

Evaluating Mental State of Final Year Students Based on POMS Questionnaire and HRV Signal

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Abstract

Final year students are normally encountering high pressing in their study. In view of this fact, this research focuses on determining mental states condition of college student in final year based on the psycho-physiological information. The experiments were conducted in two times, i.e., prior- and post- graduation seminar examination. The early results indicated that the student profile of mood states (POMS) in prior final graduation seminar showed higher scores than students in post final graduation seminar. Thus, in this research, relation between biosignal representing by heart rate variability (HRV) and questionnaire responses were evaluated by hidden Markov model (HMM) and neural networks (NN).

Key Words : heart rate, biosignal, human states, HMM, neural network.

1. Introduction

Human body will be response to given stimulant from outside e.g., working, studying, or other activities. This response could effect to the physiological states such as increment of heart rate/respiration, body temperature, saliva in mouth, or etc. It is believed that people will also react to the problems they encounter in their daily life, such as pressing of their study. The body reaction will affect metabolism of organs inside the body, such as the heart.

The electrocardiogram (ECG) is used to record the electrical signals generated by the heart. The signals are generated when cardiac muscles depolarize in response to electrical impulses generated by pacemaker cells. The ECG reveals many things about the heart, including its rhythm, whether it's electrical conduction paths intact, whether certain chambers are enlarged, and even the approximate ischemic location in the event of a heart attack. Generally the various characteristic features of ECG could be extracted and used for decision making purposes.

The heart rate varies from beat to beat. Heart rate variability (HRV) results from the dynamic interplay between the multiple physiologic mechanisms that regulate the instantaneous heart rate. Heart rate variability (HRV) has been widely used as indication to diagnose symptoms of disease or sickness in medical fields such as diabetes and cardiovascular disease. However, detecting fatigue state based on HRV is not investigated yet. In view of that fact, employing signal processing techniques to extract HRV signals for diagnosing

mental states is a challenge problem in the field of medical engineering.

There were several works studying related health problems caused by mental workload using signal processing techniques. Zhang *et al.*, [1] reported about estimating visual display terminal (VDT) mental fatigue using multichannel linear descriptors and kernel-principal component analysis-hidden Markov model (KPCA-HMM). Mizuno *et al.*, [2] examined the relationship between the job satisfaction and work-family balance of Japanese nurses. Healey and Picard [3] have evaluated mental stress in real-world driving tasks using physiological sensors.

However, the intelligent monitoring systems for determining physiological states by states have not been developed yet. Thus, in this study, evaluating mental workloads of final year students were performed by experiments during prior-post graduation seminar examination. The purpose of research is to determine mental states of students based on relation between heart rate variability (HRV) and questionnaire response.

The outline of this paper is the following. Section 2 presents the experiment procedure conducted in this study. Section 3 presents the practical used of hidden Markov model (HMM) which is employed to extract pattern of HRV. This section also describes the methodology of neural network (NN) which is used as general regression for evaluating mental states of students. Section 4 shows the experimental results of this paper. Finally, discussion and conclusions are presented in Section 5.

2. Experiment Procedure

2.1 Subjects

Eighteen male students between 22 - 23 years olds voluntary participated in two experiments. Personal data were acquired with a standardized interview before recording physiological information. They did not have any health problems during the experimental period, and that they were not being under any medication. Smoking and hard exercise were also prohibited before the experiments. None of them reported on any cardiovascular disease or neurological disorders in the past. This experiment was conducted in conformity with the Helsinki Declaration. All subjects were well informed regarding the purpose and contents of the experiment, and informed consent was obtained before their participation. They were also informed that they had the right to renounce their participation anytime.

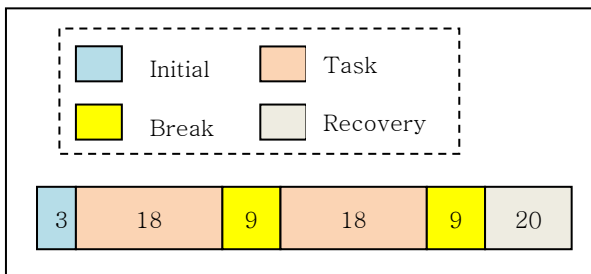
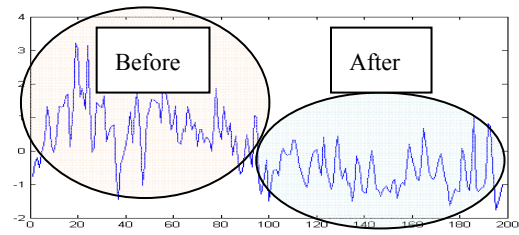


Fig. 1 Experiment Schedule

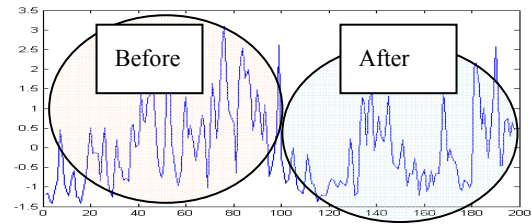
2.2 Experimental Procedure

The experiments were conducted in two periods, i.e., prior- (A) and post- (B) final examination towards final year students. Both experiments have the same intermittent schedule for doing calculation tasks: subjects were instructed to conduct 2 sets of 18 min calculation tasks with 9 min of intermediate breaks for both experiments. It should be note that the duration for each experiment was 77 minute in total for each participant doing each experiment, i.e. 3 minute for initial state, two set of 18 minute and 9 minute for intermittent schedule and 20 minute for recovery states as shown in **Fig. 1** In addition, the subjects were required to fill a profile of mood states (POMS) before and after each experiment. POMS is a measure of six identified mood factors, i.e., tension-anxiety (TA), depression-dejection (D), anger-hostility (A-H), vigor (V), fatigue (F), and confusion (C); it is commonly used for psycho-physiological studies. During experiments, electrocardiogram (ECG) physiological sensors were attached to the body to measure heart rate variability (HRV) as shown in **Fig. 2** The HRV data were recorded using commercial BioPAC MP150 systems.

Participants were comfortably seated facing a LCD display at about 50 cm. A simple calculation task with a laptop computer was taken as a mental workload in this experiment. It is a simple addition of two double-digit integers. These integers were repeatedly presented on the laptop monitor every 3.0 sec with changing figures. The subjects were instructed to input the



(a) Person A



(b) Person B

Fig. 2 The example of measured HF signal before-after graduation seminar

answer of the addition by keyboard as fast and correct as possible. Such a simple calculation task is quite similar to so-called the *Kraepelin psychodiagnostic* test and which has frequently been introduced for researches investigating physiological responses induced by mental stress. Moreover, the task has typical features of mental workload in our daily life such as routine, simple, boring, and unlimited. Thus, the result of the experiment is expected to be a practical model of mental workload in our daily life.

3. A Soft-Computing Approach for Evaluating Students Mental States

3.1 Dimensional Reduction by Using PCA

Principal component analysis (PCA) is a statistical technique whose purpose is to condensate the information of a large set of correlated variables into a few principal components while not throwing overboard the variability present in the data set [4]. The principal components are derived as a linear combination of the variables of the data sets; with weights chosen so that the principal components become mutually uncorrelated. Each component contains new information about the data set, and is ordered so that the first few components account for most of the variability.

The objective can be achieved by choosing to analyze only the first few factor principal components. The number of principal component is, ideally, known prior to the analysis. In this study, the first six principal components are determined by examining the proportion of total variance over 90% explained by principal component.

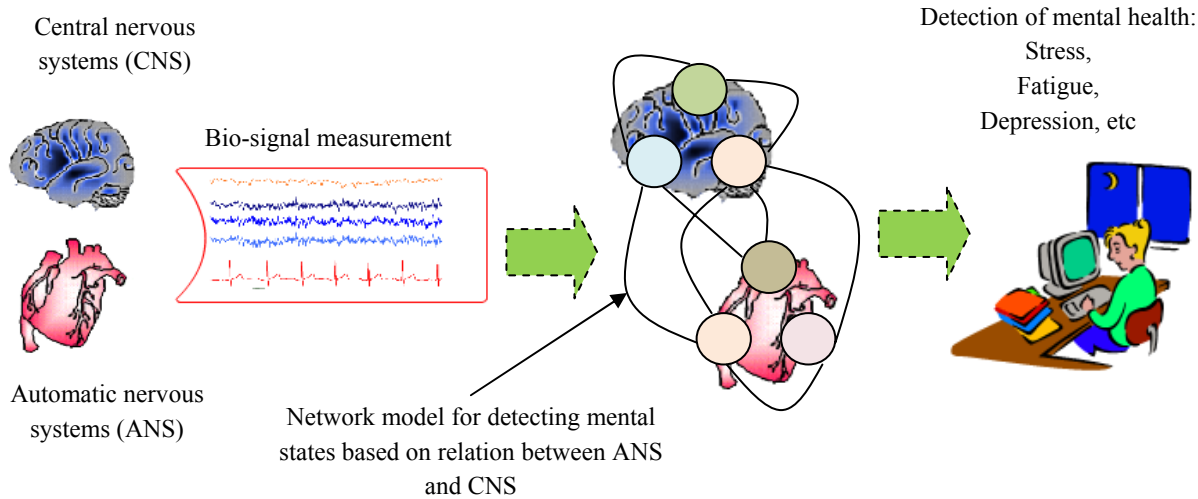


Fig. 3 Mental states detection based on psycho-physiological information using signal processing and computational intelligent methods

3.2 Evaluating Pattern of Psycho-Physiological data by HMM

The main objective of this section is to develop models and techniques which can apply in real time to track physiological signal and make inferences about the level of arousal of a subject. We envision this study being a useful building block that can be integrated into a computer that uses this information to adapt itself to the needs of the user. This more ambitious idea goes beyond the present scope of this study but is a future research topic in this area. Fig. 3 describes the framework of this study.

Human physiology behaves like a complex dynamical system in which several factors, both internal and external, shape the outcome. In approximating such system, we are interested in modeling its dynamical nature and given that knowledge of all the independent variables that affect the system is limited. We want to approach the problem in a stochastic framework that will help us model the uncertainty and variability that arise over-time. A class of models that has received much attention in the research community over past years to model complex dynamic phenomena of a stochastic nature is the class of Hidden Markov Models (HMM). HMMs have been widely used for modeling speech and gesture, and are currently an important block of speech recognition systems. Motivated by their flexibility in modeling a wide class of problem, we decided to study the feasibility of using HMMs to model physiological pattern that are believed to correlated with different affective states.

A HMM is a stochastic state machine, characterized by the following parameter set:

$$\lambda = (A, B, \pi) \quad (1)$$

where A is the matrix of the state-transition probabilities, B is

the observation probability, and π is the initial state probability.

The observation of a HMM $O = (O_1, O_2, \dots, O_T)$ are continuous signal representations, called feature vector, modeled by a Gaussian probability density function of the form:

$$b_j = \frac{1}{\sqrt{2\pi|U_j|}} \exp\left\{-\frac{1}{2}(O_t - \mu_j)^T U_j^{-1}(O_t - \mu_j)\right\} \quad (2)$$

where O_t is the observation vector at time t , μ_j is the mean vector, and U_j is the covariance matrix at state j . The estimated parameters are obtained by performing likelihood maximization $P(O|\lambda)$ of the model λ using an iterative procedure such as Baum-Welch method [5].

The physiological signal generated by human body might have strong correlation with accumulation of human states. The accumulation of human states may then be seen as one of HMM problems. Thus, in this study, the HMM network were employed to estimate accumulation human states based on the observed physiological information. The first stage is to build a system which adapting with the given data by train the HMM network. The purpose of HMM training is estimating the model parameters set $\lambda = (A, B, \pi)$ from the observation sequences data O . The HMM parameter estimation is carried out by Baum-Welch method which similar with expectation-maximization algorithms. For training purpose, the number of hidden states of the HMM was assumed having three states, i.e., high, medium, and low states. The categorization of hidden states was performed by clustering method, i.e., competitive learning algorithms based on the physiological data representative. This study only considered one Gaussian density function per state. After training, the HMM was then employed to evaluate probabilities of human states condition.

3.3 Neural Network for Analyzing Relation between Psycho-Physiological Data.

Neural Network with a back propagation learning algorithm is well known as a supervised classifier method and suitable for building adaptive pattern recognition system [6]. Mapping function of a neuron in a network can be written as

$$y = f_a(\sum w_i x_i + b) \tag{3}$$

where y is the output, f_a is activation function, w_i is weight of input x_i , b is a bias term and N is total input. In order to determine the mapping function, first, the network needs to be trained by using sample data. Learning via back-propagation involves the presentation of pairs of input and output vectors. Among several activation functions of Neural Networks, this study uses sigmoid function as activation function for hidden layers. The advantages of sigmoid functions are easier to train than threshold units, because of better smoothing function in specific range input-output and have upper-lower bound. With sigmoid function, a small change in the weights will usually produce a change in the outputs, which makes it possible to tell whether that change in the weights is good or not. The selection of an activation function of the output units should suit with the distribution of the target values. In this study, the identity or linear activation functions are employed.

In this work, Neural Network Toolbox of MATLAB was employed to make use of neural network for pattern recognition. The networks were built by three layers. The epoch and the

learning rate were set to 300 and 0.01, respectively. The weights were initialized arbitrarily. Further, the network was trained by resilient back-propagation algorithm until the error between the desired and the actual outputs below than the threshold value or until the maximum epoch was reach. Once the weights have been determined, the network can be used as a classifier. The network structure was built based on the experiment by testing several networks model and the designed layers were confirmed as the effective network structure for this problem.

3.4 Verification Methods

In this paper, the classification accuracy of neural networks was tested by the leave-one-out cross validation (LOO-CV) method [7], which can be applied when the samples are small. The procedure consists of picking up one example for testing while the rest of the data are used to train the classifiers, and then testing the removed example. After testing, the classification result is recorded. The process is repeated until all examples have been tested. The accuracy of classifier is evaluated by calculating the average error as following:

$$\bar{e} = \frac{1}{N} \sum_i^N e_i \tag{4}$$

where N is the total number of experiments conducted.

4. Result

4.1 POMS Results

The questionnaire responds are evaluated by profile of mood states (POMS) method to measure psychological mood scores as shown in Fig. 4 and Fig. 5 for experiment A and B, respectively. The self-report questionnaire reveals that subjects in the session of pre-experiment and post-experiment. POMS is a psychological test designed to measure a person's affective states. These include tension-anxiety (T-A), depression (D), anger-hostility (A-H), vigor (V), fatigue (F) and confusion (C). Unlike personality traits, profile mood states are thought to be transitory and specific to a given situation, although moods can also measured for recent prolonged periods such as the past several months.

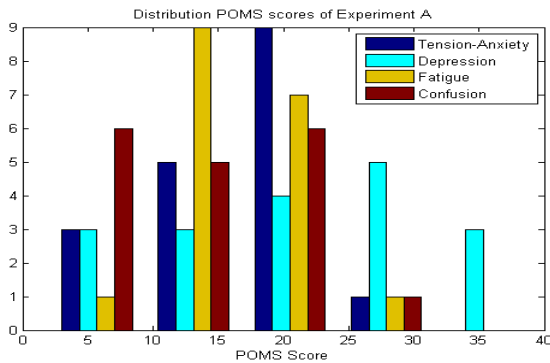


Fig. 4 Distribution POMS Values of Experiment A

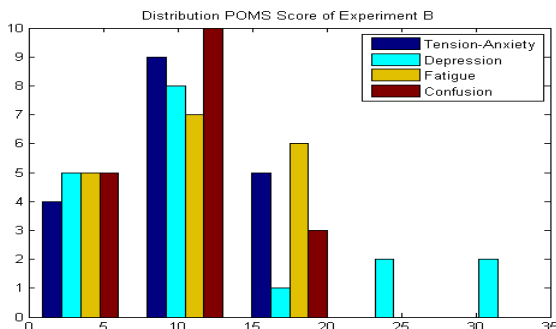


Fig. 5 Distribution POMS Values of Experiment B

Table 1 t-test results of POMS scores

T-A	D	A-H	V	F	C
**	**	*	n.s	**	**
**= $p < 0.01$		*= $p < 0.05$			
n.s = not significant					

As shown in Table 1, there are interesting factors, i.e., Tension – Anxiety (T-A), Depression – Dejection (D), Fatigue (F) and Confusion (C) which have significant

different scoring between experiment A and B based on t-test method. Thus, this study evaluated relation between psychological mood index, i.e., Tension-Anxiety, Depression-Dejection, Fatigue and Confusion towards the physiological data.

4. 2 Evaluating Performance of Proposed Systems

It is believed that physiological information generated by human body have strong relation with psychological condition such as fatigue, confusion, depression, anxiety and others, which might associate with sensitivity in the kansei engineering fields. However, monitoring human states times by times are difficult to be obtained, even performing by human. Thus, this study attempt to determine human states condition based on the psychological and physiological information by employing several information processing techniques.

First, the collected data were subject to analyze using statistical approach. The data were extracted from segment of 3 min data for all signals. To calculate heart rate variability (HRV) features, it used the instantaneous heart rate time series derived from ECG. The ratio of the low-frequency (LF) band (0.04 – 0.08 Hz) and the high-frequency (HF) band (0.15 – 0.5 Hz) were calculated to produce new data. Five statistical features were calculated from ratio of LF/HF data, i.e., the mean, the standard deviation, the slope mean, the maximum and the minimum.

The LF/HF is used as an index of sympathetic to parasympathetic balance of heart rate fluctuation. The mean, the standard deviation, the slope mean, the maximum and the minimum of the ratio LF/HF were then used as features. HF is driven by respiration and appears to derive mainly from the parasympathetic nervous system. The mean, the standard deviation, the slope mean, the maximum and the minimum of HF were used as final features in this experiment. There ten features were used to create a single vector representing each of the segments used in the recognition analysis. Totally, 648 segments were extracted from experiment A and B, i.e., 432 and 216 from task and rest periods respectively. The resulting 648 feature vectors were then analyzed by principal component analysis (PCA).

Second, the obtained features vectors generated by PCA were reconstructed, so the extracted data belongs to each subject. Totally there were 36 subjects. Each feature vector consisted of 6 features and 18 time series data. The extracted data was then set as training data for HMM network. The parameters of the HMM network were estimated by the given training data.

The output of HMM was then used as input training for neural network. The output of training data was consisting of psychological mood, i.e., T-A, D, F, and C, obtained after the intermittent calculation task. The classification accuracy was then performed by measuring the average error of classifier based on leave-one-out cross validation (LOO-CV) method.

The accuracy of classification between target and output are 72.75 %, 65.39%, 76.87%, and 66.26% for Tension-Anxiety,

Depression, Fatigue and Confusion, respectively, as shown in **Table 2**. Evaluating human feeling towards the given task using physiological and psychological information showed promising results in this study. So, there are some possibilities to build systems which have capability predicting human states condition. However, further investigation has to be made to find more clear correlation between that information.

Table 2 Performance of the proposed methods

T-A	D	F	C
72.75%	65.39%	76.87%	66.26%

5. Conclusions

This study has proposed a method to estimating human states by understanding physiological and psychological information using information processing techniques. The results showed that the proposed systems are able to estimate four POMS score in moderate level. This result is promising for further study relating to understand human states condition more objectively.

However, finding relation between physiological and psychological information is difficult to be achieved in high degree using current method. It might that, first, each person have different capability when handling mental workload. Second, the proposed model is not sufficient enough for evaluating human states condition.

This research is still preliminary study about relation between physiological information and psychological mood index based on the given task. In future, the systems which are able to explain relation between physiological measurement (objective) and psychological mood index or human feeling, (subjective) should be developed.

This information, in the future, could then be used automatically by the adaptive systems in various ways to help the person better cope with stress, fatigue or even for detecting diseases such as heart attack. The example of this might include adaptive systems which are able to analyze the stress level of a person, and give an alert or a suggestion to the person to take a break if required or even sending the critical information to hospital related to the person condition.

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Kazuo Nakamura received B. Eng. and M. Eng. in precision engineering from Tohoku University, Japan in 1969 and 1971, respectively. Worked as a researcher at Industrial Products Research Institute from 1971-1993, and at National Institute of

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