# Cognitive Biometrics Application for e-Learning Security Enhancement

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***Abstract***

*Because of the weak authentication system to get permission to access e-learning contents or more sensitive contents such as tests, an advanced remote authentication system is necessary due to the limitation of one-time authentication based on password or personal identification (PIN).To provide the continuous personal identification, we present the possibility of cognitive biometric applications by combining both eye tracking and event relevant potential (ERP) signal of brain waves. To show the possibility of ERP 300 application, the experimental results of gender differences to information technology terminologies presented as target stimulus, and the analyzed results show that P300 can be useful as acontinuous authentication method in e-learning systems.*

***Keywords:*** *cognitive biometrics, ERP 300, eye tracking, e-learning, authentication*

## 1. Introduction

Applying new informational devices for delivering learning content to learners accelerates the advancement of e-learning technologies. Combined Internet and high performance computing facilities have changed the learning environment of industries into cyber space and e-learning systems. As new technologies appear, the shape of delivering learning contents to users is also changing. Recently applying smart phones and iPad type devices have been actively adopted into classrooms; this practice is sometimes referred to as smart learning.

Also, the Internet based learning environment makes it possible to track a user's learning objectives, check their progress, and even achievement all in real-time. Through well prepared PCs and the Internet, questions and solutions are provided using computer files and this may result in paperless examinations and classrooms in the near future [1]. In spite of the advantages of e-learning and e-testing in terms of the economy and environment, there exist new issues of security.

The security problems in advanced e-learning schemes come from the nature of learning content management systems (LCMS) or learning management system (LMS) for providing learning contents to users and recording users' achievements using a client – server system, where users need to access the server to acquire contents. Among the issues examined security policies and mechanisms must be designed to support authentication, authorization, confidentiality and accountability [2, 3].

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Authentication involves validating the end users' identity prior to permitting them server access. Authorization defines what rights and services the end user is allowed once server access is granted. Similarly, the confidentiality of e-learning keeps information from being disclosed to anyone not authorized to access it. Accounting provides the methodology for collecting information about the end user's resource consumption, which can then be processed for billing, auditing, and capacity-planning purposes. To implement such a plan, it is vital to provide security to ensure that a user is exactly the person he claims to be to avoid cheating.

Typically, authorized person checking is done either by entering a password, using smart cards or using finger identification, based on biometrics [4, 10]. But, the possibility of circumvention is high in an on-line education environment, and new solutions are required as smart devices are adopted more in educational sectors. It is very important to consider situations where students cheat on exams due to the separation of instructor and students. For example, one can place their finger for identification but a friend can answer the question. That is why some authors claim that physical contact between a student and lecturer must be established and places where this can be done must exist.

One good aspect of the current advanced information delivery mechanisms is that they have adopted more information gathering capability interfaces such as web cameras or finger printing. Using these new features may lead the way to implementing more reliable person authentication systems, and we propose the combined biometrics of eye tracking and brain wave monitoring to establish a reliable e-learning system.

## 2. Brain wave and eye movement for e-learning security

Various combinations of biometric sensors are possible, but few researches report the possibility of a brain wave person authentication system. One main issue for applying a brain wave identification system is the need for effortless application and differentiation between users.

To see the possibility of ERP (Event Related Potential) application to user authentication in e-learning systems, we referred to the ERP response research that asked the following research questions; the amplitude and latency differences between two groups, the relationship between amplitude, and latency to channels taken by the brain waves.

In our research ERP was applied to show the gender discrepancy through a more scientific and objective measurement of brain waves, we found that the ERP may be applicable as a reliable personal identification due to its robustness and compact brain wave acquiring systems that were developed [5].

### 2.1 ERP 300

Among the EEG (electroencephalogram) signals, the Event Related Potential (ERP) [9] is acquired by providing information and observing the individuals cognitive response [6]. The ERP signal is related to the presentation of stimuli and event, and occurs limited times within the brain. This signal appears 250 ~ 450ms after the presentation of the stimulus, and is useful to explain the cognitive information process, showing personal decision making, attention, uncertain solutions, and verification of stimuli.

Various ERP signals may be acquired and one notable component is the P300 (P3). The P300 wave is known to elicit the decision making process related to a person's reaction process to a given stimuli. The P300 is obtained from low-probability target items that are mixed with high-probability non-target (or "standard") items.

### 2.2The characteristics of ERP and the possibility of user authentication

#### 2.2.1Methodology

We have selected subjects, 20 male and 20 female students from a middle school in Korea to examine the gender discrepancy in ERP 300 response to stimuli of "ICT and ICT-related words" presented through computer screen. While words were presented through the computer screen, students brain waves were recorded and ERP 300 signals were extracted using g.USBamp from gtec Australia.

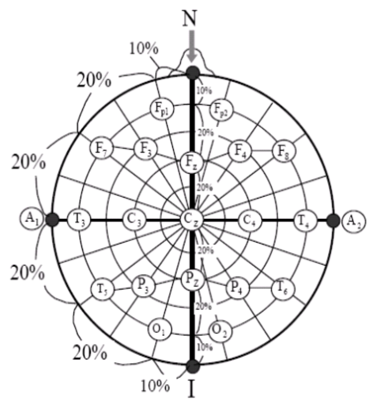


**Figure 1. The brain wave channels in 10-20 international system. Among these channels, we used 13, Fp1, Fp2, F3, Fz, F4, C3, Cz, C4, P3, Pz, P4, O1, O2, along with the central line because prior of research reporting that P300 components are usually observed along the central line**

We have extracted the target stimulus and non-target stimulus from the observed brain wave using EEGLAB based on MATLAB as shown in the Fig xx. Analysis was performed focusing on P300 related to emotional information attention and process among ERP components. The analyzed results are as following.

#### 2.2.2ERP responses and implications

Because of ERP's characteristics of capturing the cognitive function in the human brain, it is possible to verify personal identity for e-learning authentication. The P300 needs target stimulus and standard stimulus as explained in the Figure 2, and shows better results under the oddball game.

The oddball paradigm presents the high probability standard stimulus, and presentstarget stimulus randomly in between the standard stimulus [8]. The ratio of these two stimulus is 7:3 or 8:2 according to the researches, but the P300 appears clearly when the target stimulus are presented less frequently.

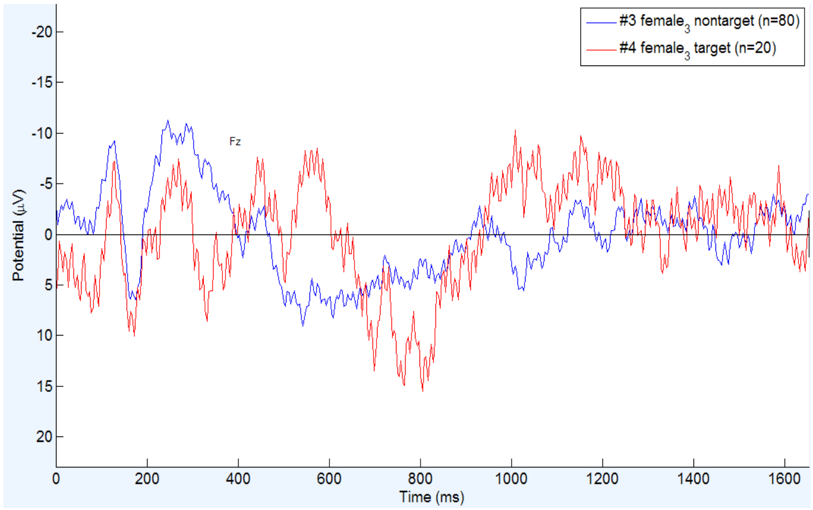


**Figure 2. The brain waves captured from the experiments. The no target (80) signal comes from the ERP response of general terminologies presented as standard stimuli, and target (20) response comes from the ERP related terminologies presented as target stimuli. The responses from female subjects (#3 and #4) to the same experiment show wave differences but have common characteristics in gender**

**Table 1. The ERP components and their appearance time window**

| ERP component | Polarity | Time Window(ms) |
|---|---|---|
| P1 | Positive | 50-150 |
| N1 | Negative | 100-200 |
| P2 | Positive | 150-250 |
| N2 | Negative | 250-300 |
| P3 | Positive | 250-450 |

From the ERP, we can see several positive peaks and negative peaks according to the various brain waves at specific times. The peaks consist of latency and polarity, and N and P are used to represent the positive and negative peaks.

The presence, magnitude, topography and timing of this signal as shown in the Figure 2 are often used as metrics of cognitive functions in decision making processes. While the neural substrates of this ERP component still remain hazy, the reproducibility and ubiquity of this signal makes it a common choice for psychological tests in both clinical and laboratory settings.

Experiments performed that relate to the P300 emotional information attention and process shows that the difference in capacity according to gender is significant in Fp1, Fp2, F3, Fz and F4 channels ($p<.05$)among ERP components. In other words, the amplitude of differences in P300 according to gender were significant in the prefrontal and frontal lobes.

**Table 2. The gender differences of P300 with respect to channels**

| | Gender | Mean | S.D. | t | P |
|---|---|---|---|---|---|
| Fp1 | M | 18.404 | 15.079 | 2.754 | .012* |
| | F | 6.535 | 7.159 | | |
| Fp2 | M | 15.275 | 14.636 | 2.324 | .028* |
| | F | 5.722 | 6.264 | | |
| F3 | M | 13.260 | 8.199 | 2.579 | .015* |
| | F | 6.744 | 5.343 | | |
| Fz | M | 11.327 | 6.471 | 2.317 | .028* |
| | F | 6.631 | 4.442 | | |
| F4 | M | 12.210 | 7.487 | 2.919 | .007* |
| | F | 5.352 | 5.168 | | |
| C3 | M | 10.968 | 4.791 | .702 | .489 |
| | F | 9.881 | 3.611 | | |
| Cz | M | 10.415 | 4.851 | -.614 | .544 |
| | F | 11.458 | 4.449 | | |
| C4 | M | 9.874 | 4.998 | .888 | .382 |
| | F | 8.509 | 3.227 | | |
| P3 | M | 13.597 | 5.928 | .487 | .630 |
| | F | 12.654 | 4.600 | | |
| Pz | M | 13.290 | 6.357 | -.658 | .516 |
| | F | 14.694 | 5.279 | | |
| P4 | M | 14.209 | 7.534 | 1.306 | .202 |
| | F | 11.437 | 3.281 | | |
| O1 | M | 15.344 | 7.353 | 1.541 | .135 |
| | F | 11.859 | 4.761 | | |
| O2 | M | 15.976 | 10.709 | 1.807 | .088 |
| | F | 10.696 | 3.666 | | |

(* The significance level is <.05)

The research suggested that boys curiosity or attention to informational devices were more than that of girls, since the prefrontal lobe is responsible for humanity, curiosity, decision-making along with reflection and the frontal lobe is responsible for concentration, focusing and working memory.

Second, in terms of amplitude, the correlation in channels showed very high correlations in the frontal lobe (Fp1-Fp2-F3-Fz-F3) and the occipital lobe (O1-O2). Third, differences in latency according to gender was shown significantly in channels Fz, F4, C3, Cz, Pz, P4, and O1 (p <.05) as shown in Figure 3.

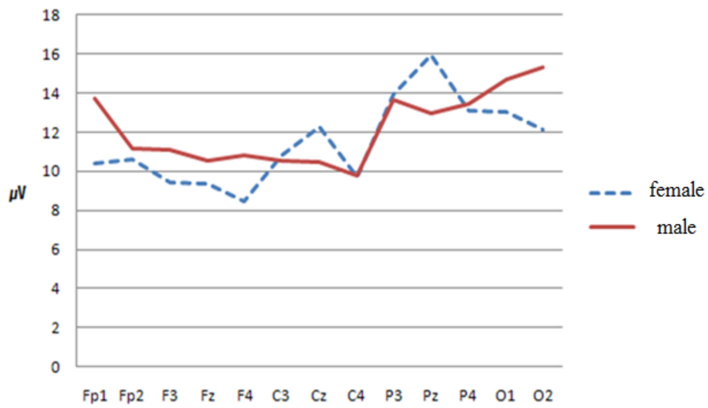


**Figure 3. The amplitude differences' between female and male students to target and non-target stimuli in ERP tests**

Fourth, the correlation between channels in latency showed very high correlations in Fp1-Fp2, C3-F3, C3-F4, Cz-F4, Cz-C3, Pz-C3 and Pz. It's confirmed that gender discrepancy measured through self-reporting surveys; interviews and standards exist through scientific and objective measurements of brain waves.

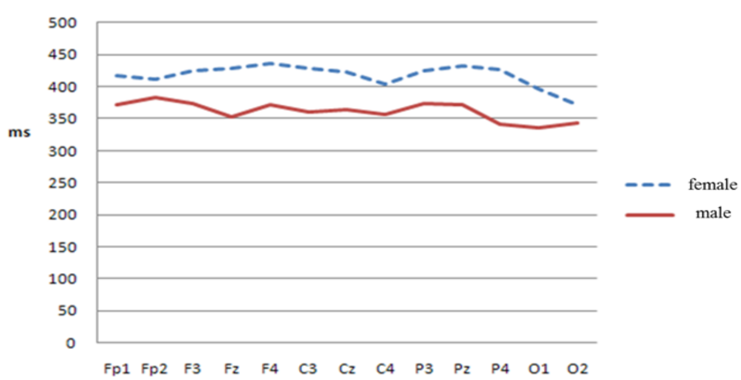


**Figure 4. The latency differences' between female and male students to target and non-target stimuli in ERP tests**

### 2.3Proposed combined biometric system for e-learning security

Unlike the traditional way of authentication where once a user logins to a system a password is used to check user validation, and continuous authentication (CA) systems need to continuously monitor user characteristics such as user behaviors or unique user features [11]. Cognitive biometrics is applicable for such purpose, and utilizes the cognitive, emotional, and conative state of an individual as the basis of user authentication and/or identification.

Nowadays, most advanced informational devices are equipped with web cameras as built in components. Therefore, to harness the camera function to interact with users research is being carried out in the field of eye feature tracking for validating users. The eye movement or facial feature is one useful source for authentication, but once a user gets permission or has been identified as an authorized user some other person may still be able to take their seat, causing the reliability to be damaged.

From the aforementioned experiments, we concluded that the ERP signal can be useful to separate each user among registered e-learning users. Therefore the ERP signal is applicable to protect impersonation threats [10] in cases of online tests by presenting the authentication stimulus in between e-learning process. The proposed continuous authentication system has two parts; using eye movement information and P 300 bio signal as a combination of biometrics as in the Figure 5.

The system first checks the user into the login e-learning system by using facial features. Different biometrics signal such as fingerprints can be used for this purpose as well. Commercially available eye tracking systems are very expensive and inappropriate to use just for authentication. Currently we are developing open source based eye tracking system to pinpoint where an e-learning user gazes at while interacting with computers.

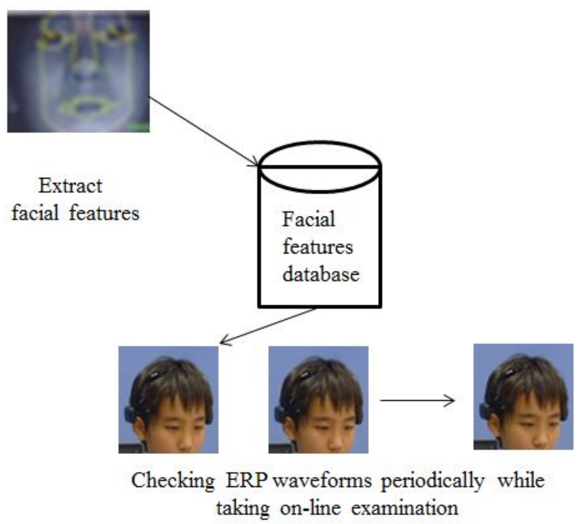


**Figure 5. The combination of EEG and eye tracker for usability test of e-learning**

The function for continuous authentication happens using a P300 signal that is very simple and easy to implement. In Figure 5 and Figure 6 the user wears a headset type brain wave recording system called EPOC, EEG device developed by Emotiv [6, 12]. To harness the P 300 characteristics, the earning contents or test questions need to be modified to contain target stimulus during the course.

**Figure 6. A snapshot of an e-learning user with combination of EPOC and remote eye tracking system. The left window shows that user facial features are extracted using Facelab 4.6 eye tracker**

Some private institutions operating e-learning sites using a VOD type service are interested to monitor user attention level while taking an e-learning course. To increase the feedback quality between e-learning service provider and user, it is necessary to monitor user participation with some bio signals. From that point, simple EEG devices that only use a limited number of channels and is easy to wear is a good candidate. Only using 2 detectors in the frontal lobe is enough in Emotiv EPOC neuro headset [12].

In particular the cameras in Pad type PC's and smartphone's can be used as personal information gathering systems. Also, the EEG taps can be designed to capture very basic signals from scalps and makes the continuous identity authentication system possible in the near future.

## 3. Conclusions

Although e-learning provides the learning opportunity of an anytime and anywhere learning environment with easy access to the Internet, many security issues have to be considered. Among these issues, e-examination needs a personal authentication that guarantees the individual who takes the examination is the right person.

We are currently trying to implement the combined biometrics of brain wave and eye tracking.TheP300 signal can also be used as a reliable observing method for identifying each person under e-learning environments. We need more experiments to verify the reliability of the proposed system, but harnessing advanced informational devices along with developing an effortless way to implement a brain wave detection system may provide a better security system for e-learning.

One thing to consider is how to provide target stimulus with learning contents. To maximize the P 300 characteristics needs 8:2 or 7:3 or non-target and target stimulus and devising such stimulus needs more research.

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## References

[1] New Scientist: South Korea's pupils to go paperless by 2015, vol. 211, Issue 2820, **(2011)** July 9, pp. 5.
[2] R. G. Cardenas and E. M. Sanchez, "Security Challenges of Distributed e-Learning Systems", Distributed And Parallel Computing, ISSADS 2005, **(2005)**, pp. 538-544.
[3] E. G. Agulla, L. A. Rifon, J. L. A. Castro and C. G. Mateo, "Is my student at the other side? Applying Biometric Web Authentication to e-learning environment", $8^{th}$ IEEE International Conference on Advanced Learning Technologies, **(2008)**, pp. 551-553.
[4] S. Asha and C. Chellapan, "Authentication of E-Learners Using Mutimodal Biometric Technology", International Symposium on Biometrics and Security Technologies, ISBAST 2008, **(2008)**, pp. 1-5.
[5] M. Duvinage, T. Castermans, T. Dutoit, M. Petieau, C. de Sadeleer, K. Seetharaman and G. Cheron, "A P300-Based Quantitative Comparision between the Emotiv EPOC Headset and a Medical EEG Device", BioMed 2012, **(2012)** February 15-17, pp. 764-071.
[6] A. Magliero, T. R. Bashore, M. G. H. Coles and E. Donchin, "On the dependence of P300 latency on stimulus evaluation processes", Psychophysiology, vol. 21, **(1984)**, pp. 171-186.
[7] A. Jalal and M. Zeb, "A.:Security Enhancement for E-Learning Portal", International Journal of Computer System Security, vol. 8, no. 3, **(2008)**, pp. 41-45.
[8] J. M. Ford and S. A. Hilyard, "Event-Related Potentials ($ERP_s$) to Interruptions of a Steady Rhythm", Psychophysiology, vol. 18, Issue 3, **(1981)** May, pp. 322–330.
[9] S. Sutton, M. Braren and J. Zubin, "Evoked potentials correlate of stimulus uncertainty", *Science*, vol. 150, **(1965)**, pp. 1187-1188.
[10] K. M. Apampa, G. Wills and D. Argles, "User Security Issues in Summative E-Assessment Security", International Journal of Digital Society (IJDS), vol. 1, Issue 2, **(2010)** June.
[11] I. Traore and A. A. E. Ahamed, "Introduction to Cognitive Metrics", Continuous Authentication Using Biometrics, **(2011)** September, pp. 1-22.
[12] Emotiv: EPOC nureoheadset, http://www.emotiv.com/apps/epoc/.