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MULTIPLE-CRITERIA DECISION-MAKING BASED ON PROBABILISTIC ESTIMATION WITH CONTEXTUAL INFORMATION FOR PHYSIOLOGICAL SIGNAL MONITORING

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We propose a multiple-criteria decision-making (MCDM) method based on Maximum A Posteriori (MAP) estimation to analyze users' physiological status either normal or abnormal. The decision-making problem is formulated using MAP estimation and is turned out to be MCDM problem given the assumption that all probability density functions (pdfs) follow exponential forms, especially Gaussian. It indicates that this MCDM equation is decomposed into direct sum of group's physiological status distribution. Group distribution is estimated by probabilistic approach using population from the same age or same sex. For verification, we applied the proposed method to public heart rate database. According to experimental results, the proposed method considering group context reduced overall classification errors by 20.42% compared to typical decision-making (TDM) method. This method is applicable to various personalized health monitoring applications, which estimates user's physiological status by referring other group distribution without prior knowledge about previous health records.

Keywords: Multiple-criteria decision-making; probabilistic decision-making; group context; physiological signal monitoring.

1. Introduction

The advent of lightweight and high performing hardware technology accelerates the development of physiological monitoring systems.[1–3] Typical decision-making (TDM) methods in these systems indicate users' physiological status whether they are under normal physiological condition or not, based on statistical analysis (mean, standard deviation, etc.) from a large data set. However, TDM methods cannot guarantee the reliable classification of all types of users, e.g. people with abnormally high heart rate during rests. Thus, the best way to accurately estimate physiological states is to adopt a personalized decision-making (PDM) method by collecting an

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individual user's physiological data in his/her everyday life. As it would require much time and efforts to collect reliable data during long periods of time, we must consider tradeoffs between TDM and PDM methods when designing physiological monitoring systems.

There have been lots of researches on decision-making with data mining method, machine learning method in the health domain for this purpose.[4–8] To minimize the effect of personal differences and to reduce the complexity of signal analysis, Jose proposed a regression model assuming that current physiological states result from previous physiological states which determined the normal heart rate of individuals depending on their age and sex.[5] In addition, Miller and Londeree made formulas for heart rate analysis considering sex.[6,7] However, most previous formulas followed deterministic approach and these methods were adapted to empirical observation in a specific task only. Other contextual information such as activity also has been considered. Wu indicated the physiological decision-making method with user's activity information.[9] They inferred users' activity with Naive Bayes classifier, and eliminated motion artifact from corrupted physiological signal. Zhang proposed diagnostic decision support model based on yinyang wuxing equilibrium approach referred by traditional Chinese medicine where he used multiple contextual information for diagnosis.[8] However, still there is no acceptable formula to be used widely and no satisfactory approaches yet for all users.

To address these issues, we explore a decision-making method to analyze physiological signals accurately for different types of people. Our method exploits multiple-group contexts such as age, sex, height, weight, etc., and its relationship. Their relationships with physiological signals are formulated using a MAP estimation to obtain ideal expectation of users' physiological status. MAP estimation has turned out to be MCDM problem given the assumption that all pdfs follow exponential forms, especially Gaussian. Each term of MCDM formula corresponds to the effect of group context such as age, sex, height, weight, etc. For analyzing the effectiveness of the proposed method, we collect normal and abnormal data of multiple users from a PhysioNet database and decide users' status using TDM, PDM, and MCDM with multiple group contexts.

The proposed method has the following advantages. By referencing similar group data distribution, MCDM method estimates users' physiological status more accurately in a short time than TDM method. In other words, it does not require large number of individual users' data; eventually it reduces training time and effort while keeping the estimation result approximated to one by using PDM method. In addition, the MCDM method has a beneficial effect on various populations because it adopts group's data distribution. It preserves performance constantly regardless of population of abnormal users. Even though there exist increased population of abnormal subjects, physiological data distributions of various populations are reflected in the result of physiological status recognition and we observe the improved results comparing to one by using TDM method in various cases.

The following section of this paper is as follows. We explain related works in Sec. 2 and the proposed analysis method in Sec. 3. Section 4 shows the experiential setup and analysis results for verifying the proposed method. Finally we conclude in Sec. 5 and illustrate the future direction of this research.

2. Related Works

In health, typical decision-making systems use statistical pattern classification methods to analyze the physiological signals.[4–8] Most previous researchers collected a large data set from hospitals and found out a set of statistical values (mean, standard deviation, etc.) of healthy and unhealthy people. However, this method may not cover all users, e.g. people with higher heart rate range than others in normal condition. To address this problem, Jose explored deterministic analysis method of abnormal heart rate detection considering age and sex.[5] He built a regression model to differentiate normal range against different personal groups. In addition, Miller and Londeree made formulas for heart rate analysis considering sex.[6,7] However, most previous formulas followed deterministic approach, which has less flexibility such that we cannot revise and modify for further analysis.

Other researchers used contextual information such as mood, activity for physiological decision-making. Wu discussed the decision-making method based on user's activity information by eliminating motion artifact.[9] These studies effectively filtered motion artifacts, but did not reflect information such as individual differences. These methods were adapted to empirical observations in a specific task and were designed to include a single decision criterion such as age, motion artifact, or activity for the analysis. However, we must embrace multiple criteria simultaneously for decision-making in health.

To deal with multiple criteria, researchers in data mining, management, and machine learning introduced various MCDM methods; utility theory-based method,[10,11] knowledge-based method,[12,13] fuzzy theory-based method,[14,15] and probabilistic model-based method.[16–18] Most commonly referred methods are utility-based and knowledge-based methods.[10–12] Torrance and Huber proposed a multiattribute utility function for health states classification, applying weights for decision-making based on empirical observation.[10,11] However, it is hard to define utility function because there is too little background theory to indicate factors which influence the physiological signals and its relationships. Therefore, some researchers suggested the decision-making method, appropriate to deal with uncertainty problem of physiological signal analysis as well as to make it in general.[14–18] Carlsson and Rao introduced fuzzy theory-based DM methods which supported uncertain reasoning under the vagueness phenomenon. However, this method requires novel knowledge to define fuzzy rule for analyzing personal differences. Unlike the above methods, probabilistic methods have advantages to deal with dependency between criteria.[16–18] Thus, we explore the way to model decision-making probabilistically and by referring to previous works about grouping method.[19]

3. Multiple-Criteria Decision-Making Based on a Group Context

In this section, we explore a MCDM method derived from MAP estimation for physiological signal analysis. Physiological analysis without considering personal differences increase the risen misdiagnosis. For example, a person who has high heart rate in normal condition may be misdiagnosed for a heart problem. Therefore, decision-making based on contextual information needs to be improved with more accurate analysis of sensing conditions and users' normal or abnormal conditions. However, we have little information to determine which factors influence physiological signal, and how much the factors are affected. Therefore, we applied probability theory for problem formation. Research on decision-making algorithms addressed uncertainty of influencing factors.[17,18] Because of the uncertainty, relationships between variables are modeled with conditional probabilities based on Bayes' theorem.[16]

The proposed decision-making method has the following procedure as shown in Fig. 1. For preprocessing of collected data, we extract features from original signals and segment certain periods of time for consistent and reliable analysis. Then, selected features are filtered by smoothing and removing third order trends. In decision-making step, we estimate a density function from the physiological signal database. Since there are numerous density estimation methods, we first check the Kolmogorov–Smirnov tests to verify the normality of the collected data. Then MAP estimation is processed based on filtered signal and estimated density function. After finding ideal data distribution, we determine 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.

For the MAP estimation, we formulate the problem as follows. First, we assume that the data distribution and error follow a Gaussian probability density function because most physiological measurements are in the middle range. It indicates

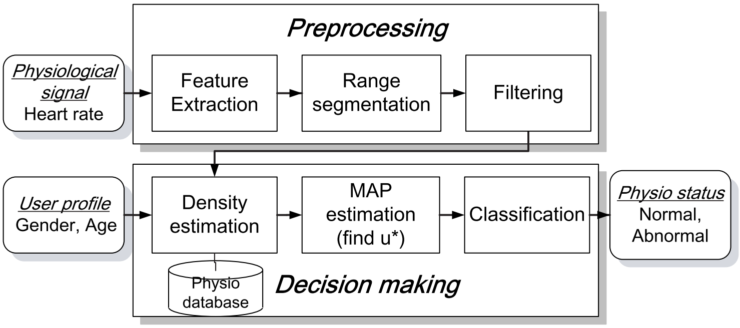


Fig. 1. Overall procedure of physiological signal decision-making.

that physiological measurement has higher probability to observe normal status subjects rather than abnormal subjects. We abbreviate the observed physiological data d following a Gaussian probability density function and the user physiological states u of observed data following Gaussian probability density function. $M = \{m_1, m_2, m_3, \ldots, m_p\}$ is the model for groups (e.g. male, female) where p is the number of models. $T = \{t_1, t_2, t_3, \ldots, t_n\}$ refers to the type of user status (e.g. normal, abnormal), and n to the number of types. To find the ideal user physiological states u, we apply the MAP estimation method. To maximize the probability of the current user status, we apply the following equation:

$$\begin{aligned} &u* = \arg\max_u P(u|d,m,t) = \arg\max_u \tfrac{P(u,d,m,t)}{P(d,m,t)} \\ &\propto \arg\max_u P(u,d,m,t) \end{aligned} \tag{3.1}$$

We assume that u is derived from the conditional probability given observation d, other group reference model m, and user states t. In Eq. (3.1), we ignore $P(d, m, t)$ because probability function in terms of d, m, t does not involve information about u ideal expectation. Therefore, we find the original MAP estimation in proportion to the joint probability of u, d, m, and t.

To simplify Eq. (3.2), we decompose the joint probability through a data-observation process, group-observation process, and status-decision process. In the data observation process, the observation data d is estimated from the given group distribution m, status information t, and expected distribution u. For the group-observation process, the group distribution is computed according to the type t and ideal expectation u. We derive the final status type from the expected distribution.

$$\begin{aligned} P(u,d,m,t) &= P(d|u,m,t) * P(u,m,t) \\ &= P(d|u,m,t) * \overbrace{P(m|u,t) * P(u,t)}^{P(u,m,t)} \\ &= P(d|u,m,t) * P(m|u,t) * \overbrace{P(t|u) * P(u)}^{P(u,t)} \end{aligned} \tag{3.2}$$

As a result, we factorize the multivariable joint probability function into several simple conditional probability functions given one or two variables (3.2). To compute each term of joint probability, we begin with some notations. If we assume that each joint pdf follows Gaussian distribution, $f(u; \theta)$, we denote potential functions associated with exponential form, where

$$f(u; \theta) \propto e^{-\langle \theta, \phi(u) \rangle} \tag{3.3}$$

Note that θ is a real-valued vector, known as Gaussian parameter and $\phi(u)$ is potential energy equation indicating distance between real-valued observation and expectation. From (3.3) and (3.2), MAP estimation in this case becomes an energy minimization problem (3.4) and turns out a MCDM problem given the assumption that all pdfs follow exponential forms, especially Gaussian.

$$
\begin{aligned}
u* &= \arg\max_u P(u,d,m,t) \\
&= \arg\max_u [P(d|u,m,t) \times P(m|u,t) \times P(t|u) \times P(u)] \\
&= \arg\max_u [e^{-\langle \theta_d, \phi_1(u,m,t)\rangle} \times e^{-\langle \theta_m, \phi_2(u,t)\rangle} \times e^{-\langle \theta_t, \phi_3(u)\rangle} \times e^{-\langle \theta_u, \phi_4(u)\rangle}] \\
&= \arg\max_u [e^{-(\langle \theta_d, \phi_1(u,m,t)\rangle + \langle \theta_m, \phi_2(u,t)\rangle + \langle \theta_t, \phi_3(u)\rangle + \langle \theta_u, \phi_4(u)\rangle)}] \\
&= \arg\min_u [\langle \theta_d, \phi_1(u,m,t)\rangle + \langle \theta_m, \phi_2(u,t)\rangle + \langle \theta_t, \phi_3(u)\rangle + \langle \theta_u, \phi_4(u)\rangle]. \qquad (3.4)
\end{aligned}
$$

We define that e_1 is an energy function of $P(d|u,m,t)$ from the difference between the observed data and the group distribution, e_2 is an energy function of $P(m|u,t)$ from the difference between the group distribution and ideal distribution, and e_3 is an energy function of $P(t|u)$ representing the difference between the status t and the ideal estimation u. Assuming that $P(t|u)$ is constant ($p = 0.5$), e_3 equals zero. e_1, e_2, and e_3 are represented as follows:

$$e_1 = \|\theta_d - \phi_1(u,m,t)\|^2, \quad e_2 = \|\theta_m - \phi_2(u,t)\|^2, \quad e_3 = \|\theta_t - \phi_3(u)\|^2 \qquad (3.5)$$

After estimating the ideal distribution of the observation, we determine whether the condition of a user is normal or not. For the recognition, we apply different thresholds calculated by group distribution labeled with group context. For example, if we have an age-group database, we categorize the data according to individual users' current physiological status (e.g. normal or abnormal), obtaining four group models: normal male, abnormal male, normal female, and abnormal female. We set a threshold at the intersection point of the normal male group distribution and abnormal male group distribution, and it figures out the current users' physiological status according to it.

4. Experimental Analysis

We evaluated our MCDM method with real data set based on heart rate of healthy or unhealthy subjects. We used the normal sinus rhythm RR interval database to identify normal sinus rhythm data and the congestive heart failure RR interval database to identify tachycardia sinus rhythm in PhysioBank.[20] Tachycardia is typically defined by excessive heart rate at rest. We associated users with tachycardia sinus rhythm to an abnormal condition. We collected the heart rate data of 54 normal subjects from the normal sinus rhythm RR interval database: 30 males aged 28.5–76; 24 females aged 58–73. We collected data about 18 subjects aged 34–79 from the congestive heart failure RR interval database (NYHA classes III) including 9 abnormal subjects and 9 normal subjects.

We extracted features from heart rate and selected 5-min long RR samples for each subject. We processed the measurements to correct artifacts smothing and to remove third order trends in RR intervals. Then, we computed feature from the

RR intervals to compute heart rate, because this factor characterizes signals in the time domain. We estimated a density function to discriminate the normal from abnormal conditions. Since density estimation methods are numerous, we verified the normality of the collected data with Kolmogorov–Smirnov tests. Finally, we obtained a probability density function about each data set.

We determined whether the current condition of a subject was normal or abnormal with an individual threshold, a group threshold, and a general standard threshold. We fixed the standard threshold at 100 bpm because we just collected fast heart beat condition of abnormal subjects. For the group threshold, we categorized the subjects based on sex and age. The two sex groups were labeled male and female. We defined three age groups: 20–39, 40–59, and 60–79 years old. Individual thresholds were computed from individual distributions following 95% certification interval of each density distribution.

Overall classification errors thanks to group contexts decreased as shown in Fig. 2. The standard threshold (under 100 bpm) significantly reduced classification errors in the case of normal subjects group. But, subjects with tachycardia sinus rhythm were often misclassified. However, our method exploiting age–sex contexts kept the low error rates for all subjects, as shown in Fig. 2. Average error rates in PDM method, proposed method with group context: age–sex, age only, sex only, and TDM method were 5% (PDM), 7.33% (age–sex), 12.59% (age only), 15.09% (sex only), and 27.75 % (TDM), respectively. We concluded that our method with age–sex contexts affects more positively than the other deterministic and TDM methods. Besides, the classification increasingly succeeded with additional contextual information. For instance, the overall classification better succeeds with age–sex than with age only. As a result, our method considering group context reduced classification errors by 20.42% when compared to TDM methods.

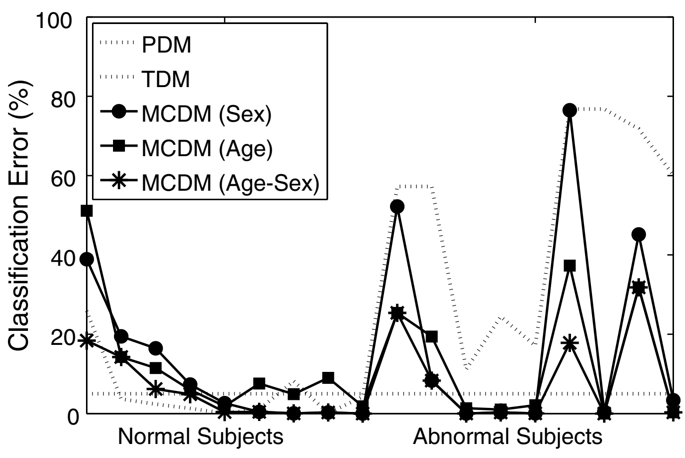
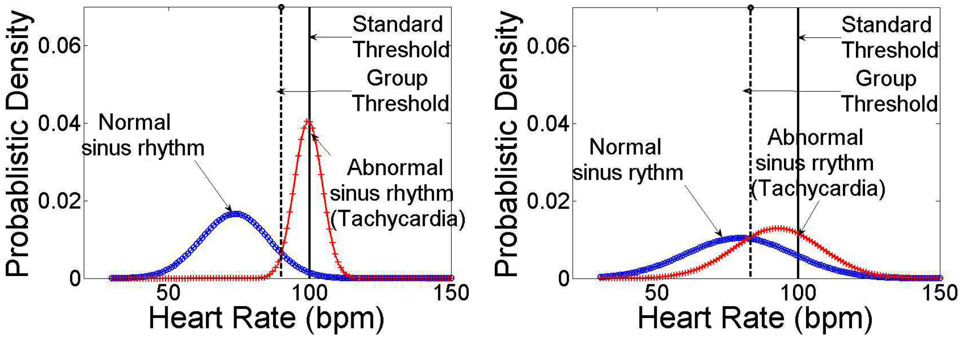
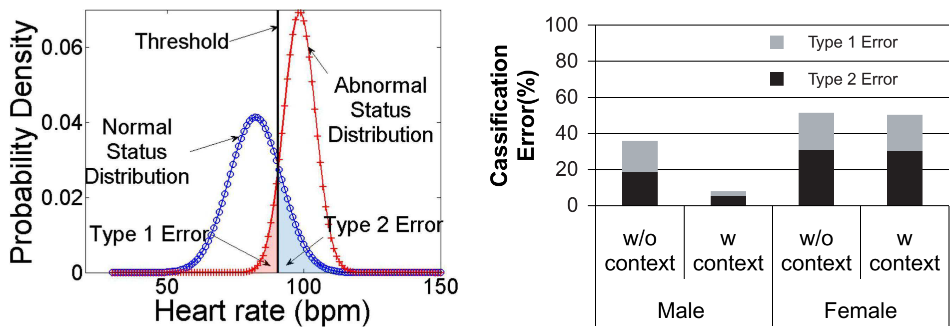


Fig. 2. Heart rate classification results of TDM, MCDM with context and PDM methods.



(a) (b)

Fig. 3. Data distribution by sex group. (a) Male group (normal subject = 70%, abnormal subject = 30%). (b) Female group (normal subject = 70%, abnormal subject = 30%).



(a) (b)

Fig. 4. Classification result by sex group. (a) Definition of type of error. (b) Classification result (normal subject = 70%, abnormal subject = 30%).

We analyzed the error type of classification by clarifying which errors increased or deduced for different thresholds. The classification result is illustrated in Figs. 3–5. Figures 3(a) and 3(b) indicate the distribution of each sex group with a population consisting of 50% normal and 50% abnormal subjects. We checked for Type 1 error and Type 2 error in each distribution as detailed in Fig. 4(a). A Type 1 error is defined by the identification of an unhealthy subject as healthy; A Type 2 error is the opposite. As shown in Fig. 4(b), the classification ratio diminishes when we apply a sex group threshold to decide the health status, assuming 50% of participation are abnormal.

In addition, our grouping analysis with age context exhibits fewer errors than a TDM method, as shown in Fig. 5. In both cases, Type 1 errors decrease dramatically but Type 2 errors do not. The TDM method extends the possibility to detect normal subjects. From this experiment, we also conclude that our method better classifies people with an age context than with a sex context. The classification

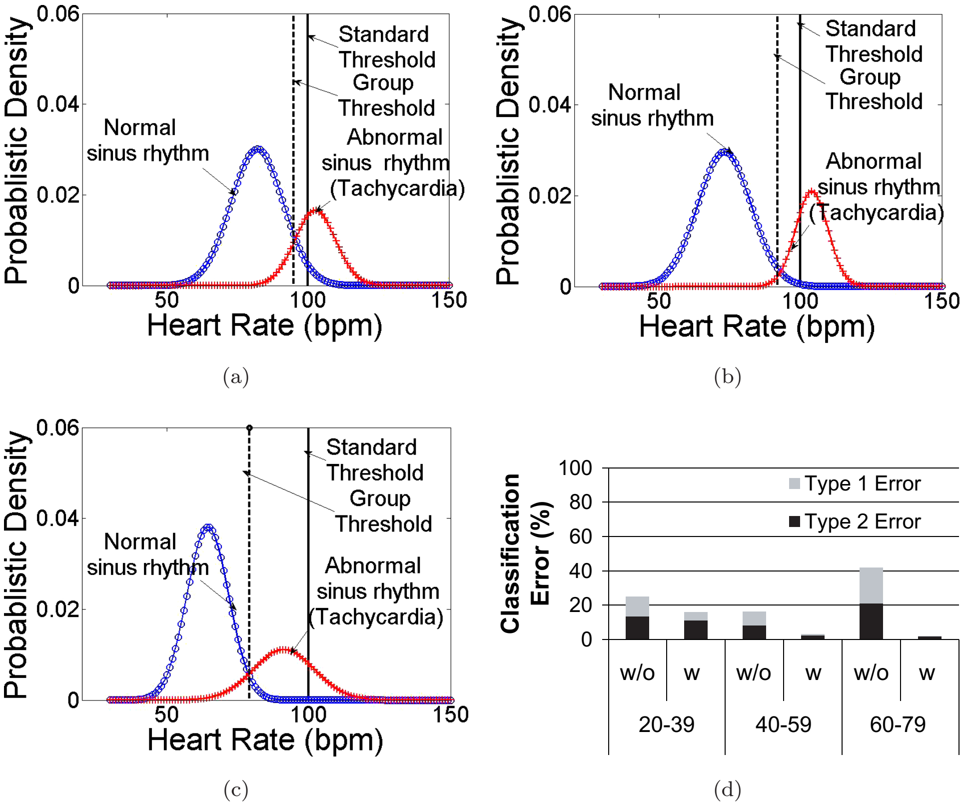
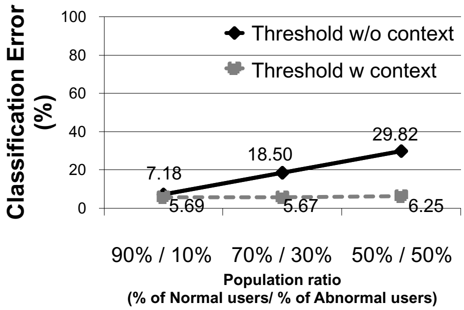


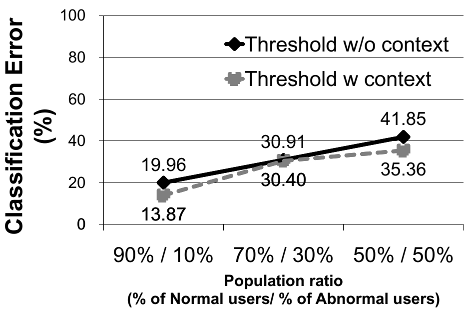
Fig. 5. Classification result by age group. (a) Distribution for 20–39 age group (normal subject = 70%, abnormal subject = 30%). (b) Distribution for 40–59 age group (normal subject = 70%, abnormal subject = 30%). (c) Distribution for 60–79 age group (normal subject = 70%, abnormal subject = 30%). (d) Classification result (normal subject = 70%, abnormal subject = 30%), where “w/o” is without context, “w” is with context.

errors are reduced by a group-based MCDM method as well as by a PDM method. Accordingly, age and sex contexts, especially age, can improve the estimation of the user status without knowledge of his/her data distribution. However, it is hard to get benefit using MCDM method in the case of sex group classification, especially female group, because the collected data is broadly distributed.

In addition, we compared the classification results for different prevalences of unhealthy subjects as shown in Figs. 6 and 7. We tested for three population profiles: 50%, 70%, and 90% in normal. Overall context improved classification results. For a portion of abnormal subjects reaching 50% in 60–79 age group, the classification rate improves by 31.59%, in most cases, errors with the TDM method along with the proportion of abnormal users. The MCDM method performs constantly, regardless of the proportion of abnormal users. Our method considered normal subjects as well as abnormal subjects; thus, it indicated good classification ratio to increased

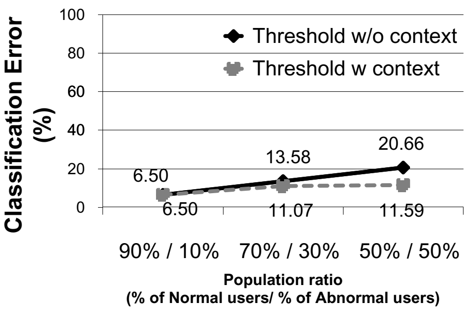


(a)

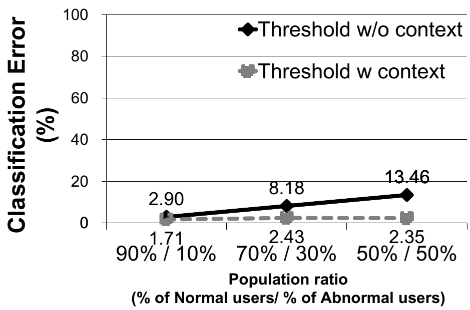


(b)

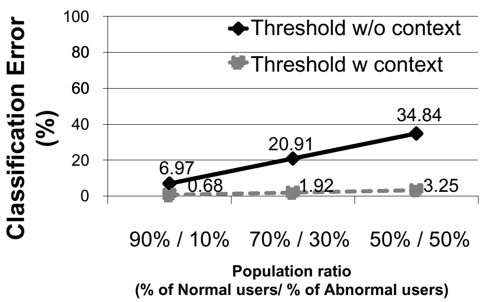
Fig. 6. Classification result by sex group with population. (a) Male group. (b) Female group.



(a)



(b)



(c)

Fig. 7. Classification result by age group with population. (a) 20–39 age group. (b) 40–59 age group. (c) 60–79 age group.

abnormal population. Especially, the analysis result in 60–79 age group and male group indicated greater improvement rather than the other group. Female group, 20–39 aged group showed little effects on using contextual information because female groups' distribution of collected data is widely distributed; thus, it is hard to characterize the data features of that group.

5. Conclusions and Future Works

We proposed a MCDM method for physiological signal analysis and tested these ideas with a public physiological data set. The problem was formulated using MAP estimation for obtaining ideal expectation of users' physiological status. MAP estimation eventually was rearranged by MCDM problem given the assumption that all pdfs followed exponential forms, especially Gaussian. From the experiment conducted, we achieved 20.42% improvement of physiological status classification by applying the MCDM method with age–sex group context than TDM methods. Furthermore, MCDM method with various populations also produced better classification results than TDM method. If a portion of abnormal subjects of age group reached from 10% to 50%, classification rate was improved by 6.29% and 31.59%, respectively.

In future studies, we will consider external variables such as air temperature and humidity in addition to internal variables. We expect such contextual information to improve normal physiological status. These additions will support the creation situation of a model to estimate in diverse situations. Finally, we expect that this work is applicable to various personalized physiological signal monitoring applications, especially daily health monitoring in which we easily collect several sensory data from heterogeneous resources. In this environment, system estimates user's physiological status by referring other group distribution without prior knowledge about previous health records in real time.

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References

1. H. H. Asada, H. H. Jiang and P. Gibbs, Active noise cancellation using MEMS accelerometers for motion tolerant wearable bio-sensors, in *Proc. 26th Int. Conf. IEEE Engineering in Medicine and Biology Society*, eds. D. L. Hudson, Z. P. Liang and G. Dumont (San Francisco, California, 2004), pp. 2157–2160.
2. R. Matthews, N. J. McDonald, P. Hervieux, P. J. Turner and M. A. Steindorf, A wearable physiological sensor suite for unobtrusive monitoring of physiological and cognitive state, in *Proc. 29th Int. Conf. IEEE Engineering in Medicine and Biology Society*, eds. J. Rousseau, G. Delhomme and M. Akay (Lyon, France, 2007), pp. 5276–5281.
3. U. Anliker, J. A. Ward, P. Lukowicz, G. Troster, F. Dolveck, M. Baer, F. Keita, E. B. Schenker, F. Catarsi, L. Coluccini, A. Belardinelli, D. Shklarski, M. Alon, E. Hirt, R. Schmid and M. Vuskovic, AMON: A wearable multiparameter medical monitoring and alert system, *IEEE T. Inf. Technol. Biomed.* **8** (2004) 415–427, doi:10.1109/TITB.2004.837888.
4. R. A. Miller, Medical diagnostic decision support systems–past, present and future: A threaded bibliography and brief commentary, *J. Am. Med. Inf. Assoc.* **1** (1994) 8–27, doi:10.1136/jamia.1994.95236141.

5. A. D. Jose and D. Collison, The normal range and determinants of the intrinsic heart rate in man, *Cardiovasc. Res.* **4** (1970) 160–167, doi:10.1093/cvr/4.2.160.
6. B. R. Londeree and M. L. Moeschberger, Effect of age and other factors on HR max, *Res. Q. Exerc. Sport* **53** (1982) 297–304.
7. W. C. Miller, J. P. Wallace and K. E. Eggert, Predicting max HR and the HR-[latin capital V with dot above]2 relationship for exercise prescription in obesity, *Med. Sci. Sports Exerc.* **25** (1993) 1077–1081.
8. W. R. Zhang and S. S. Chen, Equilibrium and nonequilibrium modeling of yinyang wuxing for diagnostic decision support in traditional Chinese medicine, *Int. J. Inf. Technol. Decision Making* **8** (2009) 529–548, doi:10.1142/S0219622009003521.
9. W. H. Wu, M. A. Batalin, L. K. Au, A. A. T. Bui and W. J. Kaiser, Context-aware sensing of physiological signals, in *Proc. 29th Int. Conf. IEEE Engineering in Medicine and Biology Society*, eds. J. Rousseau, G. Delhomme and M. Akay (Lyon, France, 2007), pp. 5271–5275.
10. G. W. Torrance, D. H. Feeny, W. J. Furlong, R. D. Barr, Y. Whang and Q. Wang, Multiattribute utility function for a comprehensive health status classification system: Health utilities index mark 2, *Med. Care* **34** (1996) 702–722, doi:10.1097/00005650-199607000-00004.
11. G. P. Huber, Multi-attribute utility models: A review of field and field-like studies, *Manage. Sci.* **20** (1974) 1393–1402, doi:10.1287/mnsc.20.10.1393.
12. Y. Peng, G. Kou, Y. Shi and Z. Chen, A descriptive framework for the field of data mining and knowledge discovery, *Int. J. Inf. Technol. Decision Making* **7** (2008) 639–682, doi:10.1142/S0219622008003204.
13. D. J. Hall and R. A. Davis, Engaging multiple perspectives: A value-based decision-making model, *Decision Supp. Syst.* **43** (2007) 1588–1604, doi:10.1016/j.dss.2006.03.004.
14. C. Carlsson and R. Fuller, Fuzzy multiple criteria decision making: Recent developments, *Fuzzy Sets Syst.* **78** (1996) 139–153, doi:10.1016/0165-0114(95)00165-4.
15. C. Rao and J. Peng, Fuzzy group decision making model based on credibility theory and gray relative degree, *Int. J. Inf. Technol. Decision Making* **8** (2009) 515–527, doi:10.1142/S0219622009003533.
16. G. Parmigiani, *Modeling in Medical Decision Making: A Bayesian Approach* (Wiley, London, 2002).
17. M. Öztürk and A. Tsoukiàs, Modeling uncertain positive and negative reasons in decision aiding, *Decision Supp. Syst.* **43** (2007) 1512–1526, doi:10.1016/j.dss.2006.06.005.
18. H. Eskandari and L. Rabelo, Handling uncertainty in the analytic hierarchy process: a stochastic approach, *Int. J. Inf. Technol. Decision Making* **6** (2007) 177–189, doi:10.1142/S0219622007002356.
19. H. K. Alfares and S. O. Duffuaa, Determining aggregate criteria weights from criteria rankings by a group of decision makers, *Int. J. Inf. Technol. Decision Making* **7** (2008) 769–781, doi:10.1142/S0219622008003174.
20. A. L. Goldberger, L. A. N. Amaral, L. Glass, J. M. Hausdorff, P. C. Ivanov, R. G. Mark, J. E. Mietus, G. B. Moody, C. K. Peng and H. E. Stanley, PhysioBank, PhysioToolkit and PhysioNet: Components of a new research resource for complex physiologic signals, *Circulation* **101** (2000) e215–e220.