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Research on a Smart Input Device using Multimodal Bio-signal Interface

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Abstract. This paper presents a smart input device based on multimodal analysis methods using human bio-signals. The core of the smart input device is software modules, which consist of an intelligent driving function and an analysis processing function for bio-signals. The smart input device utilizes a multimodal interface that analyzes and recognizes human bio-signal patterns. The multimodal analysis system can recognize a user's emotional and stress status by analyzing an electrocardiogram (ECG), and it can determine the user's level of concentration from electroencephalogram (EEG) patterns. To analyze the concentration, stress, and emotional status of the user, the EEG rendering system and ECG analysis system use five signal values, i.e., MID_BETA, THETA, ALPHA, DELTA, GAMMA, and the P, Q, R, S and T waves. A reformation of SVM and a clustering algorithm were applied to the user's EEG and ECG signal patterns for body context recognition. In our experiment, the on/ off status of the user's stress status controls the difficulties of the game, such as the selecting the type of race course or the number of obstacles. In addition, the speed of the car can be controlled depending on the concentration or non-concentration status of the user. The stress status of the user was predicted with an accuracy of 83.2% by the K-means algorithm, and the concentration status was predicted with an accuracy of 71.85% by the SVM algorithm. We showed that a bio-signal interface is quite useful and feasible for new games.

1 Introduction

Today, even though computer science and technology in the 21st century are developing very rapidly, humans still know themselves only to a very limited extent. Most of all, advances in human computer interaction and virtual reality techniques are very important. Computing environments are moving to the human body or to human residence space from computer space in hardware development. Until intelligence inundates “to create intelligence how” the problem which is than “to deliver how” to be important, this becomes conclusion with problem of interface. Currently, it is entering the stage in which the progress of technique surpasses users’ requirements, so the interface will become an efficient means for reducing the gap between the product and the user. Renovation of the interface will become an efficient means of making a priority of the effect over performance upgrade. The multimodal biology interface uses analyzed ECG and EEG signal results. Making the multimodal biology interface technique more natural and effective is the focus of the field of virtual reality, which has been developed with techniques associated with the visual/ auditory sense centers. Biofeedback games use various sensor links in the body, and the user’s electroencephalogram/ electrocardiogram/ electromyograms signals are reflected in real time. Preschoolers and disabled people, for example, find existing edutainment contents difficult to use (e.g., by keyboard, mouse). The multimodal biology interface is based on this new concept, so production paradigms of the new contents are needed.

This paper presents a smart input device that consists of a multimodal signal processing interface. For this study, equipment was used to measure the user’s EEG and ECG signals, which are used to determine the condition of the driver. A smart device is used to ensure safe driving and to prevent risks to the driver. Users can know location using normalized values between 0 to 100. At the same time, an ECG is used to determine the emotional state and stress of the user while the user is concentrating on driving. Acquiring such biological information is applicable to the existing embodied system based on Bayesian theory. This device is suitable for driving whether or not there is a follow-up operation based on the user’s location. During the process, a safe angle of rotation and safe vehicle speeds are cleverly controlled. So, the input device environment that is provided is able to cope with any emergency situations that the user may encounter. A similar situation occurred in the present experiment compared with the previous simulation environment. So, the intelligent module distinguishes the event once or repeats it by checking section status and using stored data. The intelligent module determines whether the event is temporary or ongoing. Finally, the intelligent module warns of a rapid change in risk in a specific section based on degree of similarity value.

In chapter 3 explains the composition of multimodal biology interface. Section 4 presents the results of an experimental evaluation of clustering accuracy using the reformed k-means based on EM algorithm to compare human emotion recognition performance.

2 Previous Work

The complexity context of the human body’s signals to interactively recognize emotions relies on the detection of a physiological change attributable to an affective stimulus, followed by adequate classification of the change. Previously, most of the methods used to classify emotions using physiological signals have been based on off-line analysis of statistical features extracted from large quantities of data [1]. Systems to dynamically detect, classify, and utilize emotions, based on instantaneous responses from the input device, are still lacking. Using a combination of auto associative neural networks (AANNs) and sequential analysis, a novel mechanism was developed to detect changes in physiological signals associated with emotional states [2]. Brain Computer Interface (BCI) technology represents a rapidly growing field of research, with applications ranging from prosthetics and control systems to medical diagnostics. In this research, the experiment considers only BCI technologies that use sensors that measure and interpret brain activity (commonly referred to as neural bio-recorders [5]) as a source of input. The oldest established method of neural bio-recording, which was developed in 1927 by Berger [4], is the application of electrodes that survey the changes in field potential over time arising from synaptic currents. "In 2003, taxonomy by Mason and Birch identified MEG, PET, and fMRI as unsuitable for BCI applications, due to the equipment required to perform and analyze the scan in real time, but more recent attempts to use fMRI as a BCI input device have demonstrated significant future potential in this area [3]." Brain-computer interfaces have become a topic of research interest, both as a means for obtaining user input and for studying responses to stimuli.

In our research, we controlled the speed of the car by concentration value of brain signals and the color of the car by emotional context at driving simulation content. Also, when the stress value was excessively high, the car files for overcome obstacles.

3 Design of Smart Input Device using Physiological Signals

3.1 Acquisition Devices of Physiological Signals

We developed two different devices to measure EEG and ECG signals. The device on the right upside of Fig. 1 acquires brainwave signals from the frontal lobe of the brain. The four sensors must be attached to the forehead positions of the human brain. The EEG device has four channels with electrode disposition. To acquire the users' ECG signals, we also developed the ECG sensor device. The device on the left upside of Fig. 1 was used to measures the user's ECG signals. Both devices send the detected signals to a computer by Bluetooth.

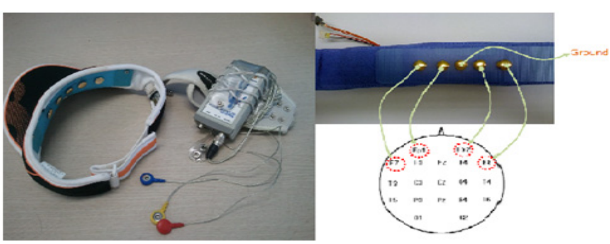


Fig. 1. The External of EEG(right) and ECG(left) sensor device

3.2 Overall Architecture

Software modules were divided into two parts. The first part is the network software module with an I/O device, and the second part is the context manager software module for biometric data. The first part has two base modules, i.e., a client module and a server module. The client module consist of an EEG/ ECG network, and it has three modules, i.e., the initialize module, the connect module, and the data manager module. The data manager module takes charge of the radio communication data reception department, a data processing department, and the data transmission department. The server module consists of modules that interpolate game contents. The contents network server module also has three parts, i.e., an initializer module to initialize the server, a client manager module that manages the EEG/ ECG data from the client module, and a module for receiving data from the client with a Command Processor that processes the received data. According to concentration values in the range of 0 – 100, it transmits SPEED_UP or SPEED_DOWN commands and the value of the contents. Thus, it is possible to control the speed of the car in the game through concentration. The brain wave extraction is so advanced that it can extract an electromyogram signal from the blinking of the eyes.

Eye blinking occurs at regular intervals, and it delivers a left-turn command to contents. When the eye is winked twice, a right-turn command is delivered to contents. In addition, it recognizes emotion and the changes in emotion that results from the color of the car, i.e., a happy state was associated with a red car, and a sad or fearful state was associated with a blue car. Table 1 provides a definition of the interlock protocol for the physiological signal I/O device between software modules and contents. This emotion feedback technique is useful in additional contents, e.g., games and simulations. For instance, if the users are hiding from an enemy, the enemy can locate them when their emotions (stress, fear) are heightened. Thus, it is important for the mind to be calm.

Table 1. Interlock protocol list of the device

Command	To Server	From Client		Comment
		ACK	Value	
SPEED_UP	0 x 02	0 x 02	0～100	Concentration Value
SPEED_DOWN	0 x 03	0 x 03	0～100	
LEFT	0 x 04	0 x 04		Blink one time
RIGHT	0 x 05	0 x 05		Blink two times
FLY ON	0 x 06	0 x 06	0～100	Stress and Non Stress State
FLY DOWN	0 x 07	0 x 07	0～100	
HAPPY	0 x 09	0 x 09	0～100	Analyze Emotion as 2 Part
SAD	0 x 10	0 x 10	0～100	(Happy, Sad)

Table 2 shows the protocol for the ECG sensor device, which communicates with the sensor recognition utility. The sensor recognition utility transmits one byte value

(0 x 08 and 0 x 09) to the electrocardiogram sensor to acquire the user's temperature and pulse.

Table 2. Command list of the ECG device

Command	To Sensor	From Sensor				Command
		ACK	#1	#2	#3	
Sensor on	0 x 03	0 x 30				Power On
Sensor off	0 x 04	0 x 40				Power Off
Normal Mode	0 x 05	0 x 50				Set up Normal Mode
Stream Mode	0 x 06	0 x 6F	#D1	#D2	…	Set up Stream Mode
Battery Status	0 x 07	0 x 71	#B			Battery(MIN)0 x 00 ~ 0 x ff(MAX)

Fig . 2 shows the structure of the context manager for various signals (e.g., biology). The context manager processes context in two steps to analyse the pattern of the various contexts acquired from the sensor devices. First, the context extractor normalizes the seven contexts between 0.1 and 0.9; all normalized contexts are used as input values to the predictor. Second, the context manager stores all contexts in the database for creation of association rules.

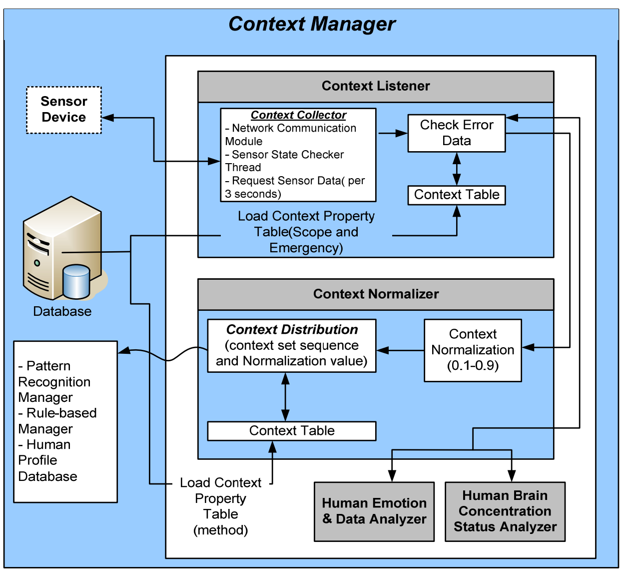


Fig. 2. Structure of Context Manager

The design of the biometric (EEG, ECG) analyzing algorithm has three parts, as listed below:

1) Normalization Module: In about biometric signal from person deviation by normal function
2) Post-Processing Module: Analysis function of wavelet by signals/ nonlinear dynamics/ high dimensional statistical/ Laplacian mapping
3) Analytical Study Module: Analytical function of user's intention about biometric signals

4 Experimental Environment

4.1 Implementation of Physiological Analysis Program

We are developing a program to analyze a user's concentration status from brainwave signals. Fig. 3 shows the program that classifies EEG signals. It measures the dimension of the power of concentration with EEG signals, and it finds the direction in which the power of concentration is displayed by winking the eye. This program can identify concentration easily to use progress bar. Also, we can detect the blink action from an image on the screen.

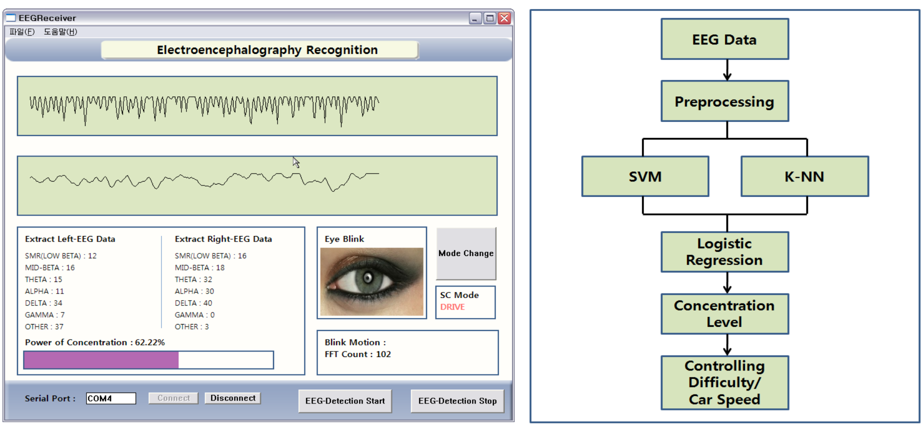


Fig. 3. EEG rendering program

The EEG rendering program has the following steps:

1) Input EEG data from EEG acquisition device
2) Perform pre-processing such as noise reduction and FFT analysis
3) Computation result of EEG analysis by SVM and K-means algorithm
4) Perform logistic regression for difficulty level increase/ decrease expression then two kinds of indicators, one or more values exceed certain limits of concentration status
5) Output difficulty level by user's feeling

We used a non-parametic method for quantitative assessment of the EEG. Fast Fourier transformation can be used to convert the time-domain function to a frequency-domain function.

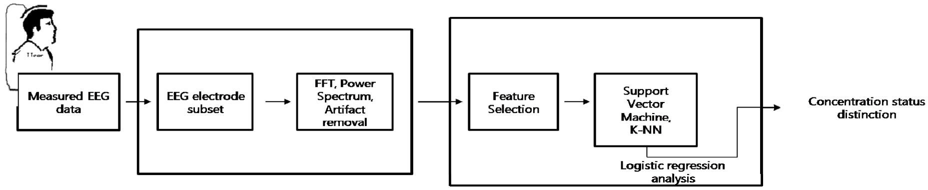


Fig. 4. System architecture for mining the EEG feature

Fig. 5 shows how the ECG signals are acquired and analyzed. This program assesses and displays the user's current state of emotion or stress.

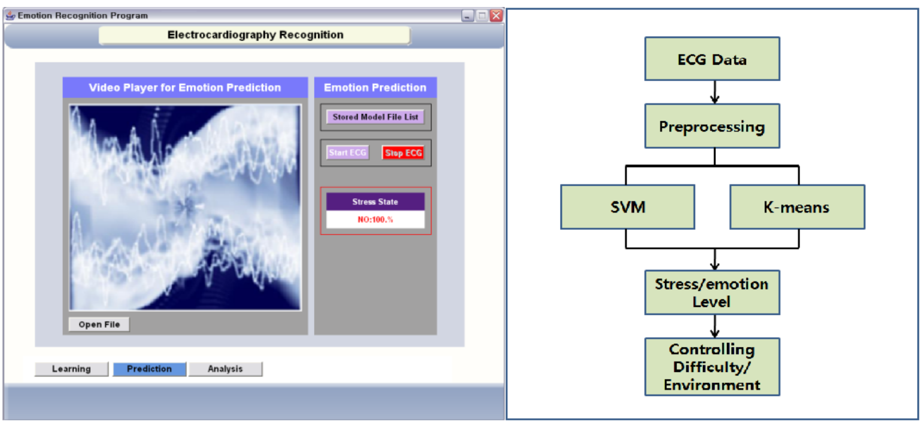


Fig. 5. Human Emotion Analyzer

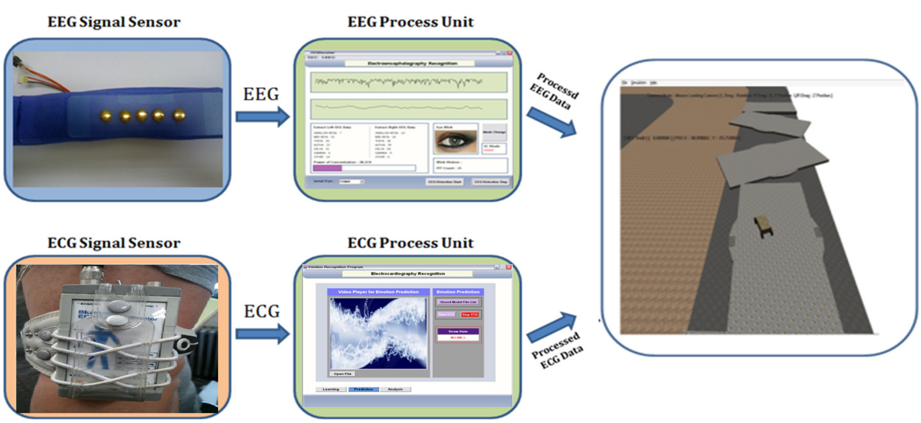
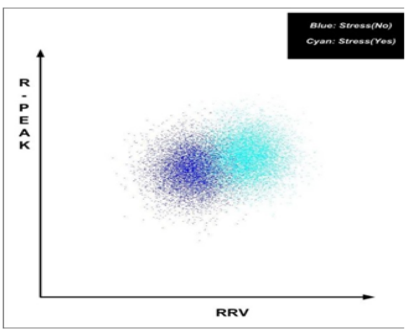


Fig. 6. Overview of contents apply multimodal biology interface

Fig. 6 shows the overview screen of the contents applied in the multimodal biology interface. The direction of the input device was decided by an eye blink (EMG signal) of the user, and the input device moves according to the state of intensity of the EEG. Further, when the user feels plentiful concentration or is stressed, the input device slows down or overcomes obstacles with its flying skill, embodied with the artificial intelligence model.

4.2 Performance Results

The EM-based, K-means algorithm, which is applied in this experiment and see reformation, uses unsupervised learning with supervised learning algorithms. To verify the performance of the Human Emotion Analyzer, we used a protein data set as the input value of the human emotion analyzer. The Human Emotion Analyzer acquires electrocardiogram data (P, Q, R, S, and T waves) from the electrocardiogram sensor device and applies the peak of all waves and the RRV (r-r interval) as input values. As shown in Fig. 7, all distributions were normal. In our experiment, only the R-R interval and the R peak showed small differences in emotion and stress changes. The neural emotion showed the highest accuracy, with the range of the three emotions at approximately 56 to 75%. Stress recognition showed a high performance result of 83%. Table 3 shows the accuracy of the performance results based on our analysis.



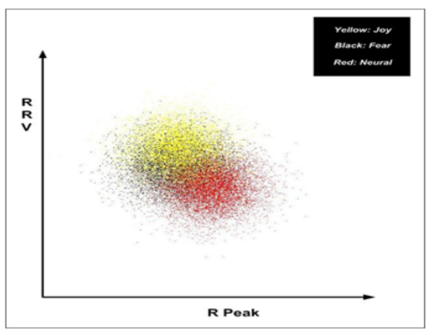


Fig. 7. Distribution of RRV and R peak of stress/ non stress and three emotions states

Table 3. Result of emotion / stress recognition

Emotion	Correctly Classified Instances		Incorrectly Classified Instances		Accuracy (%)	
Algorithm	SVM	K-means	SVM	K-means	SVM	K-means
Fear	503	662	683	524	42.4	55.8
Neural	737	891	449	295	62.1	75.1
Joy	637	801	549	385	53.7	67.5
Stress(yes)	1058	1247	440	251	70.6	83.2
Stress(no)	1058	1247	440	251	70.6	83.2

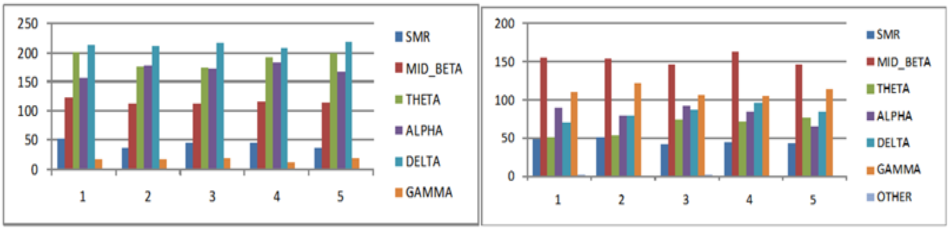


Fig. 8. Brain wave data of non-concentration state (left) and concentration state (right)

Fig. 8 show experimental data of the non-concentration and concentration states from brain waves, respectively. The EEG rendering system extracts the brain wave feature set using the FFT algorithm. Before we decrease error factor by trend removal technique.

The concentration formula is as follows:

Concentration Indicators = Power Ratio of (SMR + M – Beta) / Theta **(1)**

Theta rhythm decreases in the concentration state, and the SMR and Mid-beta rhythms indicate increases in unfocused and focused attention, respectively. Therefore, focus indicators can be quantified by the ratio of (SMR + M – beta rhythm) to Theta rhythm. Also, we convert absolute power to relative power of the FFT value for sophisticated results. The EEG rendering program calculates the concentration distinction value using SVM and the K-NN algorithm. The SVM in these experiments used the set of parameters that resulted in the highest correct rate of classification among all SVMs tested. SVMs were tested with RBF kernels with $\sigma = 0.5$. The SVMs were trained and tested using Platt's sequential minimal optimization (SMO) algorithms [6, 7, 8].

Table 4. Result of concentration recognition

Classifier	Concentration State	Non-Concentration State	Average Accuracy (%)
SVM	71.5	72.2	71.85
k-NN	67.5	71.3	69.40

5 Conclusion and Future Work

In this paper, we have reported efforts to produce architecture for building intelligent content effects that have more efficiency than the requirement of a user's status recognition and an expedient environment. This paper describes an intelligence and complexity context analysis system using ECG and EEG patterns. The Human Emotion Analyzer evaluates differences in emotion or stress levels. We also demonstrated a sensor device that acquires continuous brainwave signals from the frontal lobe.

In this experiment, we developed a technique that analyzes the multimodal physiological signal for contents. In this paper, we proposed a method for supplying optimized information within a car and provided analysis of human body biometric signals in a driving environment to allow a user to become easily live in comport to driving in the contents. Also, physical value examined theory to achieve basic physics feedback anything. Technology than can analyzes brain waves and recognize the status of the human body is very important and can provide a foundation for research in the future. The analysis method and the intelligent system presented in this paper can be used in a wide range of diverse fields of study in future research work.

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