Multimed Tools Appl (2017) 76:11305–11317
DOI 10.1007/s11042-016-3444-9

Multi-level assessment model for wellness service based on human mental stress level

Yuchae Jung [1] **· Yong Ik Yoon** [1]

Received: 1 April 2015 / Revised: 3 February 2016 / Accepted: 14 March 2016 /
Published online: 22 March 2016

Abstract In this paper, we measure human physiological changes from different body parts to quantify human mental stress level by using multimodal bio-sensors. By integrating these physiological responses, we generate bio-index and rule for the prediction of mental status, such as tension, normal, and relax. We also develop an inspection service middleware for analyzing health parameters such as electroencephalography (EEG), electrocardiography (ECG), oxygen saturation (SpO2), blood pressure (BP), and respiration rate (RR). In this service middleware, we use the multi-level assessment model for mental stress level that consists of three steps as follows; classification, reasoning, and decision making. The classification of datasets from bio-sensors is enabled by fuzzy logic and SVM algorithm. The reasoning uses the decision-tree model and random forest algorithm to classify the mental stress level from the health parameters. Finally, we propose a prediction model to make a decision for the wellness contents by using Expectation Maximization (EM).

Keywords Mental stress · Multi-level assessment · Wellness · Inspection middleware

1 Introduction

In modern society, stress is one of the major problems in many countries around the world. A small amount of stress in work or study can be act as positive. However, high level stress for long-term can be chronic and it can cause many chronic disease. Chronic stress can result in serious health conditions including anxiety, insomnia, muscle pain, high blood pressure and a weakened immune system.

✉ Yong Ik Yoon
yiyoon@sm.ac.kr

Yuchae Jung
jungjuri7@sm.ac.kr

[1] Department of Multimedia Science, Sookmyung Women's University, Seoul, Korea

It is important to keep monitoring mental stress level for prevention of chronic disease and early treatment. Several technologies have been developed to recognize stress level; some methods are based on physiological signals: blood pressure [24], heart rate [24], heart rate variability (HRV) [4, 24], and skin conductance [8, 20]. Activity-aware mental stress detection is also available using Bayesian network and SVM.

Continuous monitoring of an individual's stress levels is essential for understanding and managing personal stress. A number of physiological markers are widely used for stress assessment, including: galvanic skin response, several features of heart beat patterns [4], blood pressure [4, 24], and respiration activity. Fortunately, miniaturized wireless devices are available to monitor these physiological markers. By using these devices, individuals can closely track changes in their bio-signals in order to maintain better health condition.

The technology of monitoring human physiological changes for the detection of human mental stress level has been developed rapidly. Tiny multimodal sensors can measure various vital signs, such as body temperature, pulse rate, heat rate, respiration, blood pressure, electroencephalography (EEG), electrocardiogram (ECG), and electromyography (EMG). These sensors are wearable or implanted in the body, or installed in patients' homes and workplaces. The purpose of these biosensors is to help patients to monitor their health state by themselves and their caregivers to update patient health status in real-time using intelligent environment [13].

In this paper, we introduce a multi-level assessment model for monitoring a health/mental condition that can be used for the prediction of abnormal mental status using multi-modal bio-sensors in dynamic situation. This monitoring model considers biometrics data as well as the environmental sensor data based on our previous studies [26, 27]. The measurements are used for the bio-index generation for prediction of mental stress level. This health/mental monitoring model has four modules as follows: (1) monitoring biometrics data (body temperature, EEG, ECG, respiration rates, SpO2 and blood pressure) and environmental sensor data (location, time, weather, temperature and humidity) (2) index assessment from measurements using fuzzy logic and SVM, (3) risk assessment and rule generation using decision tree, (4) activity assessment using maximized mental stress ratio based on Expectation Maximization (EM) algorithm.

The remainder of this paper is organized as follows. The section 2 reviews the recent technology for monitoring mental/physical health status. Section 3 introduces the overview of multi-level assessment model for recommendation of wellness service. Section 4 provides the monitoring step for sensor data, and section 5 provides index assessment, section 6 addresses risk assessment. Section 7 describes activity assessment algorithm based on EM. Finally, section 8 provides results from multimodal biosensor and section 9 summarize our proposal and direction for future work.

2 Related work

2.1 Mental stress and physiological response

Stress is a physiological response to the mental, emotional or physical challenges that we experience. Small amounts of stress may be desired, beneficial, and even healthy. But excessive stress may lead to bodily harm and increase the risk of disease [18]. High level of stress can be a risk factor for hypertension, heart attacks, ulcers, mental illness, and depression [19, 23]. Continuous monitoring of an individual's stress level is important for understanding object emotional status and managing personal stress. A number of health parameters using physiological changes are widely used for stress assessment, including: heart beat patterns [1], blood pressure [9], and respiration activity [3].

2.2 The relationship between human physiological response and human mental stress level

Because the physical health and mental health are closely connected [19], continuous monitoring of physiological changes using bio-sensors can reflect human mental stress level. The detection of human mental stress level is not easy because each person is different on their physiological response to physical, mental, and emotional stress. For the detection of mental stress level, choi et al. [3] monitored heart rate variability using nonlinear system identification. Silberstein [21] have focused on external effects on human emotions using EEG measurements for determining the level of attention of a subject to a visual stimulus. Murugappan et al. [17] classified dynamic emotional content into five discrete emotions (disgust, happy, surprise, fear and neutral) based on Electro-encephalography (EEG) signal. Recently, EEG-based emotion recognition using deep learning network with principal component improved classification accuracy compared to SVM and naïve Bayes classifier [12].

2.3 Characteristics of bio-sensor data (EEG, ECG and blood pressure)

In ubiquitous healthcare age, large number of bio-sensors including smartphone is used to u-healthcare services by monitoring physical conditions [5]. With the development of wearable smart device, u-healthcare is available to everyone, everywhere in anytime [28]. Because human emotion is complex, it is difficult to detect human mental stress level. This requires updated knowledge on the human bio-signals for accurate detection of human physiological response. These bio-signals include blood glucose level, respiration rate, blood pressure, skin temperature, electroencephalogram (EEG), electrocardiography (ECG), and electromyography (EMG). However, these measurements have varied primarily due to the environmental conditions (e.g. characteristics and positioning of electrodes, nature and characteristics of equipment, anatomical minor differences, presence of glands and blood vessels, different tissue fat levels, etc.) under which they are obtained, there are commonalities among them.

3 The overview of multi-level assessment for monitoring mental wellness in dynamic situation

The work-flow of multi-level assessment for monitoring health/mental status is shown in Fig. 1, based on our previous study [26, 27]. This health condition monitoring model has four major steps, (1) data collection from biosensor and environmental sensor, (2) sensor data filtering and index assessment based on SVM (3) risk assessment for prediction of mental stress level using decision tree, and (4) decision making for wellness contents recommendation based on EM algorithm.

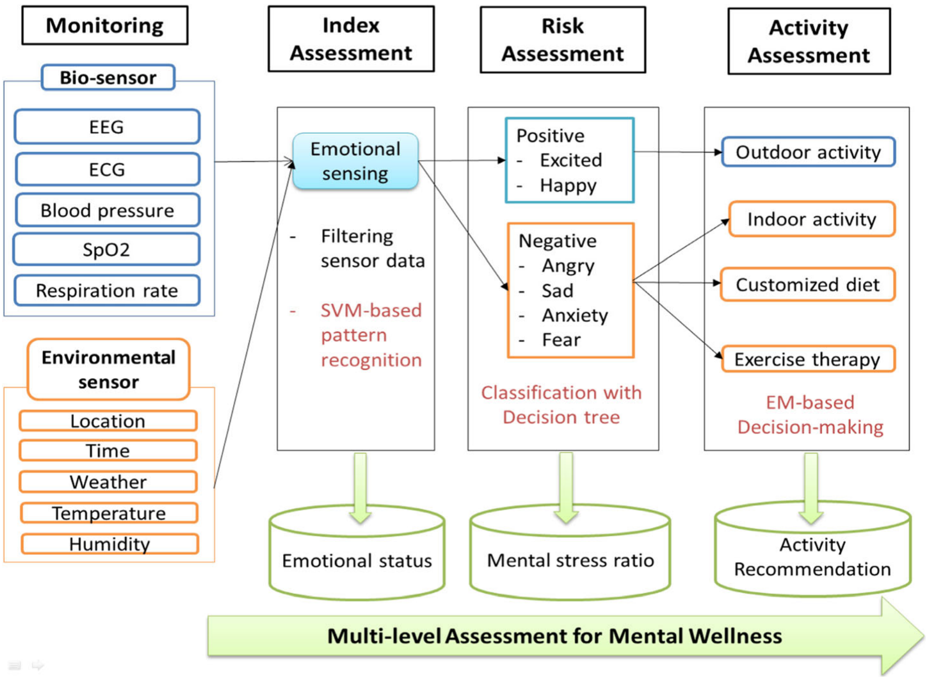


Fig. 1 The workflow of health and mental status monitoring system based on EM for wellness contents recommendation system (*1*) Data from multimodal bio-sensors and environmental sensors are collected. (*2*) Biometrics data combined with environmental information are analyzed for index assessment using SVM. (*3*) Risk assessment step classify emotional status into positive and negative (*4*) EM-based decision making and recommendation of proper activity considering user preferences

The first step is the collection of bio-sensor dataset, which extracts features from input variables for prediction of mental stress level. In this step, environmental factors, such as location, time, and weather are also considered for situation-awareness.

Index assessment step is a filtering sensor datasets and recognize a pattern of the filtered data using predefined health parameters (Table 1). In risk assessment step, bio-index for emotion sensing can classify emotional status into two statuses (positive and negative). Depending on emotional status and user preferences, proper activities (indoor activity, outdoor activity, customized diet, and exercise therapy) are recommended based on EM. For recommendation of proper activity, user preferences and profiles (age, sex, and diet) are considered.

4 Monitoring vital sign and environmental status

In monitoring step, three health parameters (blood pressure level, heart rate, and respiration rate), which known to be related with mental stress are measured using biosensor (BMS-AE-DK). Embedded software in biosensor is used for noise filtering as shown in Fig. 2. Based on our previous study [26, 27], these data are measured repeatedly and continuously from each person. All measurements are categorized into 3 levels (high, normal, and low) based on previous studies [16] using neuro-fuzzy logic and SVM.

Table 1 Bio-emotional index assessment for mental wellness using health parameters

	Health parameters	Patterns	Mental stress level
EEG	Alpha wave (8–13 Hz)	Increase	Relax
	Theta wave (4–7 Hz)	Increase	Creative
	Beta wave (14–30 Hz)	Increase	Tension, Excited
	Beta/Alpha	Increase	Mental workload (not considered)
BP	Blood pressure (>120 mmHg)	High	Tension
	Blood pressure (90–120 mmHg)	Normal	Normal
	Blood pressure (<90 mmHg)	Low	Relax
HR	Heart rate (90–120 bpm)	High	Increased workload, tension
	Heart rate (50–100 bpm)	Normal	Normal
	Heart rate (20–70 bpm)	Low	Relax
RR	Respiration rate (17–25 bpm)	High	Tension, attentive, awakening
	Respiration rate (12–20 bpm)	Normal	Normal
	Respiration rate (5–12 bpm)	Low	Relax

4.1 Sensing emotion from measurements

In order to simplify input variables from biosensor, we use fuzzy logic which categorizes the input variables as linguistic variables. For the filtering of the patterns, the monitoring step defines the criteria for filtering using SVM algorithm. This step categorizes input variables into

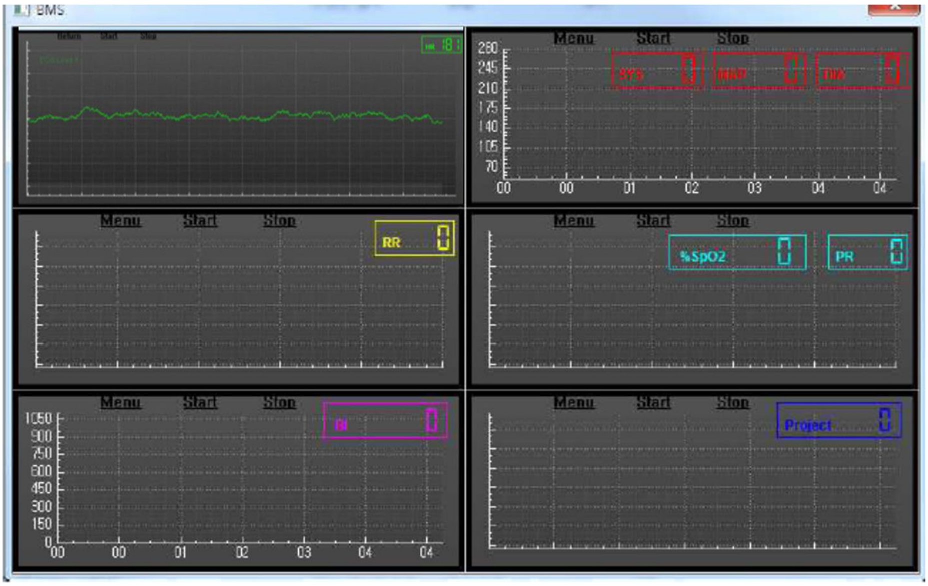


Fig. 2 Window interface of multimodal bio-sensor for monitoring health condition using Bio Medical System Analog & Embedded Development Kit (BMS-AE-DK). This kit has five modules such as ECG, NIBP, respiration rate, SpO2, and bio-impedance

3 levels (high, normal, and low) as below. Three health parameters (BP, HR, and RR) known to increase with anxiety or stress are selected based in previous studies [2, 10, 11, 22, 25].

(1) Electroencephalogram (EEG) the recording of electrical activity on the scalp. [11, 25]
These frequency bands from low to high frequencies, respectively, are called Delta (1–3 Hz), Theta (4–7 Hz), Alpha (8–13 Hz), Beta (14–30 Hz), and Gamma (31–50 Hz).
(2) Blood pressure (BP) is maximum value of blood pressure during one breath. BP is known to increase with anger, fear and anxiety [10].

low (<90 bpm), normal (90–120 bpm) and high (>120 bpm)

(3) Heart rate (HR) is the speed of the heartbeat and HR is known to increase with anxiety or stress [22].

: low (20–70 bpm), normal (50–100 bpm) and high (90–120 bpm)

(4) Respiration rate (RR) is the number of breaths taken per time interval. RR is known to increase with anxiety. [2]

: low (5–10 bpm), normal (7–20 bpm), and high (15–24 bpm) : low (100–121 mm Hg) normal (110–134 mm Hg) and high (120–147 mm Hg)

4.2 Environmental sensing for situation awareness

To obtain the situational information, monitoring step collects from environmental sensors in smart device using mobile applications [6]. For accurate situation awareness, we used mobile application, which supports light sensor, proximity sensor, gyroscope sensor, accelerometer sensor, orientation sensor, sound sensor and temperature sensor. Using environmental sensors in mobile device, we inference situational information, such as weather, time, location, and temperature. For understanding user-context, knowledge from situational information is combined with physiological changes and used for bio-emotional index assessment.

5 Index assessment for the prediction of human mental stress level

In Table 1, categorized health parameters are matched to mental stress level by analyzing patterns (increase or decrease) of input variables using predefined information [7]. Based on our previous study on senior health risk [27], the health parameters are matched to mental stress level for bio-emotional index assessment. The EEG sensor represents 4 types as follows; Alpha, Beta, Theta, and Alpha/Beta [11, 25]. It is known that Alpha wave is related with relaxed state and Beta wave is closely linked with tension state. As shown in Table 1, health parameters are classified into 3 mental stress levels (tension, relax, excited, and normal). For example, when brain wave ranges in 7.5–13 Hz from EEG sensor called Beta wave and it represents a person is in tension or anxiety state. When a systolic blood pressure is high (120–147 mmHg), the mental stress level is in tension.

6 Risk assessment considering biosensor datasets and situational information

The risk assessment step defines the mental stress ratio using association rules and decision tree as shown in Fig. 3. In this step, four features (EEG, BP, HR, and RR) known to be associated with mental stress level are selected and the rules for sensing mental stress level are generated [15]. The accumulated mental stress ratio is classified into four levels, such as normal, low, middle, and high using decision tree in Fig. 3. For example, the mental stress ratio (MSR) is high as following conditions: EEG sensor represents Beta waveform and systolic blood pressure, heart rate and respiration rate are in 'tension' categories.

6.1 Rule for sensing mental stress ratio

For the risk assessment step, we define association rules between health parameters and mental stress level by monitoring physiological changes as below. The correlation between health parameters (input) and the mental stress level (output) is done with set of fuzzy rules. Each rule uses AND/OR connectors to connect various input factors with mental stress level. As Beta wave in EEG sensor is related with mental stress, anxiety and tension as we mentioned in Table 1, we assumed (EEG is Beta). Then, we checked the status of systolic blood pressure, heart rate, and respiration rate.

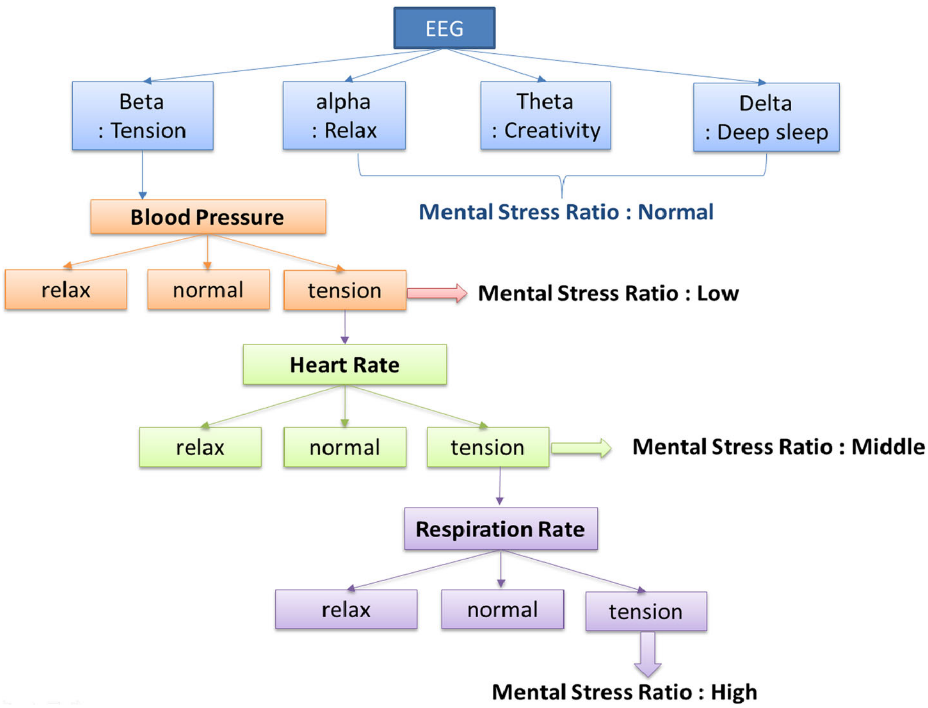


Fig. 3 Decision tree for maximization of accumulated mental stress ratio using association rule and decision tree

If (EEG is *Beta*) and (BP is *Normal*) and (HR is *Normal*) and (RR is *Normal*) then (MSR is normal)
If (EEG is *Beta*) and (BP is *Normal*) and (HR is *High*) and (RR is *Normal*) then (MSR is low)
If (EEG is *Beta*) and (BP is *High*) and (HR is *High*) and (RR is *Normal*) then (MSR is middle)
If (EEG is *Beta*) and (BP is *High*) and (HR is *High*) and (RR is *High*) then (MSR is high)

6.2 Evaluation of mental stress ratio using decision tree

Figure 3 represents a decision tree for the determination of mental stress ratio (high, middle, and low) from association rule. Based on our previous study [27], we have enhanced the decision tree model for measuring accumulated mental stress level. To evaluate the mental stress ratio, four levels decision-tree is constructed as shown in Fig. 3. The four features (EEG, BP, HR, and RR) have the three levels of mental stress level (such as relax, normal, and tension) as predefined in Table 1. As these four features are known to increase with mental stress, we matched high level into tension and low level into relaxed state.

In EEG level, root level, data from EEG sensor can be classified into Alpha, Beta, Theta, and Delta waveforms depending on users' emotional status. Especially, Beta wave from EEG sensor is known to be associated with 'anxiety' or 'tension' status. In second level, when BP is higher than 120 mmHg, MSR becomes low. In third level, the heart rate is checked. When the HR is higher than 84 bpm, MSR becomes middle. In Last level, respiration rate is checked if higher than 15/s. In this case, MSR evaluate high.

7 Activity assessment algorithm based on EM

To recommend the proper activity, we propose an activity assessment model based on Expectation Maximization (EM) algorithm to suggest a proper activity for users' mental wellness. The EM is a method for finding maximum likelihood estimates of parameters from unobserved latent variables [14]. The latent variables (maximized mental stress ratios) are variables that are not directly observed. But these variables are rather inferred from other variables such as objects' physiological changes, time, weather, and location type. For this purpose, the activity assessment step defines a mental stress ratio EM algorithm that uses an accumulated mental stress ratio. This algorithm has extended the

Table 2 Activity recommendation depending on MSR

No. of tension	MentalStressRatio	Activity recommendation
0	Normal	Outdoor activity : climbing, camping
1	Low	Indoor activity : cooking, cleaning
2	Middle	Customized diet : nutrition balance
3	High	Exercise therapy : running, walking

Table 3 Profiles of subjects for measuring

	Sex	Age	Occupation
Person A	Male	35	Sales
Person B	Male	42	Office worker
Person C	Female	37	Research
Person D	Female	26	Student

senior health risk ratio EM algorithm on previous study [27]. As described in Algorithm 1, the mental stress ratio EM model consists of two steps such as expectation step (E-step) and maximized step (M step).

```
Algorithm1 Mental stress ratio EM for decision making based on
mental stress level
  Input:
   a sequence of MentalStressRatio (Normal, Low, Middle, and High)
    currentLL ← ∞
  repeat prevMSR ← currentMentalStressRatio
    calculate MSR
   until
      check max MSR < ε
      If (EEG is not Beta) then (Normal)
      elseIf (BP is tension) then (MSR is Low)
      elseIf (HR is tension) then (MSR is Middle)
      else (RR is tension) then (MSR is High)
   Output:
      Recommend activity based on MSR level
      If (MSR is Normal) then (recommend indoor activity)
      If (MSR is Low) then (recommend outdoor activity)
      If (MSR is Middle) then (recommend customized diet)
      If (MSR is High) then (recommend exercise therapy)
```

In E-step, the mental stress ratio is repeatedly updated into input variables to understand the user's mental stress level in dynamic situation. The maximization for mental stress ratio is calculated with cumulative mental stress ratio based on number of 'tension' in index assessment step in Algorithm 1.

Table 4 Measurements from multimodal biosensor and activity recommendation based on MSR

	NIBP	HR	RR	MSR	Activity
Person A	Normal	Normal	Tension	Low	Indoor
Person B	Normal	Normal	Normal	Normal	Outdoor
Person C	Normal	Normal	Normal	Normal	Outdoor
Person D	Tension	Tension	Normal	Middle	Customized diet

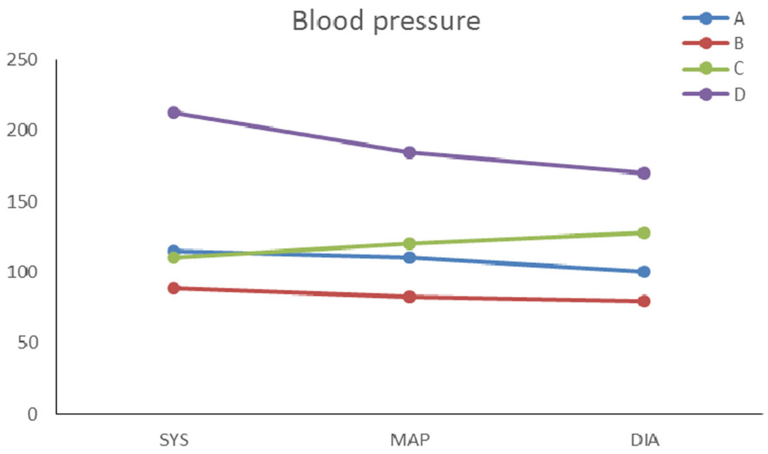


Fig. 4 Non-invasive blood pressure in systolic, mean arterial pressure (MAP), and diastolic

In M-step, by using the MSR, a proper activity is recommended. For activity recommendation, a mapping table is defined as shown Table 2. So, activity recommendation is accomplished by using the mental stress ratio (MSR) level.

8 Results

Using multimodal biosensor, blood pressure, heart rate (ECG), respiration rate, and heart rate are measured repeatedly and data are collected from four persons as Table 3 and Table 4. Sensor data is analysed with embedded software and pre-processed for multi-level assessment for wellness service.

Non-invasive blood pressures (NIBP) from four persons were measured as Fig. 4. Person D shows increased blood pressure as BP shows 213 mm Hg and DBP shows 170 mmHg. MAP is the mean arterial pressure.

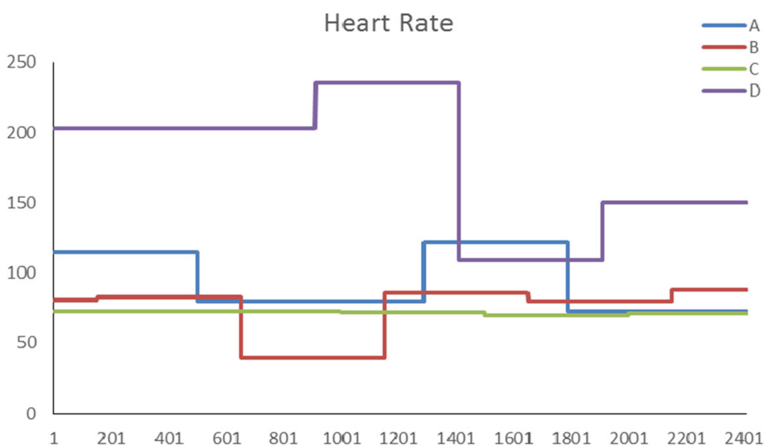


Fig. 5 Heart rates are measured from ECG sensor

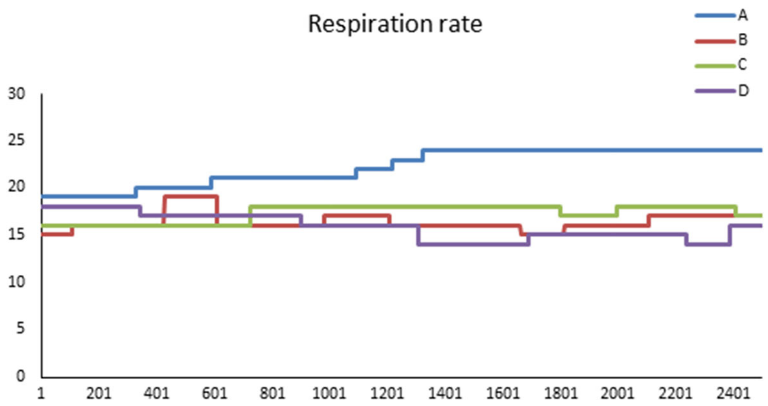


Fig. 6 Respiration rate are measured from four person

The heart rates from ECG sensor are measured from four persons as shown in Fig. 5. Person D shows increased heart rates compared to other persons. If person D represents Beta wave in EEG sensor, person D has middle level of mental stress ratio based on decision tree (Fig. 3). Because person D shows high blood pressure and increased heart rate with Beta wave in EEG sensor.

The respiration rates are measured from four people as shown in Fig. 6. Person A showed increased respiration rate and person B, C, and D show normal respiration rate. As person A shows increased respiration rate, normal range of heart rate and respiration rate. Person A is classified into low level of mental stress ratio based on Table 3.

As a conclusion, the mental stress ratio (MSR) in four persons is described as Table 3. Depending on the MSR, a proper activity is recommended to user for wellness service. Because person B and C showed normal range of NIBP, HR, and RR, MSR is assigned as 'Normal' and 'Outdoor activity' is recommended. As person A shows low level of MSR, 'Indoor activity' is recommended for user. Person D shows high level of NIBP and HR, MSR is assigned 'Middle' and 'Customized diet' is recommended to user.

9 Conclusion

This paper outlines multi-level assessment (risk, index, and activity) for the prediction of mental stress level by monitoring health parameters such as EEG, BP, HR, and RR in dynamic situation. In index assessment step, SVM algorithm was used for categorization of input variables into relax, normal and tension status. In risk assessment step, decision tree was used for classification of bio-emotional index assessment and prediction of mental stress level. In activity assessment step, EM algorithm was used for decision making based on mental stress ratio (MSR) and used for recommendation of proper activity. This paper classifies mental stress ratio (MSR) into 4 levels, such as normal, low, middle and high. For further studies, more accurate sensing with advanced biosensors is required for classification of complex emotional sensing. Customized healthcare service for mental wellness is also required using smart healthcare system.

Acknowledgments This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Science, ICT & Future Planning (2013015884).

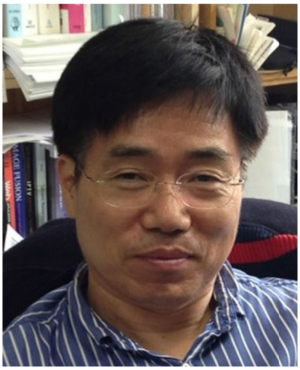
This research was also supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (NRF-2013R1A1A2058969)

References

1. Andre P, Joanna J, Chi W et al. (2013) Heart rate and heart rate variability in panic, social anxiety, obsessive–compulsive, and generalized anxiety disorders at baseline and in response to relaxation and hyperventilation. Int J Psychophysiol
2. Bernardi L, Wdowczyk-Szulc J, Valenti C, Castoldi S, Passino C, Spadacini G, Sleight P (2000) Effects of controlled breathing, mental activity and mental stress with or without verbalization on heart rate variability. J Am Coll Cardiol 35:1462–1469
3. Choi J, Gutierrez-Osuna R (2009) Using heart rate monitors to detect mental stress. Wearable Implant Body Sens Netw
4. Dishman R, Nakamura Y, Garcia M, Thompson R, Dunn A, Blair S (2000) Heart rate variability, trait anxiety, and perceived stress among physically fit men and women. Int J Psychophysiol 37:121–133
5. Fahim M, Lee S, Yoon Y et al. (2014) SUPAR: Smartphone as a ubiquitous physical activity recognizer for u-healthcare services. 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society
6. Feese S, Burscher M, Jonas K et al. (2014) Sensing spatial and temporal coordination in teams using the smartphone. Hum Cent Comput Inf Sci 4
7. Hadi B, Mobyen U, Amy L (2013) Data mining for wearable sensors in health monitoring systems: a review of recent trends and challenges. Sensors 13:17472–17500
8. Hernandez J, Morris R, Picard R (2011) Call center stress recognition with person-specific models. Affect Comput Intell Interact 6974:125–134
9. Ikuo H, Yuri M (2008) Breathing rhythms and emotions. Exp Physiol 93:1011–1021
10. Innes G, Millar WM, Valentine M (1959) Emotion and blood-pressure. Br J Psychiatry 105:840–851
11. Jatupaiboon N, Pan-ngum S, Israsena P et al. (2013) Real-time EEG-based happiness detection system Hindawi
12. Jirayucharoensak S, Pan-Ngum S, Israsena P et al. (2014) EEG-based emotion recognition using deep learning network with principal component based covariate shift adaptation. Hindawi Publishing Corporation
13. Juan A, Vic C, Diane C, Achilles K, Ichiro S (2013) Intelligent environments: a manifesto. Hum Cent Comput Inf Sci 3:12
14. Logothetisa A, Krishnamurthyb V, Holst J et al. (2002) A Bayesian EM algorithm for optimal tracking of a maneuvering target in clutter. Sign Process 473–490
15. Menaouer B, Baghdad A, Nada M (2013) Dynamic knowledge mapping guided by data mining: application on healthcare. J Inf Process Syst 9:1–30
16. Mohammad M, Omayya M (2013) Artificial neuro fuzzy logic system for detecting human emotions. Hum Cent Comput Inf Sci 3:3
17. Murugappan M, Ramachandran N, Sazali Y (2010) Classification of human emotion from EEG using discrete wavelet transform. J Biomed Sci Eng 3:390–396
18. Sano A, Picard R (2013) Stress recognition using wearable sensors and mobile phones. Humaine Association Conference on Affective computing and Intelligent Interaction
19. Sapolsky R (2004) Why Zebras don't get ulcers. St. Martins Press (37)271
20. Setz C, Arnrich B, Schumm J, Marca R, Tröster G, Ehlert U (2010) Discriminating stress from cognitive load using a wearable EDA device. IEEE Trans Inf Technol Biomed 14:410–417
21. Silberstein R (1990) Electroncephalographic attention monitor. US Pat 4:388
22. Taelman J, Vandeput S, Spaepen A, Huffel S (2013) Influence of mental stress on heart rate and heart rate variability. IFMBE Proc 22:1366–1369
23. Tylor A, Faulkner G (2008) Mental health and physical activity. Inaugural editorial (1)1–8
24. Vrijkotte T, Doornen L, Geus E (2000) Effects of work stress on ambulatory blood pressure, heart rate, and heart rate variability. Hypertension 35:880–886

25. Wang X, Nie D, Lu B et al. (2011) EEG-based emotion recognition using frequency domain features and support vector machines. ICONIP 734–743
26. Yuchae J, Yongik Y (2015) Ontology model for wellness contents recommendation based on risk ratio EM. Proc Comput Sci 52:1179–1185
27. Yuchae J, YongIk Y (2016) Monitoring senior wellness status using multimodal biosensors. BigComp 2016 BigData4Healthcare Workshop
28. Zanifa O, Fredrick M, Bing W, Ciaran D (2011) Ubiquitous healthcare information system: assessment of its impacts to patient's information. Int J Innov Sci Res 1:71–77

Yuchae Jung Ph.D, Major in Multimedia Science/ Computational Biology, Sookmyung Women's University, Korea Research area: Middleware, Recommendation System, Smart Wellness, User Behavior, Situation-Awareness, Bioinformatics



YongIk Yoon Professor Major in Multimedia Science/ Distribution system Sookmyung Women's University, Korea Research area: Smart Wellness, Context-Awareness, Situation-Awareness, Middleware, Mobile Computing, Cloud Computing, Smart Service, Collaboration Filtering, Recommendation System