Context-Based Decision Making Method for Physiological Signal Analysis in a Pervasive Sensing Environment

Ahyoung Choi and Woontack Woo

GIST U-VR Lab., Gwangju 500-712, S.Korea
{achoi,wwoo}@gist.ac.kr

Abstract. With the advent of light-weight, high-performance sensing and processing technology, a pervasive physiological sensing device has been actively studied. However, a pervasive sensing device is easily affected by the external factors and environmental changes such as noise, temperature or weather. In addition, it is hard to deal with the internal factors of a user and personal differences based on physiological characteristics while measuring physiological signal with a pervasive sensing device. To address these issues, we propose a context-based decision making method considering pervasive sensing environments in which it concerns users' age, gender and sensing environments for detecting normal physiological condition of a user. From the research conducted, we found that the context-based physiological signal analysis for multiple users' regular data showed reliable results and reduced errors.

Keywords: Context-based decision making, Pervasive sensing environment, Physiological signal analysis.

1 Introduction

Pervasive physiological sensing devices for daily monitoring have been studied extensively [1-2]. However, these devices are not commonly used by normal consumers because analysis results are fragile to environmental noise. In addition, these devices are easily changed according to internal changes and personal differences. Smart environments now provide a wide range of resources, such as distributed and embedded sensing devices. These environments are quite useful and practical in the area of physiological signal sensing. This involves information on numerous external factors, like outdoor temperature, weather, humidity, and luminance, as well as user profiles, which include information of user activity, energy expenditure, gender, and age. By fusing this contextual information, we can obtain more reliable analysis results from a noisy sensory input. Knowing the previous condition before measuring the physiological signal provides clues for more precisely understanding user's status.

However, general decision support system in health domain has commonly used statistical pattern classification method for analyzing the signal. They collected a large number of data and found out the general threshold to cover all different types of users. Wanpracha proposed the classification method to determine epilepsy from

Y. Shi et al. (Eds.): MCDM 2009, CCIS 35, pp. 325–332, 2009.

the EEG signal [3]. However, each patient had different classification results. In the field of pervasive sensing and analysis, previous work of physiological decision making has focused on filtering noisy signals. Asada developed a ring-type sensor and minimized its' errors by using a reference signal on the other side [4]. Rosalind proposed a stress analysis program by using a wearable computer [5]. However, these studies were effective for filtering the motion artifact, but did not reflect the personal differences and adaptive analysis pertaining to individual users. Winston indicated the decision making method with user's activity information [6]. They decided that physiological status of current user should be integrated into activity inference results.

In this work, we propose a context-based decision making method of physiological signal based on a probabilistic decision making process which considers users and environmental conditions. The information is analyzed based on the uncertainty of influencing factors. The proposed method supports the context adaptive signal analysis and improves the normal physiological status classification rate. In addition, this model provides an adaptive framework for a dynamic and changeable user's condition during monitoring. For analyzing effectiveness, we collect normal physiological condition of multiple users and decide users' status with standard, personalized, and group threshold values with a PhysioNet database. Finally, we conclude that the proposed context based decision making model has an effect on improvement of physiological status recognition.

The following section of this paper is as follows. We explain the proposed analysis method in section 2. Section 3 shows the experiential setup and analysis results for verifying the proposed method. Finally we conclude in Section 4 and illustrate the future direction of this research.

2 Context-Based Decision Making of Physiological Signal

Physiological signal status analysis during a certain period of time may increase the chances of an incorrect diagnosis. For example, the human heart beats faster after exercise and, if a user were to visit a hospital soon after exercising, the possibility exists for a misdiagnosis of heart problems. Therefore, the decision making with contextual information needs to be improved in order to accurately analyze both sensing conditions and users' conditions. However, we do not know which factors is influence to the physiological signal and how much the factors are affected. Therefore, we need to include probability theory to model the decision making algorithm. There have been researched of decision making algorithm addressing uncertainties [7-8].

We find out ideal user status and classify normal conditions based on user's type (gender, age) and other group models. The information of the current user's model is not given. We assume that both data distribution and error have a Gaussian probability density function. $T= \{t_1, t_2, t_3, \ldots, t_n\}$ refers to the type of user information (e.g. normal and abnormal), and n is the number of types. $M= \{m_1, m_2, m_3, \ldots, m_p\}$ is the model of other groups (e.g. gender, age) where p is number of models. We abbreviate user state as notation u, while 0 and 1 are normal and abnormal conditions, respectively. In order to find the ideal user physiological status u, we apply the MAP decision making method. For maximizing probability of current user status, we model the following equation:

$$\begin{aligned} u^* &= \arg\max_{u^*} P(u \mid d,m,t) = \arg\max_{u^*} \frac{P(u,d,m,t)}{P(d,m,t)} \\ &\propto \arg\max_{u^*} P(u,d,m,t) \end{aligned} \tag{1}$$

For simplifying the equation, we assume the following conditions:

$$\begin{aligned} P(u,d,m,t) &= P(d \mid u,m,t) * P(u,m,t) \\ &= P(d \mid u,m,t) * \overbrace{P(m \mid u,t) * P(u,t)}^{P(u,m,t)} \\ &= P(d \mid u,m,t) * P(m \mid u,t) * \overbrace{P(t \mid u) * P(u)}^{P(u,t)} \end{aligned} \tag{2}$$

Finally we obtain a joint probability density function in terms of current observation *d*. If we assume that each joint pdf is a normal distribution from the energy equation,

$$E = e_1 + e_2 + e_3 + f(\Delta u) \tag{3}$$

Where e1 is an energy function of *P(d|u,m,t)*, e2 is an energy function of *P(m|u,t)*, and e3 is an energy function of *P(t|u)*.

$$u^* = \arg\min_{u^*} E = \arg\min_{u^*} \{e_1 + e_2 + e_3 + f(\Delta u)\} \tag{4}$$

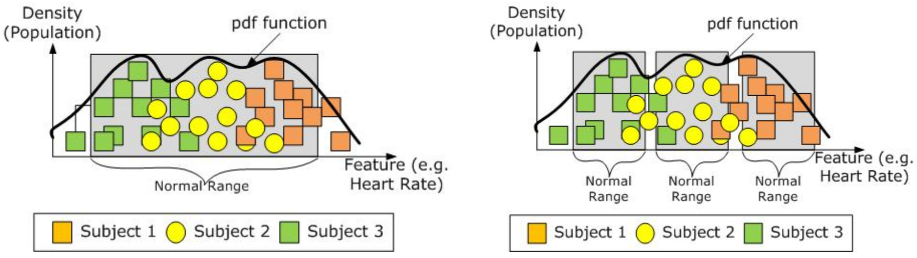
Where, e_1, e_2 and e_3 are as follows:

$$e_1 = d - f_1(u,h,t), \quad e_2 = m - f_2(u,t), \quad e_3 = t - f_3(u) \tag{5}$$

We define that e_1 is a function of difference between individual distribution and group-type distribution. e_2 is a function of difference between group distribution and ideal type distribution. Finally e_3 is 0, because we assume that *P(t|u)* is constant, 0.5.

The context-based analysis concept is described in Fig. 1. Most previous works apply a statistical approach to establish a standard threshold and then proceeds to analyze under this standard. In this case, accuracy of analysis results improves as size of the data increases. The basic concept of adaptive physiological signal analysis is depicted in Fig. 1(b). In the proposed context-based analysis with user type information, we assume that the problem domain is a pervasive sensing device which records personal data and contextual information in real time over a long period of time. Physiological information is labeled dynamically and the labeling information can be provided directly by user's input or by sensing information from heterogeneous sensors and services. We utilize the context labeled physiological signal information in user database to determine physiological status individually. For data labeling, we utilize contextual information.

In order to solve the problem, we first estimate the ideal signal of distribution by assuming that observation and ideal signal are very similar and noise information is quite small. From the observation, we estimate current ideal user signal. Then, we estimate density of the proposed signal by using a normality test of signals obtained from three channel sensors. If distribution of measurement is normal, we model the signal in a parametric manner, Gaussian distribution. If distribution is abnormal, we model measurements in a non-parametric method.



(a) (b)

Fig. 1. Concept diagram (a) Previous standard Decision making (b) Context-based Decision making

In estimation step, we use Kalman filter and assume the ideal estimation based on observations. In addition, we assume that X includes x_1 and x_1 (dimension: 2) and $x_1(t)$ and $x_2(t)$ are mutually independent. In case of states variation according to time is const. The current observation $y(t)$ consists of original states and noise is white Gaussian noise. After getting the final decision making model, we compute differences between previous and current estimate parameters. If differences are small, we ignore changes of estimated results. However, if estimation shows a large distinction, we update user model parameters. Finally, in classification step, we compute the classified result assuming a 95% confidence interval.

3 Experimental Analysis

For this experiment, we evaluated the proposed context-based decision making method with real observations from the measurement equipment. We made use of Normal Sinus Rhythm RR Interval Database and Congestive Heart Failure RR Interval database in PhysioBank [9]. In Normal Sinus Rhythm RR Interval database, RR interval of heart rate was obtained from 54 normal subjects. 30 subjects were male aged 28.5 to 76 and others were female aged 58 to 73. Congestive Heart Failure RR Interval data base included subjects' heart failure measurement data (NYHA classes III). The subjects were aged 34 to 79. For the analysis, we selected 18 subjects from data set, 9 sample measurements from abnormal condition subjects and the others from normal subjects. Among the time series measurement, we selected 5 minutes RR sample series from each subject. The measurements were preprocessed for correcting artifacts with smoothing method and for removing 3rd order trends of RR interval.

After collecting the measurement data, the ideal pulse signal was estimated using Kalman filter. After estimating the pulse signal, we computed feature from RR interval to compute heart rate, because this factor was able to characterize signals in the time domain. We estimated a density function to determine normal and abnormal conditions of current observation. Since there were numerous density estimation methods, we first checked the Kolmogorov-Smirnov tests in MINITAB to verify the normality of the collected data. Finally, we obtained a probability density function about each data set.

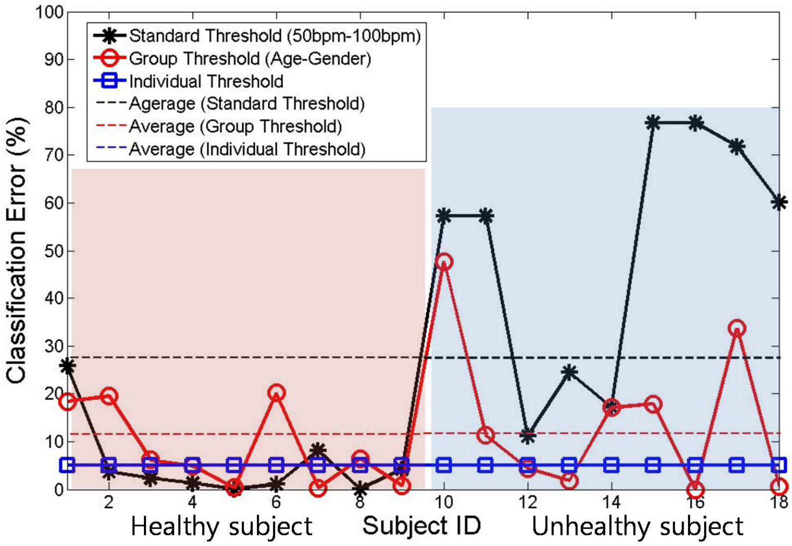
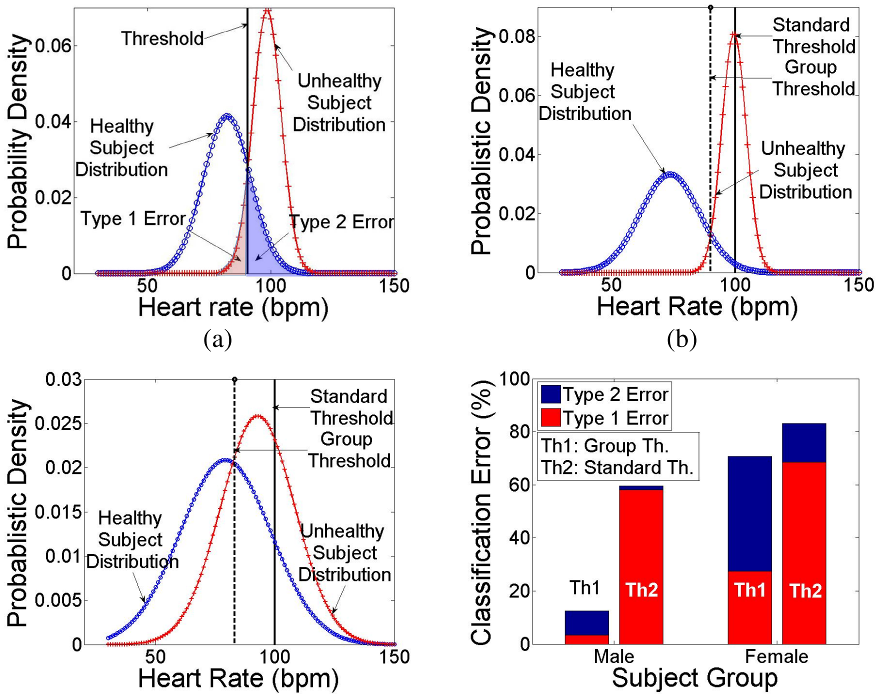


Fig. 2. Concept diagram (a) Previous standard Decision making (b) Context-based Decision making

In decision making step, we determined whether current condition of a subject was normal or abnormal by several thresholds such as an individual threshold, a group threshold, and a general standard threshold. In case of a standard threshold, we referred range under 100bpm because we just collected fast heat beating condition of abnormal subjects. For a group threshold, we categorized subjects into two groups with the context of gender and age. Gender group had two classification criteria, male and female. Age group was categorized into three ranges, 20-39 aged people group, 40-59 aged people group, and 60-79 aged people group. Individual threshold was computed by individual distribution following 95 percentage certification interval of each density distribution.

From the experiment, overall classification performance with group threshold increased as displayed in Fig.2. When we applied the standard threshold under 100bpm, most classification errors were significantly reduced in case of normal sinus interval group. On the other hand, subjects who had heart-related disease (NYHA classes III) had large classification errors. However, age-gender group analysis kept the classification rate in normal subjects' case as well as abnormal subjects' case as shown in Fig.2. Average error rate in personalized analysis, group analysis with age-gender context, and standard analysis was 5%, 19.23%, and 33.13%, respectively. From these experiments, we concluded that the group analysis with age-gender contexts had a positive effect on physiological status classification results comparing to other deterministic and static classification threshold.

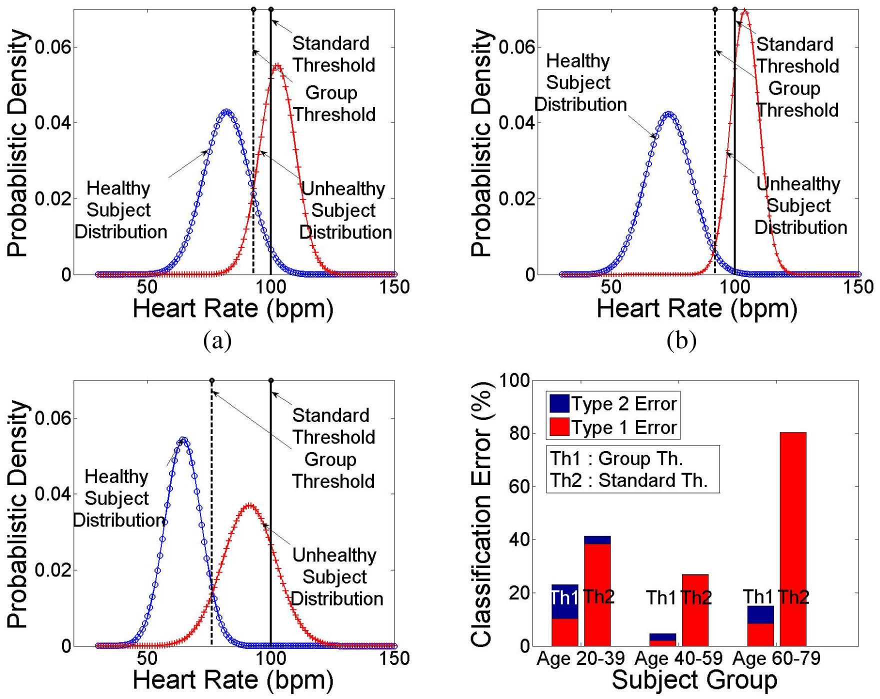
In addition, we compared the classification result in detail with several group thresholds as shown in Fig.3 and Fig.4. For analysis, we checked types of errors in each distribution, which were Type 1 Error and Type 2 Error as in Fig.3(a). In case of Type 1 error, we defined that we had a positive result ("The subject was healthy") but it was from unhealthy subjects. In case of Type 2 error, we missed correct result of normal condition subject. Fig.3(b)-(c) indicated the distribution of each gender group. From the observation of Fig.3(d), we found that overall false classification ratio was reduced when we applied gender group threshold to decide the heart status. In addition, grouping analysis with age context also indicated lower classification error than standard analysis. However, in both cases, Type 2 errors increased because standard threshold extended possibility to detect normal condition subjects. From this experiment, moreover, we observed that group analysis with age context indicated more beneficial classification result rather than applying age context. As a result, we concluded that the classification error rate was reduced by group based decision making method as well as personalized decision making method. Accordingly, we found that age and gender context, especially age context, could be used to estimate the current user status to some extend without knowledge of the user's current density distribution.



(a) (b)

(c) (d)

Fig. 3. Gender group classification result (a) Definition of Type of Error (b) Distribution of male group (c) Distribution of female group (d) Classification result



(a) (b) (c) (d)

Fig. 4. Age group classification result (a) Distribution of age 20-39 group (b) Distribution of age 40-59 group (c) Distribution of age 60-79 group (d) Classification result

4 Conclusion and Future Work

In this work, we propose a context-based decision making method of physiological signals which achieves better results than other deterministic methods; standard threshold. The proposed method supports the probabilistic decision making method with the context of gender and age. From the experiment conducted, normal status decision result of heart rate with the context of gender and age, produces better classification results than by applying standard threshold. We expect that user type context information as well as gender and age information can also improve normal heart status detection ratio. For future study, we will analyze the lower heart failure case with other database to complete analysis. In addition, we will extend the context information for grouping to user body constitution and clinical history. Furthermore, we will build the model to estimate the current status from the user's history, other group models, and user type with pervasive sensing devices by applying the observed relationship.

Acknowledgments. This research was supported by the CTI development project of KOCCA, MCST in S.Korea.

References

1. Robert, M., Neil, J.M., Paul, H., Peter, J.T., Martin, A.S.: A Wearable Physiological Sensor Suite for Unobtrusive Monitoring of Physiological and Cognitive State. In: IEEE EMBC 2007, pp. 5276–5281. IEEE Press, New York (2007)
2. Urs, A., Jamie, A.W., Paul, L., Gerhard, T., Francois, D., Michel, B., Fatou, K., Eran, B.S., Fabrizio, C., Luca, C., Andrea, B., Dror, S., Menachem, A., Etienne, H., Rolf, S., Milica, V.: AMON: A Wearable Multiparameter Medical Monitoring and Alert System. IEEE Transactions on Information Technology in Biomedicine 8, 415–427 (2004)
3. Wanpracha, A.C., Oleg, A.P., Panos, M.P.: Electroencephalogram (EEG) time series classification: Applications in epilepsy. Annals of Operations Research 148, 227–250 (2006)
4. Asada, H.H., HongHui, J., Gibbs, P.: Active noise cancellation using MEMS accelerometers for Motion tolerant wearable bio-sensors. In: IEEE EMBC 2004, pp. 2157–2160. IEEE Press, Los Alamitos (2004)
5. Rosalind, W.P., Charles, Q.D.: Monitoring stress and heart health with a phone and wearable computer. Motorola Offspring Journal (2002)
6. Winston, H., Wu, M.A., Batalin, L.K., Au, A.A., Bui, T., William, J.K.: Context-aware Sensing of Physiological Signals. In: IEEE EMBC 2007, pp. 5271–5275. IEEE Press, New York (2007)
7. Dianne, J.H., Robert, A.D.: Engaging multiple perspectives: A value-based decision-making model. Decision Support Systems 43, 1588–1604 (2007)
8. Meltem, O.z., Alexis, T.: Modelling uncertain positive and negative reasons in decision aiding. Decision Support Systems 43, 1512–1526 (2007)
9. Goldberger, A.L., Amaral, L.A.N., Glass, L., Hausdorff, J.M., Ivanov, P.C., Mark, R.G., Mietus, J.E., Moody, G.B., Peng, C.K., Stanley, H.E.: PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals. Circulation 101(23), e215–e220 (2000)