial 1</th>
<th>Trial 2</th>
<th>Trial 3</th>
<th>Trial 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda$ for all patterns</td>
<td>0.656 ± 0.129</td>
<td>0.655 ± 0.129</td>
<td>0.639 ± 0.115</td>
<td>0.562 ± 0.078</td>
</tr>
<tr>
<td>$\lambda$ for 3-dot patterns</td>
<td>0.699 ± 0.139</td>
<td>0.674 ± 0.126</td>
<td>0.621 ± 0.095</td>
<td>0.572 ± 0.069</td>
</tr>
<tr>
<td>$\lambda$ for 4-dot patterns</td>
<td>0.659 ± 0.122</td>
<td>0.657 ± 0.142</td>
<td>0.645 ± 0.115</td>
<td>0.577 ± 0.093</td>
</tr>
<tr>
<td>$\lambda$ for 5-dot patterns</td>
<td>0.674 ± 0.131</td>
<td>0.673 ± 0.128</td>
<td>0.626 ± 0.095</td>
<td>0.566 ± 0.077</td>
</tr>
</tbody>
</table>
should be selected. Although this study simultaneously recorded EEG signals, the focus of this article is on an analysis of the behavioral indices of fatigue; the results of the EEG analysis will be reported in another paper.

For a deeper investigation, the effects of different stimulation patterns on behavioral indices were taken into consideration. In this task, two kinds of stimulations, target and nontarget, were used and subject responses to each were recorded. Evaluation of reactions for each kind of pattern stimulation was done based on the mean RTs, which revealed that nontarget stimulations had consistently decreased in value. However, the decreasing trend for target stimulations in the fourth trial changed direction and increased. The decreasing trend of this parameter was a sign of the unwillingness of subjects to continue and their tendency to click to end the task. The few increases in RTs in the last trial in contrast to the third one could be a result of the increased motivation of some subjects to finish the task with an improve outcome.

4.2. Response Strategies Analysis

As it was mentioned, behavioral indices’ mean variation was used to differentiate trials; however, because of averaging, we may have missed each subject’s strategy in responding. Based on behavioral indices, the results of k-means and FCM were similar and showed three clusters of strategies as follows:

- In the first cluster, subjects’ attenuation of attention occurred trial by trial. Reduction of RT and sensitivity index and addition of error responses in subsequent trials were indicators in this group. Moreover, subjects’ stringent unwillingness to continue working was expressed in their self-scoring.

- The second group’s behavioral indices showed the same variation as the first group but just for trials 1–3. Subjects of this group behaved better in the fourth trial compared with the third one. This means downward changes in the average RT and upward mean error variation stopped and even reverse trends were observed. This behavior can be interpreted as increased motivation to complete the task better. Another reason for this behavior is the results of detection target stimulations (4-dot patterns). Subjects of this cluster displayed better performance in detection of target stimulation in the last trial. Similar results were also achieved by a study on motivation by Boksem et al. [12].

- Performance of some subjects during task varied periodically from one trial to another. In other words, subjects in one trial responded to stimulation attentively and in the next one showed fatiguing symptoms alternatively. Although several studies [9, 18, 31] have reported behaviors similar to that of the first and second groups, the behavior of the third group has not been reported elsewhere.

To investigate if there were differentiable clusters in responding stimulations, other feature vectors were extracted. Parameters extracted from nonlinear analysis of RTs’ time series were used to create new feature vectors. In this method, the ratio parameter extracted from the return map was used as the first index of feature vectors. The other index was Lyapunov exponent for RTs’ time series. Results of clustering according to these new feature vectors were similar to the results of behavioral indices and the three previously specified clusters were separated.

4.3. Chaotic Behavior Analysis

Another way of analyzing the mental behavior of subjects during an attentive task is to use a nonlinear investigation of behavioral indices. As mentioned before, changes in chaotic quantifiers were expected to be related to changes in mental behavior. When mental fatigue occurred, focusing and responding ability to different stimulations decreased which led to a decrease in chaotic behavior. In some studies, the nonlinear analysis of EEG signals during mental fatigue was also investigated to demonstrate different mental states [14, 15, 17]; however, nonlinear analysis of RT as a simple behavioral index has not been discussed vividly in previous studies.

In this study, it was shown that distinguishing mental states by a nonlinear analysis of RTs is much simpler than using EEG signals. Return map analysis was the first method used to show nonlinear variation of behavioral indices during a fatiguing task. As represented in Figure 3, usually in the first trial, constructed maps were spread wide in the region. When mental fatigue occurred, the covered region centralized into a narrow space. Calculating the covered area in each trial seemed to be a good criterion to use. Figure 3 shows that the distribution area occupied by the dots shrinks from trial 1 to trial 4; therefore, $\rho$ parameter decreases which is calculated based on the relevance of the number of dots outside a specific circle to the dots inside (Table 4). The transition from attention to mental fatigue can be expressed as follows. When RTs to stimulations became limited in range, the dots in return map became similar and the occupied region decreased. This situation appeared when subjects’ attention decreased and answering was disengaged from stimulation which meant that they just answered without any attention. On the other hand, when subjects attended to stimulations, because of the need to have diverse cognition responses, the variation of RTs increased, accordingly, the occupied region increased. This reduction of the occupied area and $\rho$ parameter are symptoms of reduction in the chaotic behavior of the phenomenon.

The Lyapunov exponent, as the common criterion used to investigate chaotic behavior of a system, was finally...
used. The positive aspect of this feature deals with the chaotic behavior of a system. In this study, as the results in Table 5 express, the average Lyapunov exponents were bigger than zero in all trials. The variation trend of this feature showed a decrease in complexity as the trials continued (from 0.65 to 0.56).

These parameters show that even with a nonlinear analysis of behavioral indices extracted during a mental fatiguing task, one can recognize the transition from an attentive task focus to mental fatigue. This finding may help in applying better indicators of mental fatigue for effective behavioral measures such as EEG signals. Although EEG signals were simultaneously recorded, this article only focuses on the usual behavioral indices used in psychological investigations first to show that this task may lead to mental fatigue, and then, more importantly, to indicate that nonlinear analysis of behavioral indices is capable of differentiating mental behaviors.

5. CONCLUSION

Based on the behavioral indices, three issues related to mental fatigue were investigated in this study. First, a variation of behavioral indices was explored during a simple attentive task followed by mental fatigue. Then subjects' strategies for continuing the task were clustered on the basis of different feature vectors. Comparing subjects' strategies in responding to four trials showed that although in the final trial all of them had experienced mental fatigue, variation of attention in subjects from the second trial to the last one was different. Finally, two different nonlinear analyses of RT displayed that, regardless of how subjects reached mental fatigue, that occurrence could be determined through complexity variation. To bring about further resolution of mental fatigue detection and differentiate fatigue from attention, the use of other behavioral indices or features that can show mental state variation as it occurs is suggested.

REFERENCES