Interb-blink intervals detection and analysis for mental state recongition

**Full paper**

**Jurnal**

**Teknologi**

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| **Article history**  Received :8 August 2015  Received in revised form :  Accepted :15 October 2014  **Graphical abstract** | **Abstract**  In this paper we propose a novel idea to recognize mental activity by means of a computer vision system and statistical analysis of inter-blink intervals. Overall 19 students participated in the experiment, however due to noise and recording artifacts 10 students were selected. The experiment consisted of four phases: 5 minutes of rest, 10 minutes of IQ test, 5 minutes of rest and 10 minutes of memory test. We also developed software that guided students during the experiment and measured number of correctly solved problems. During each phase blinks were detected and cumulative statistics were calculated. We found that depending on mental activity there are differences in estimated statistics. We believe that such differences can be further generalized to distinguish mental activities.  *Keywords*: Mental activity recognition, Blink dynamics  © 2015 Penerbit UTM Press. All rights reserved. |  |

**1.0 INTRODUCTION**

Being able to recognize mental state of mind by analyzing eye blink dynamics has a wide range of applications. Knowing a persons attention can play an important and vital roll in human endeavors, From drivers attention perception to online education systems the areas this can be applied is infinite as attention is key to human performance.

Lack of concentration and/or falling asleep while driving is a major cause of road accidents. Some of these accidents are the result of the driver's medical condition. However, a majority of these accidents are related to driver’s fatigue, drowsiness, and driver inattention caused by various distractions inside and outside the vehicle. Car accidents associated with driver fatigue are more likely to be serious leading to serious injuries and deaths. The European Transport Safety Council [1] states that driver fatigue is conservatively estimated to be a factor in about 20% of road crashes in Europe. In the United States [2] an estimated 1.35 million drivers were involved in a drowsy driving related crash between 1998 and 2003.

This hot area of Abstract. We present a method for evaluating ICA separation of artifacts from EEG (electroencephalographic) data. Two algorithms, Infomax and

FastICA, were applied to "synthetic data," created by superimposing simulated

blinks on a blink-free EEG. To examine sensitivity to different data

characteristics, multiple datasets were constructed by varying properties of

the simulated blinks. ICA was used to decompose the data, and each source

was cross-correlated with a blink template. Different thresholds for correlation

were used to assess stability of the algorithms. When a match between

the blink-template and the decomposition was obtained, the contribution of

the source was subtracted from the EEG. Since the original data were known

a priori to be blink-free, it was possible to compute the correlation between

these "baseline" data and the results of different decompositions. By averaging

the filtered data, time-locked to the simulated blinks, we illustrate effdriver’s safety and accident prevention caused by drowsy and inattentive drivers attracted the immense attention of psychologists, engineers, and specialists in the area of computer vision. One of the approaches to aid this problem comes from visual monitoring of a driver's awareness through tracking and analyzing blink activity. By analyzing driver’s blink duration and frequency mental state can be extracted and in the case of drowsiness or lost of concentration a special signal could warn a driver to either keep concentration or take a break.

The other application of mental analysis through analyzing blinks is distance learning. According to the 2012 survey of online learning [3], more students than ever are taking online courses. The study revealed that the number of students taking at least one online course has now surpassed 6.7 million. Thirty-two percent of higher education students now take at least one course online. There are many arguments supporting or condemning online education. Advocates say online education offers greater flexibility in terms of selection of course work, class time, and choice of school is not a matter of geographical proximity. On the other hand, there are a number of drawbacks generally rooted from the lack of interaction. While there is a basic opportunity to interact in real-time, it is generally limited to raising and receiving questions. However, when the teacher is physically taken out of the classroom there is a potential handicap to the classroom learning dynamics. Since the teacher is unable to acutely observe a student’s body language and thus give the necessary commands and feedback required to stabilize and augment the learning environment there is an increased potential risk of learner inattention. This is especially true if lectures are prerecorded. To add to this handicap, online education is often home based which further exacerbates the contrast between an online class and an actual classroom in which disruptive factors are minimized. As a result, attention monitoring and classroom control are pressing issues in online education. Yet at least one clear advantage of having the convenience and the ability to use online lectures is the vast control the learner is bestowed. In the case of the learner being potentially drowsy, or tired, he or she can take a break and return to the lecture at an appropriate time.

A large body of research work has investigated the relationship between blinking characteristics and degree of attention. Importantly, it was found that eye blinks are not only a consequence of physiological processes driven by peripheral reasons, but properties of eye blinks such as duration and frequency also reflect processes in central nervous system. J.A. Stern et al. [4] performed a review on the relationship between fatigue and eye blink rate with the conclusion that blink frequency increases as a function of the time-on-task. Such tasks include reading, driving a car, and maneuvering an airplane. Nakayama et al. [5] provide experimental data showing the increase in the blink rate in accordance with increasing task difficulty. Fukuda et al. [6] also support the observation that cognition demanding tasks specifically a running memory task is related to the increase in blink frequency. On the other hand Yamada [7] presents somewhat contradictory data. He measured eye blink activity of children while they were a) watching an animation cartoon, b) playing a video game and c) performing a mental test. According to his experimental results, the eye blink activity was lowest while playing the video game and highest while watching an animation which was reported by 8 out of 10 participants as the most boring activity. Based on these results Yamada made the conclusion, that eye blink activity is a good indicator of attention concentration and task pleasantness of a mental task. Karl F. Van Orden et al. [8] also reports that eye activity correlates to workload during a visuospatial memory task. However, they state that the more complex the memory task is, the lower the eye blinking rate and longer duration. It should be noted that compared to previously mentioned works, the latter one was considering relatively short measurement times and thus there is a probability for the blink rate to increase for longer time frames. The majority of researchers [6-8] agree that the rate of eye blink changes with the degree of mental workload, yet the question on how eye rate changes, still needs further investigation and clarification. As Caffier at el. found [9] the blink duration is significantly longer (about 50ms) during the drowsy than during the alert conditions.

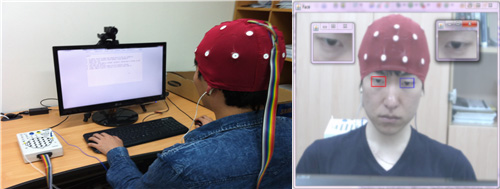
The focus of this paper is to test the hypothesis of mental state activity recognition using a computer vision algorithm. However, instead of estimating eye blink rate we propose to extract and analyze the dynamics of inter-blink intervals.

In section 2, an experimental setup and the developed testing software is described. Section 3 elaborates on the concept of inter-blink intervals and its analysis. In section 4 we analyze obtained results and talk about out future work.

**2.0 EXPERIMENTAL SETUP**

**2.1 Data acquisition**

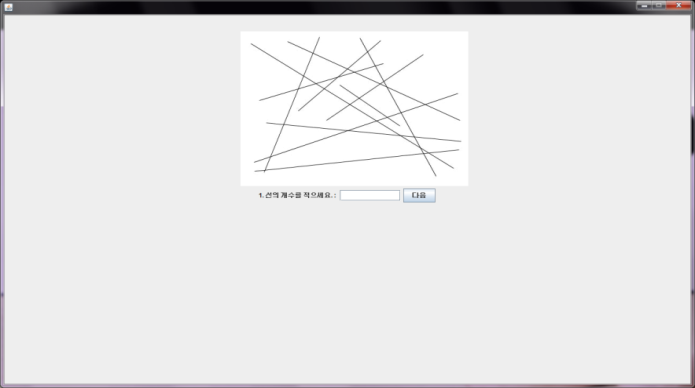
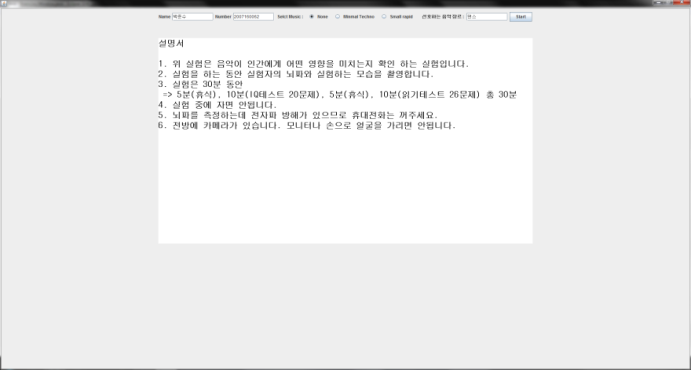
For the purpose of collecting data we developed special testing software, and software for detecting eye blinks in the capture video stream. The video stream was captured with a 120 fps color PointGrey Flea3 USB camera. Video stream was stored on a disk drive and later processed. Simultaneously we were also recording EEG signals to be able to compare the quality of detected eye blinks using blink detection software. The experimental setup is shown on the left of figure 1.



**Figure 1** (left) Expeimental setup, (right) camera view

**2.2 Testing procedure**

The recording session consisted of four stages: (a) resting, (b) the IQ test, (c) resting, and (d) the memory test. The testing software was developed in Java in such a way that it does not required any interventions. The whole testing session took 30 minutes, 5 minutes resting before the IQ, 10 minutes the IQ test, 5 minutes resting stage and 10 minutes the memory test. The IQ test consisted of 20 questions. In the memory test a passage about Ethiopia was given. After reading the passage for five minutes a user was presented questions one by one. On the left and right sides of figure 2 an example of an IQ test question and a memory test question is shown correspondingly.

**Figure 2** User’s interface

**2.3 Eye blink detection procedure**

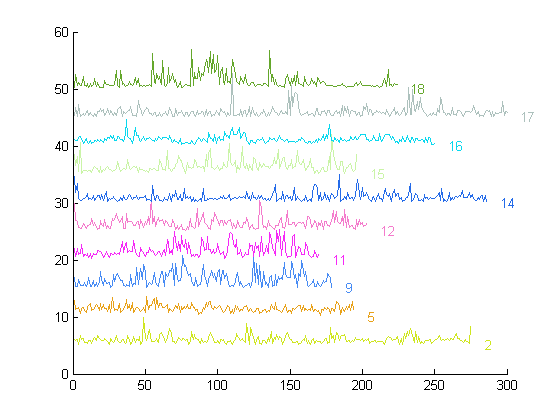
Video was recorded while participants were taking the tests and later analyzed by the developed software. The software was implemented in Java using computer vision library (OpenCV). OpenCV comes with Haar feature-based cascade classifier for object detection [10] and pretrained features for face and eye detections. The process of blink detection can be summarized in the following steps: (a) face detection is performed using a cascade classifier, (b) both eyes are detected within facial region using the casscade, (c) image is binarised and two largest, circular components are considered as irises. When position of an eye is detected it is being tacked using template matching. The next step is to detect blinks. During the blink detection algorithm a gray scale histogram with projection to a vertical axis is constructed. Such histogram is built for a closed eye and later compared to the histogram built online. When two histograms match the measurement function becomes close zero, and that is a sign of a closed eye. On the left of figure 3, closed eyes correspond to the value one on the graph and opened eyes correspond to zero.



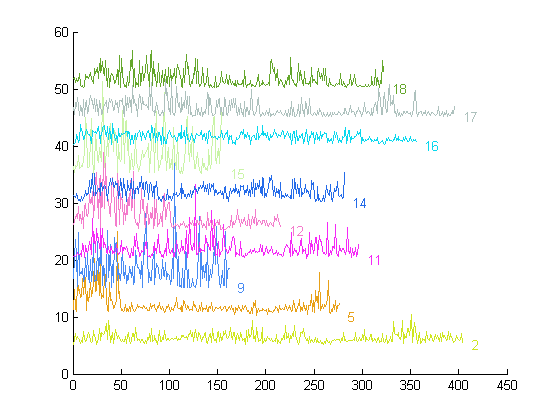
**Figure 3** (left) Real-time eye blink detection, (right) extracted IBI

Overall 19 subjects participated in the experiment. The subjects were recruited among undergraduate students, whose age varied from 19 to 28 years old. Students were instructed to relax during the resting stages and concentrate during IQ and memory testing. Only records of 10 students were selected for further analysis. The remain students were excluded due to excessive movements or because of temporarily nodding during resting stages.

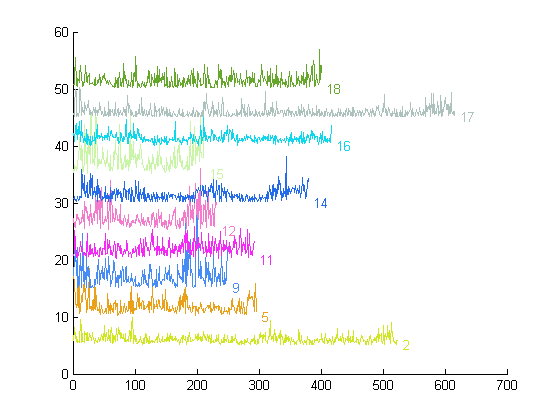
**3.0 METHODS**



**Figure 1** IBI during 2nd resting stage



**Figure 1** IBI during IQ test



**Figure 1** IBI during memory test

**3.0 RESULTS AND DISCUSSION**

**Table 1** Average number of blinks

| ***Subjects*** | IQ test | Rest | Memory |
| --- | --- | --- | --- |
| 1 | 75 |  | 34 |
| 2 |  |  |  |
| 3 |  |  |  |
| 4 |  |  |  |
| 5 |  |  |  |
| 6 |  |  |  |
| 7 | 45 |  | 53 |
| 8 |  |  |  |
| avg ± std | 84.64±4 |  | 64.24±2.3 |

**4.0 CONCLUSIONS**

This paper proposed a new optimal dimension of heat sink design using particle swarm optimization method. Presented results demonstrate high heat dissipation under various sets of constraint parameters for single and multi objective approaches. Furthermore, the effect of design variables as well as PSO parameters for the optimum result was suggested. The proposed variables have been analyzed and can be used for further analysis in order to produce a suitable heat sink dimension with heat dissipation increased by 79.33% and size of heat sink reduced about 27.15%.

**Acknowledgement**

The authors would like to thank for the support given to this research by Ministry of Higher Education (MOHE) and Universiti Teknologi Malaysia (UTM), under FRGS grant Vot: 4F243, Optimization of Heat Sink Design for Central Processing Unit Based on Heat Transfer Model Using Artificial Intelligent Method.

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