Prediction Model for Mental and Physical Health Condition using Risk Ratio EM

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***Abstract* — Recently, mobile applications which provide health services at anytime and anywhere are on demand due to the growth of mobile wireless technologies. For the health service, an inspection service middleware is needed for monitoring health condition such as observing and analyzing EEG (electroencephalography), ECG (electrocardiography) and EMG (Electrocardiogram) waveforms from wearable ECG devices under the coverage of a wireless sensor network (WSN). For the inspection service middleware, we propose a new notion of prediction model based on risk ratio Expectation Maximization (EM) by monitoring real-time bio-signals. The prediction model can detect abnormal health condition by the monitoring system. In this paper, we explain the detail algorithms and results for these steps based on EM. There are the five modules as follows: (1) The measurement of bio-signals such as body temperature, EEG, ECG and EMG, (2) Object assessment from measurement wavelength, (3) Situation assessment from GPS in smart device, (4) Maximized health condition using risk ratio EM, (5) Knowledge update and decision making for healthy life.**

Keywords—inspection service middleware; bio-signal monitoring; health condition ; Expectation Maximization (EM)

I. INTRODUCTION

Ubiquitous systems are actively studied and their popularity has been facilitated by increasing availability of smart mobile devices and context aware technology. Ubiquitous computing systems have been employed in many fields, for example, in education [1], [2], military [3], [4], transportation [5] and tourism [6]. Among them, ubiquitous healthcare (u-healthcare) is an emerging field in ageing population with limited human resources as well as increase in chronic disease, such as cancer, diabetes, obesity and heart failure [7].

In u-healthcare age, bio-signal monitoring technology as well as physical activity recognition techniques have 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 multimodal biosensors is to help patients to monitor their health state by themselves and their caregivers to update patient health status in real-time using wireless network.

In this paper, we introduce Expectation Maximization (EM)-based health condition tracking model that can be used for the prediction of abnormal health condition using multimodal biosensors in dynamic situation. This health state tracking model considers vital signs from biosensors as well as the environmental factors, such as time and object location information from smart device with GPS function. This EM-based healthcare tracking model can be used for the prediction of disease status and can be used for decision making such as proper diet and exercise.

II. RELATED WORK

A. *Ubiquotus healthcare*

The demand for u-healthcare monitoring has been increasingly raised because of the increase of life span and chronic disease. In U-healthcare age, large number of environmental and bio-sensors are used to monitor and improve patients' physical and mental conditions [7]. With the development of wearable smart device, ubiquitous healthcare is available to everyone, everywhere in anytime [8]. HealthPal is an intelligent small portable device that uses wireless (Bluetooth) or wired connectivity [9], which collect patients' health information, such as glucose level, blood pressure, body weights and pulse rates. These patients' health information will be transmitted to healthcare professionals and proper healthcare will be provided to the patient based on measurement in real-time.

B. *Physical health and mental health are inextricably linked*

It is well known that physical health has been closely linked to mental health [10, 11]. Poor mental health is associated with an increased risk of diseases such as cardiovascular disease, cancer and diabetes, while good mental health is a known protective factor for disease risk. For example, patient who has chronic disease with poor physical health condition would have increased risk of mental problems. In opposite, good mental health condition reduces the risk rate of chronic disease. Thus, mental health as well as physical health is considered as part of public health and proper investment is required for public health.

C. *Characteristics of Biosignals (EEG ECG and EMG)*

Accurate knowledge of different signals from the brain and other body parts are very important in understanding many physiological and pathological functions of the brain and the body parts. This requires updated knowledge on the human bio-signals for better signal processing techniques. These signals include blood glucose level, respiration rate, blood pressure, electroencephalogram (EEG), electrocardiography (ECG), and electromyography (EMG). However, these measurements results 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.

III. PHYSICAL AND MENTAL HEALTH CONDITION MONITORING IN DYNAMIC SITUATION BASED ON EM

The work-flow of smart health condition monitoring model is shown in Figure 1. This health condition monitoring model has three major steps, object assessment, situation assessment, and risk assessment based on cumulative risk ratios. The object assessment is the step, which extracts features from the detected wavelength in EEG, ECG and EMG multimodal biosensors. Based on vital signs, the object health condition will be classified into healthy, low energy, constant tired state and also considers location of object and situation information. The risk assessment step is the most important step in the health condition monitoring model. This step maximize abnormal health condition risk ratio and decision making for emergency situation will be made for medical treatment.

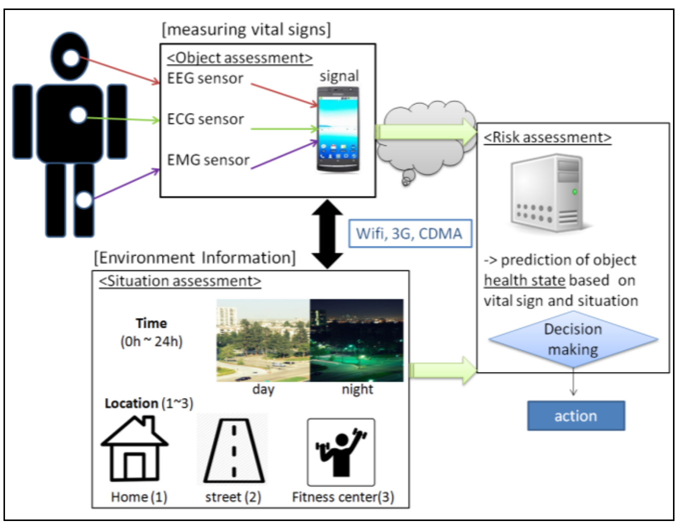

Figure 1 The workflow of health condition monitoring model: Bio-signals from multimodal bio-sensors and situation information were sent to the smart device and analyzed based on risk ratio EM model. This model consists of the three major steps as follows; (1) Object assessment from multimodal bio-sensors. (2) Situation assessment from environment information. (3) The analysis of cumulative abnormal risk ratio based on EM model and decision making.

A. ***Object Assessment***

It is known that mental health and physical activity is fundamentally linked [11]. Based on our previous study on physical activity recognizer SUPAR [12], we consider EEG signal from brain, which categorized into Theta, Alpha, and Beta depending on object mental condition. We also consider heart rate from ECG sensor and EMG from muscle. These bio-signals will help us to predict object health condition as well as mental condition (Figure 2).

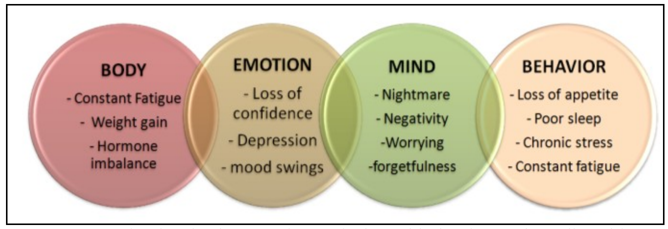

Figure 2 Monitoring body, emotion, minds and behavior and predict object Healthy-Fatigue level by measuring multi-modal bio-signals using EEG, ECG and EMG.

Table 1. The characteristics of bio-signals from multimodal biosensors in smart device

Signal	Bandwidth(Hz)	Amplitude range (mV)	Quantization(bits)
Electroencephalogram (EEG)	0.01 – 150	0.001 - 1	4 – 6
Electrocardiography (ECG)	0.01 - 300	0.05 - 10	10 – 12
Electromyography (EMG) -Internal	0.01 - 15K	0.2 -20	4 – 12
Electromyography (EMG) -External	10 – 8K	0.01 - 100	4 - 12

(A) Electroencephalography (EEG)

EEG is the measurement of electrical activity produced by the brain as recorded from electrodes placed on the surface of the scalp. When these EEG signals are analyzed, they are used in clinics to diagnose sleep disorder, brain death, tumor and stroke in combination with fMRI and CT.

(B) Electrocardiography (ECG)

ECG is a graphic produced by an electrocardiograph, which records the electrical activity of the heart over time [13]. When electrical waves caused by the heart muscle to pump pass through the body, skin-attached ECG sensors will provide the activities of the heart muscle. Using an ECG, the voltage between pairs of these attached electrodes, and the muscle activity that they measure can be used for the prediction of heart problems and pulmonary disorders.

(C) Electromyography (EMG)

This is a method for evaluating and recording physiologic properties of resting and contracting muscles. It is used to detect the electrical potential generated by these muscle cells when they contract as well as when they are at rest. EMG is used as a diagnostics tool for identifying neuromuscular diseases, assessing low-back pain, disorders of motor control and neuromuscular monitoring in general anesthesia. EMG signals are also used as a control signal for prosthetic devices such as prosthetic hands, arms, and lower limbs. The electromyograph produced from EMG sensor, which detects the electrical potential generated by muscle cells when these cells contract and at rest. External EMG potentials range from about 100 μV to 100 mV, depending on the muscle under observation. Typically, measured frequency range from 14 Hz to 8 kHz, again based on the muscular activity under consideration. For internal EMG, the signal amplitude ranges from 1μV to 5 mV while the frequency range is about from DC to 15 KHz.

(D) Respiration rate

Usually monitoring a patient's respiratory status takes place in a hospital and may be the purpose for a patient being observed. The signs of respiratory distress may present as short of breath, having an increased work of breathing, use of their accessory muscles, changes in skin color, and loss of consciousness. When the initial respiratory monitoring show evidence of a patient's inability to adequately oxygenate their blood, the patient may require mechanical ventilation

B. *Situation Assessment and Risk rate EM Learning Algorithm*

In this section, environmental factors such as location type and time information are collected from GPS in smart device are analyzed for prediction of object health status. For the prediction, we categorized time into four categories morning, afternoon, midnight, and night. Location also classified into four types, home, street, fitness center and workplace. Bio-signals from multimodal biosensors and situation information are analyzed together for the prediction of object health state (Figure 3).

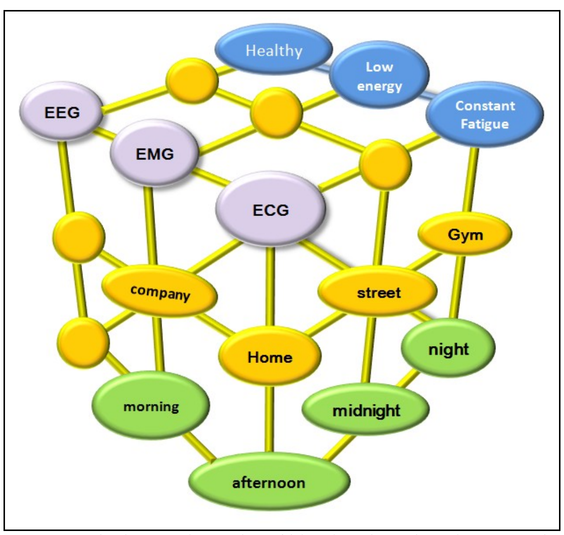

Figure 3 The interaction cube of bio-signals and environmental factors (time and location) in risk ratio EM model

C. *Risk Assessment Considering Object trajectory and regional safety level*

Depending on the time and location type, object health state (bio-signal) can show different result. For example, at home EEG sensor will represent alpha wave, which represents object is in relaxed state. At workplace during the daytime, EEG sensor will show theta wave because object is in focused attention state. Depending on the time and location of object, health condition can be updated and classified into healthy, low energy, and constant fatigue.

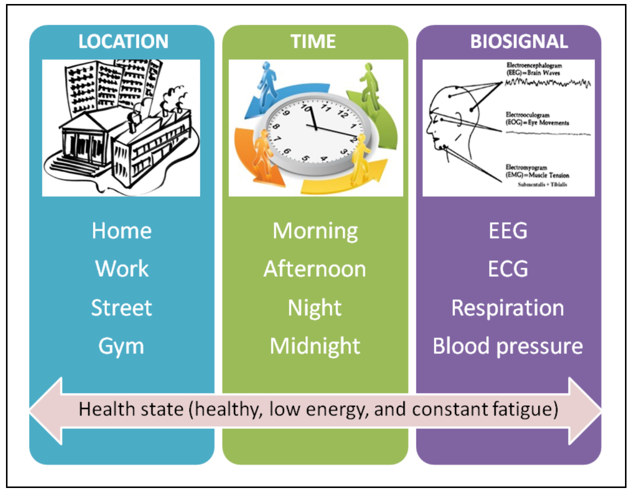

Figure 2 Health state can be classified into 3 levels (healthy, low energy, and constant fatigue) considering location, time, and biosignal

IV. PROPOSED ALGORITHM

In this section, we proposed core algorithm of risk rate EM to detect object health condition. Risk ratio EM model consists of two steps, expectation step (E-step) and maximized step (M step). In E-step, input variables from biosensors and situation information are updated repetitively.

Algorithm1 Learning object health condition from object and situation assessment using risk ratio EM

Input :
a sequence of EEG (E1, . . . , En)
a sequence of ECG (C1, . . . , Cn)
a sequence of EMG (M1, . . ., Mn)
a sequence of time (T1, . . . , Tn)
type of location (home, street, workplace, and gym)
currentLL $\leftarrow \infty$
repeat
prevLL $\leftarrow$ currentLL
($\Sigma e'$, $\Sigma c'$, $\Sigma m'$, $\Sigma t'$, $\Sigma l'$) $\leftarrow$ LearnRiskRatio (Σe, Σc, Σm, Σt, Σl)
currentLL $\leftarrow$ Σt logP (Oe|Σe, Σc, Σm, Σt, Σl)
until
| prevLL - currentLL $<$ ε |
Output :
estimated parameters (Σe, Σc, Σm, Σt, Σl)

These bio-signals from multimodal biosensors and situation information repeatedly updated into input variables to understand the object health sate in dynamic situation. Risk rate EM model maximizes cumulative disease risk ratio in E-step considering object health condition, situational information (Figure 5). In M-step, by comparing maximized risk rates final decision making is recommended by learning algorithm. Expectation Maximization (EM) is a method for finding maximum likelihood estimates of parameters from unobserved latent variables [15]. Latent variables (maximized risk rates) are variables that are not directly observed but are rather inferred from other variables that are observed from object health state, time, and location type.

```
Initialisation :

    //Input data
    Object_health condition [ health, low energy, constant fatigue ] ;  // object assessment
    Time [ morning, afternoon, midnight, night ];  // situation assessment
    Location_type [ home, street, gym, workplace ] ; // situation assessment

    //predefined data
    Maximum risk rate < 0.3 ;
    Object health condition: healthy = 1 ; low energy = 2 ; constant fatigue = 3 ;
    Time : morning =1 ; afternoon = 2 ; midnight = 3 ; night = 4;
    Location : home =1 ; street =2 ; gym = 3 ; workplace = 4;
    While ( i = 0; i < n ; i ++)
    {

E-Step:
    //calculate risk rates using Viterbi algorithm
    Risk ratio = compute_probability (Object_health condition; Time; Location_type) ;

    //calculate state
    Abnormal_Health_Condition = compare_disease_state (disease_state) ;

M-Step:
    // decision_making depending on maximized risk ratio
    Decide_object healthcare (diet, exercise, medication, hospital checkup);

end
}
```

Figure 5 *Pseudo* code for disease risk ratio EM

EM is an iterative method which alternates between performing an expectation (E) step, which computes the expectation of the log-likelihood, evaluated using the current estimate for the latent variables, and maximization (M) step, which computes parameters maximizing the expected log-likelihood found on the E step. These parameter-estimates are then used to determine the distribution of the risk ratio in the next E step. Risk ratio EM model would calculate probability of maximum risk ratio from object health condition. If we know the value of the parameters, such as location and time information, we can predict maximized risk ratio of abnormal health condition.

V. RESULTS

A. *Implementation of Risk rate EM using WEKA*

We tested 14 training datasets using machine learning tool WEKA [15-16] developed by the University of Waikato with default settings. We implemented EM-based clustering in WEKA explorer and it showed log likelihood estimates : -3.99762 (Table 2, 3). It showed 4 groups based on location or EEG signal.

Table 2 EM-based clustering based on location

Location	Group 1	Group 2	Group 3	Group 4
home	1	1	1	9
gym	1	4	1	1
work	1	1	6	1
street	8	1	1	1

Table 3 EM-based clustering based on location

EEG	Group 1	Group 2	Group 3	Group 4
alpha	2	1	1	8
beta	1	1	1	1
theta	7	1	6	2
delta	1	4	1	1

In Table 4, the result of the SMO is presented in a confusion matrix over the 10-fold cross validation. The activities alpha, beta, theta are recognized with high accuracy (91.3043 %).

Table 4 10-flod cross validation using BinarySMO

EEG	alpha	beta	theta	delta
alpha	7		1	
beta				
theta	1		11	
delta				3

VI. CONCLUSION

In this paper, we suggested advanced health condition monitoring model based on EM algorithm for the prediction of object health state. In this study, we classified object health condition into three categories, healthy, low energy, and constant fatigue. The risk ratio EM tracking model has three steps as follows; (1) object assessment from multimodal bio-sensors (2) situation assessment from environment (3) analysis of the accumulated risk ratio of abnormal health condition and decision making depending on health condition.

Disease risk rate EM model would calculate maximized risk rates collected from object health condition and environmental situation. Based on object health condition and situation knowledge database, risk rate EM model would predict patient health condition and recommend for proper diet and exercise for the prevention of abnormal state.

Future research on monitoring ubiquitous healthcare can consider healthcare checkup notice from smart device using wireless network. Lately, there has been increasing interest in public healthcare and this healthcare monitoring system can be used for the prevention of disease and increase the quality of individual healthcare service.

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