Attention Monitoring and Alarming for Live Education Based on Brainwave Analysis and Computer Vision Technology

CHEN Shaoling[1*], DENG Linsui[1], ZENG Jiahua[1], WU Yichang[2], ZHANG Sijia[1], HUANG Zhihong[1]
School of Mathematics[1], School of Physics[2]
Sun Yat-sen University
Guangzhou, China
Sherlynchan0@gmail.com[*]

***Abstract*—Live Education has become more and more popular nowadays. However, little has been done to distinguish the attention status and learning effects of the audiences. In this paper we proposed an attention monitoring and alarming system based on brainwave analysis and computer vision technology. With a Mindwave and PC camera, the system will automatically remind the audience when he/she is losing focus. It will also alarm the teachers when most of audiences are distracted.**

Keywords- EEG; Opencv; Attention; Live Education.

I. INTRODUCTION

With the rapid development of the Internet industry, live video platforms have rapidly emerged in recent years. As of the first half of 2017, the number of online live video platforms in China was close to 200, with market size and platform users up to 19.48 billion RMB and 392 million respectively. In this situation, the live education platform has also developed rapidly, such as YY voice, Jingle classroom, Cctalk, etc. "Education + Live video" has brought the industry an opportunity to upgrade.

Compared with traditional online education, live courses pay more attention to interactivity. Although traditional recording courses are rapidly sweeping across the globe with their openness and large scale, they are faced with difficulties in achieving personalized learning and flexible teaching methods. The emergence of live online education supplements the deficiencies of the traditional online courses, allowing educators and learners to communicate in real time.

Live online courses have been proved to be effective by Ozgur Yilmaz in [1]. However, there are still many challenges. Although the interaction between teachers and students has improved, there is still a lack of emotional communication between them. Students are sometimes distracted during online courses without being discovered in time, which inevitably leads to a decrease in learning efficiency. Therefore, to make live courses and platform design more in line with the actual situation of students, and to establish a learner-centered, multi-dimensional, efficient, and interactive learning environment have become our urgent problems to maximize the effectiveness of “cross-temporal learning at distance”.

Our project aims to monitor online learners’ attention based on brainwave analysis and computer vision technology so that we can remind both teachers and learners themselves when the learners are distracted, and improve the live online education efficiency in this way.

The rest of the paper is organized as follows. Section II describes the related work. Section III and IV explain the equipments and methods used and the experiment designed respectively. Section V describes the data collection, processing details and the results. Conclusions are presented in Section VI.

II. RELATED WORK

"Education + Live video", which began in 2011, has only been developing for 6 years and the corresponding academic research is still in its infancy. The existing researches mainly focus on the concept of live online education platform, platform product design and class design.

In the aspect of the status quo of live online education platforms, Liu Qingsong [2] briefly reviewed the status quo of the development of Chinese live online education platforms in terms of the definition, recent development and the advantages and disadvantages of the platforms. Hao Yi et al [3] analyzed the existing live education web site and pointed out that the “Education + Live video” is developing slowly and is still in its infancy. Liu Jia [4] believes that “Education + Live video” model represents a future development direction for interactive learning and computer environment construction which will be sought after by more learners keen on digital teaching.

In the aspect of platform product design, Xing Qiudan [5] discussed the issues faced by online interactive education based on cloud computing and the characteristics of big data. He also set up an online interactive platform model and realized efficient interaction between online lecturers and learners by data mining. Guo Lingling [6] proposed the concept of “Internet learning community” and set up an online learning model based on it, in which learners and lectures can collaborate with each other online, thereby interacting and promoting each other.

In the aspect of online courses design, Hao Xiaolin [7] put forward ideas on how to improve the teaching results based on some existing problems. Quan Jingchao [8] summed up the practical experience of teaching management, and put forward reasonable suggestions on issues of live online education system from the aspects of management organization, technical support, teacher teaching, and student participation. Luo Yunxia [9] conducted a case study of simultaneous live-learning class offered to normal students at Huazhong Normal University.

To summarize, most of existing study on “Education + Live Video” is about qualitative analysis and empirical exploration. For the lack of quantitative research, it’s hard to provide more powerful theoretical support for live online education. For example, due to the lack of systematic analysis of online learners, there is no way to provide practical guidance for further platform product and course design.

III. METHODS

A. EEG-Based Attention Detection

1) EEG

Electroencephalogram(EEG) records the electric activity of brain. It measures the electric fluctuations of brain electrophysiological activity in the cortex caused by brain neurons. Modern clinical EGG research has shown that human brain generates spontaneous physiological activity while working, which can be indirectly detected by specific recording devices as the form of brain waves as EEG, effectively.

2) Introduction of Mindwave

Mindwave is an electrophysiological signal acquisition system which can collect electrophysiological information timely by a simple EEG headset and output EEG signal data to computer as specific format.

Mindwave deals with the electrophysiological signal, relying on ThinkGear chip technology. ThinkGear chipset amplifies the original EEG signal collected and removes noises caused by muscle, pause or other facilities utilizing particular noise filter to ensure the clearness and accuracy of EEG signal. Meanwhile, by eSense algorithm, Thinkgear chipset can output the electrophysiological data of eight different frequency bands, blinking data and other related data, then it can calculate and transfer the attention and mediation parameter of subjects to computer to achieve brain interaction.

By using blue tooth communicate module, Mindwave can transmit data to any device with blue tooth receive module.

Figure 1. EEG headset.

3) Moving Average Filter Algorithm

It's also called moving sliding window algorithm [10].

Assume g(x,y) is grey-scale value of an unprocessed image, while f(x,y) is grey-scale value of a filtered one. S_{xy}, including M points, represents the neighboring windows of chosen pixel. $f(x,y) = \frac{1}{M}\sum(m,n)\,\epsilon S_{xy}\,[g(m,n)]$; namely we choose an neighboring area S of every pixel in original image with noise, and then use the mean of S' s grey value on behalf of f(x,y), the average pixel value in spatial domain. The grey value of smoothing image, f(x,y), is given by mean of g(x,y) located in predetermining area neighboring (x,y).

B. Computer Vision-Based Attention Detection

Opencv [11] is an open source library of cross-platform computer vision under the BSD license, realizing a great deal of general algorithms about image manipulation and computer vision. In this article, we adopted the cascade classifier for target detection based on Haar features to detect and trace the faces, eyes and smiles.

In order to improve the speed and accuracy of detection, Paul Viola and Michael Jones provide Viola–Jones object detection framework, which unites Haar feature, Adaboost algorithm and Cascade classifier together. In the face detection field, this system holds high detection rate and good generalization ability, and performed well at eye tracking and smile recognizing. Additionally, the detector runs at 15 frames per second in real-time application without image difference technology, and have universality without skin-color detection.

Harr-like feature construct classifiers directly by translating message of specific region, such as boundary feature, central feature, linear feature, etc.

Adaboost algorithm trains different classifiers for the same training set, aiming to constitute a stronger classifier. Assume the basal resolution ratio is 24*24, the matrix feature sets of each image are more than 180000, which will lead to a large number of computation. Since a fraction of features are able to build an effective weak classifier in learning process, Adaboost provides a strong classifier with little computation.

Cascade structure can improve detection performance and reduce the computing time simultaneously. It can reject non-target windows while detecting almost all of targets. Cascade structure uses weak classifier to remove quantities of non-targets sub-windows at first, then classify the reminder by strong classifier, which can reduce the false alarm rate remarkably.

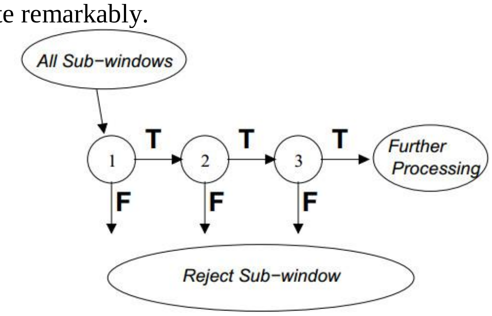


Figure 2. Cascade structure

IV. EXPERIMENT DESIGN

The experiment was divided into two stages, including pre-experiment and formal experiment, which could be seen in Figure 3.

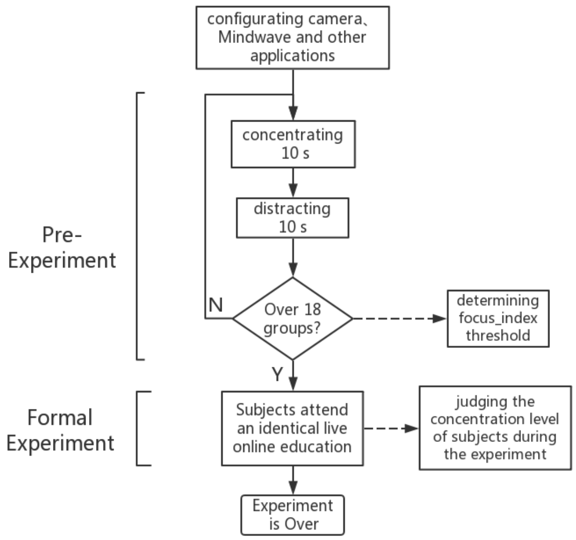


Figure 3. Experiment Design

A. *Pre Experiment*

Each subject was required to conduct 18 sets of pre-training, which included concentration stage and distraction stage. In the concentration period, subjects were required to focus on the sign "+" in the center of the screen for 10 seconds, while in the distraction period, the screen was blank and subjects were required to be distracted both in mind and at appearance, such as closing eyes, not watching screen, talking to others, etc.

24 healthy subjects participated in the pre-experiment. All are from Sun Yat-sen university, at an average age of 20. We recorded their Attention and Meditation values of EEG in the two different stages respectively using Mindwave and captured the subjects' faces, eyes and smiles using camera.

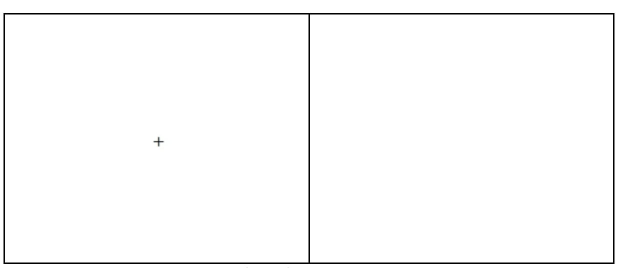


Figure 4. Interface for concentration and distraction.

B. *Formal Experiment*

We recorded eight subjects' (4 males and 4 females) brainwave and computer vision identification data while their attending a live online course.

V. EXPERIMENTAL DATA AND ANALYSIS RESULTS

A. *Brainwave Detection and Focus_Index Threshold Determination*

1) *Analysis Process*

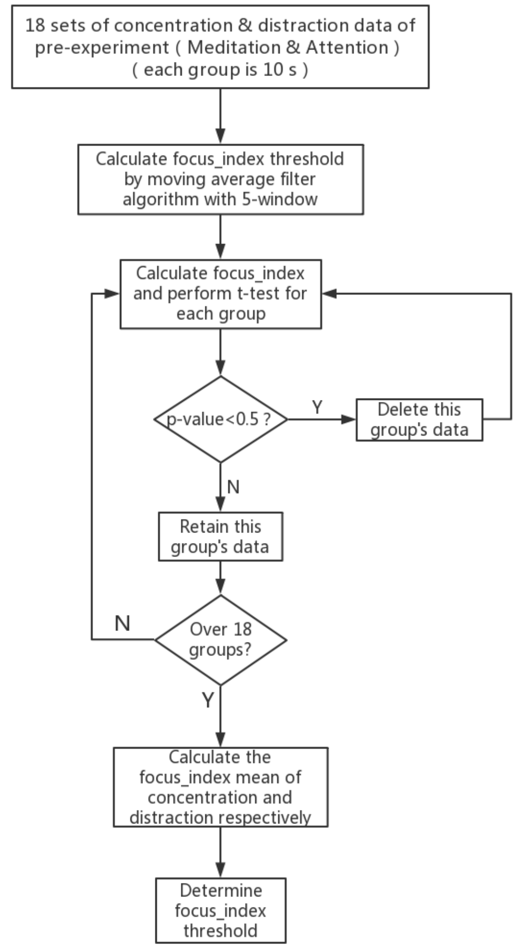


Figure 5. Brainwave Analysis Flow.

2) *Data Smoothing*

The following figures are the Attention and Meditation value.

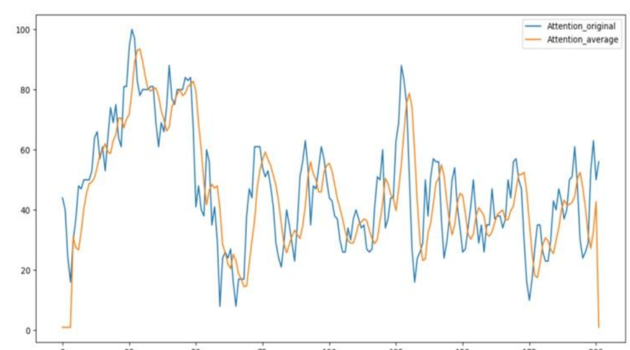


Figure 6. Attention value before and after mean smoothing.

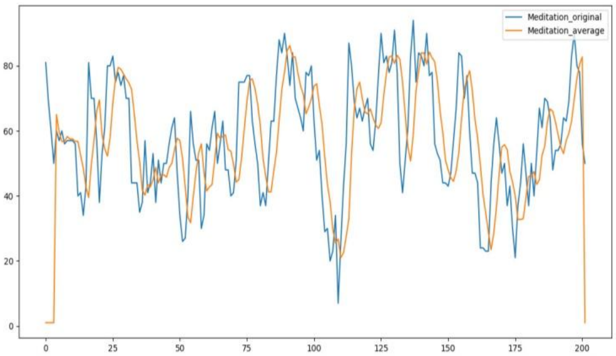


Figure 7. Meditation value before and after mean smoothing.

3) Concentration Index Threshold

The higher the Attention value is, the more focused and conscious the subjects are. The higher the Meditation value is, the more tired the subjects are.

We defined Focus_Index to measure the attention status.

$$\text{Focus\_Index} = \frac{\text{Attention}}{\text{Meditation}}$$

Figure. 8 shows the Focus_Index of subjects in the state of concentration and distraction respectively. It shows Focu_Index in the state of concentration was always higher than that in the distraction state.

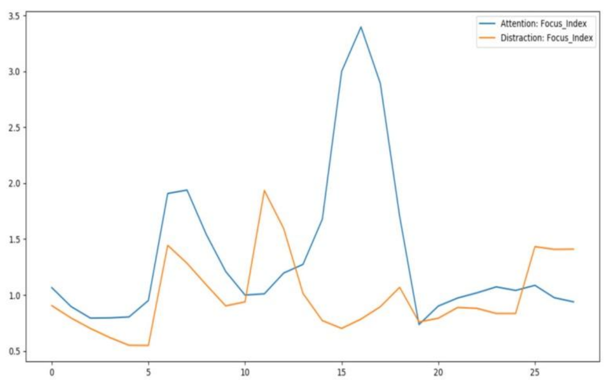


Figure 8. Focus_Index under concentration and distraction state.

4) T-test

In order to ensure the accuracy of the Focus_Index threshold, we performed a two-sample unilateral T-test on the 18 data sets for each subject during the pre-experiment, and removed invalid data.

H_0: The mean Focus_Index of the concentration group is higher than the distraction one;

H_1: The mean Focus_Index of the concentration group is not higher than the distraction one;

If p-value>0.05, the null hypothesis is not rejected and the data in this group is considered valid; otherwise, the data in the group is deleted.

5) Focu_ Index Threshold Determination

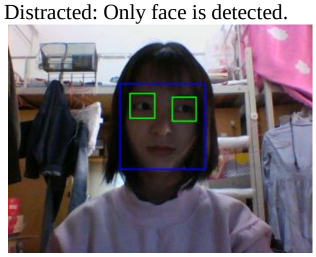
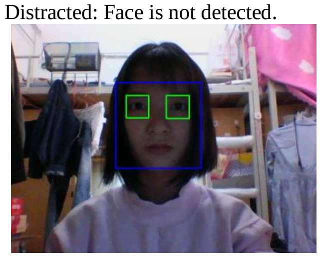
We used the mean of Focus_Index under concentration and Focus_Index under distraction as the Focus_Index Threshold.

B. Accuracy of Attention Judgement by Computer Vision Detection

Brainwave analysis can better determine the subject's attention level, but there is still the problem of instability of the device. With the auxiliary help of computer vision technology, we can greatly reduce the problem of misjudgment.

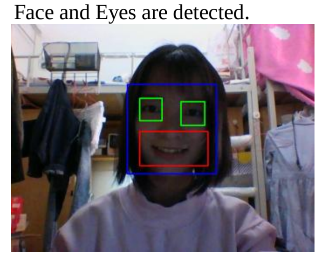
Figure 9 shows the different states of the subject in front of the PC camera.


Distracted: Only face is detected. Distracted: Face is not detected.

Distracted:
Face and Eyes are detected.

Concentrated:
Face and Eyes are detected.

Distracted: Subject is off. Highly Concentrated: Smile is detected.

Figure 9. Subjects' different states before the PC camera.

We conducted detection and identification using opencv's Haar classifier. If the face or the eye were not be detected for more than 5 seconds, the subject was judged to be distracted. In 18 sets of test among 24 subjects, the average identification accuracy was up to 70%.

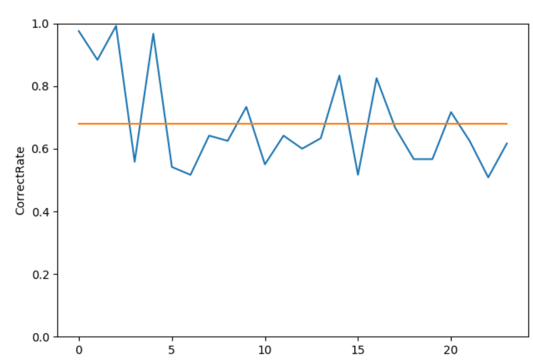


Figure 10. Accuracy of Attention Judgement.

C. Attention Monitoring and Alarming System

Through the analysis of pre experiment, we finally determined the Focu_Index threshold of the 8 subjects who participated in the formal experiment.

There is a significant difference in the subject's attention level, which indicates that it is necessary to adopt a specific threshold for different subjects.

Subject	Average Focus_Index (Concentrated)	Average Focus_Index (Distracted)	Threshold of Focus_Index
1	1.0459012	0.52717012	0.78653566
2	0.8224471	0.6756078	0.74902745
3	1.04345979	0.80483633	0.92414806
4	1.13806734	0.87067851	1.00437293
5	1.02307623	0.666138	0.84460711
6	1.02566772	0.78092833	0.90329803
7	0.75079581	0.6892811	0.72003846
8	1.34834315	1.10265959	1.22550137

Table 1. Eight subjects' Focus_Index Data.

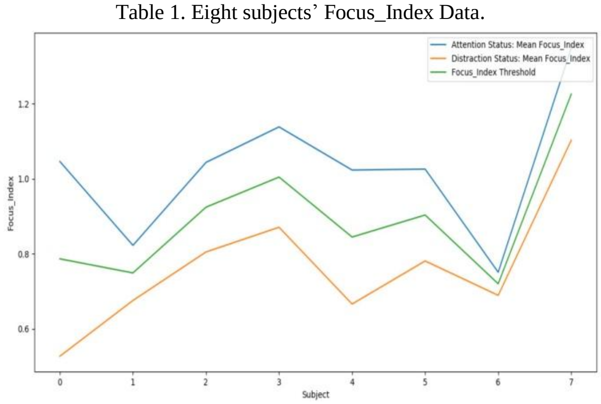


Figure 11: Focus_Index Threshold

Based on the above results, we designed the Attention Monitoring and Alarming System as follows:

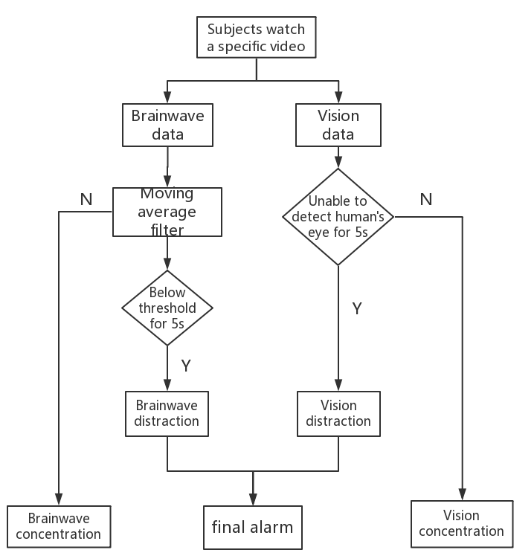


Figure 12: Attention Monitoring and Alarming System.

(1) When the Focus_Index of the subject was lower than the threshold value for 5s consecutively, the brainwave warning would alarm;

(2) When the subject was judged to be distracted for 5 times consecutively by the camera detection, the computer vision warning would alarm;

(3) When the brainwave and computer vision alarming occurred at the same time, the system would give an reminding to the subject.

The results are shown in Table 2.

Subject	Brainwave Monitoring Alarming Times	CV Monitoring Alarming Times	Distraction Alarming Times	Experiment Duration(s)
1	809	3268	794	3355
2	389	2497	261	3389
3	21	1423	6	3409
4	0	2083	0	3404
5	705	1389	286	3387
6	1344	2424	985	3418
7	0	3549	0	5208
8	3534	279	200	5184

Table 2. Alarming results during the formal experiment.

Figure 13 showed the number of subjects concentrated during the live course. At the beginning, most of subjects remained focused, but after about 55 minutes, there was only 1 or 2 subjects keep listening carefully.

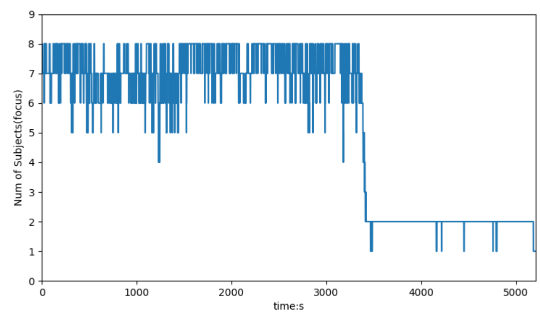


Figure 13. The number of concentrated subjects.

Figure 14 showed the number of listeners who were captured with smiling faces during the experiment. It could be seen that, when most listeners were distracted, the timely attention and interaction of the lecturers could effectively focus the learners' attention.

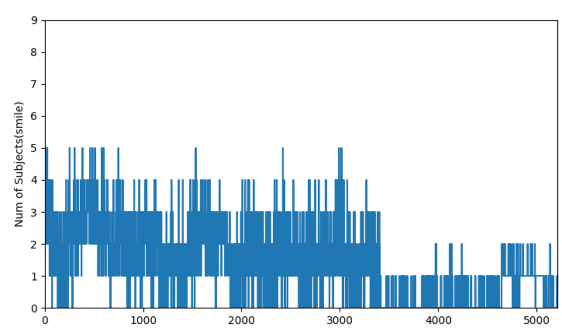


Figure 14. The number of subjects with smiling faces being captured.

VI. CONCLUSIONS

In this paper, we built an Attention Monitoring and Alarming System for "Education + Live Video" through analyzing online learner's Focus_Index under concentration and distraction status with the help of brainwave analysis, and computer vision technology, to realize real-time monitoring.

Our system both benefits live learners and lectures, which can not only increase effective interaction, but also improve both learning and teaching effectiveness of live education.

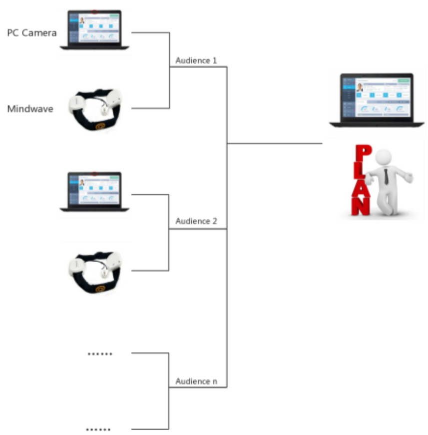


Figure 11. Live Education Attention Monitoring and Alarming System.

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