

Non-invasive Diabetes Detection using Metabolic Heat Conformation Technology and Heart Rate

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ABSTRACT

Screening and early detection of type 2 diabetes are important to prevent diabetic complications. Commonly, type 2 diabetes is detected by blood glucose measurement. However, the compliance for existing invasive devices is insufficient because these devices can potentially cause pain, infection, and tissue damage due to needle use. Thus, we have been developing a non-invasive diabetes detection method that uses metabolic heat conformation (MHC) technology. Our previous method using only MHC technology could not detect diabetes accurately, therefore, a novel non-invasive diabetes detection method using additional bio-signal needed to be developed to improve accuracy of early diabetes detection. Heart rate is considered as an additional bio-signal which can be measured by non-invasive devices. The previous studies report that there is a relation between heart rate and diabetes. The objective of this study is to propose a novel non-invasive diabetes detection method using both MHC technology and heart rate. The proposed method detects diabetes by machine learning technique using skin surface temperature data based on MHC technology and heart rate. In the experiment, the proposed method and our previous method were compared by using 95 samples bio-signal dataset obtained from 5 participants including 2 diabetes patients. The results showed that the proposed method could detect diabetes with accuracy higher than 90 %, which is significant improvement in comparison to our previous method, which detected diabetes with accuracy less than 80 %. The results support the possibility that the proposed method using both MHC technology and heart rate can be applied for non-invasive early diabetes detection.

Keywords: Diabetes detection; Non-invasive; Metabolic heat conformation technology; Heart rate; Machine Learning Technique.

INTRODUCTION

In recent years, the number of diabetes patients has rapidly increased [1]. Type 2 diabetes patients are at particular risk of complications due to progress of diabetes since it is difficult to

recognize the progress by the patients themselves [2]. It is considered that an early detection of type 2 diabetes is important to prevent diabetic complications. Commonly, type 2 diabetes is detected by blood glucose measurement [3, 4]. However, the compliance for existing invasive devices is insufficient because these devices can potentially cause pain, infection, and tissue damage to the patients due to use of a needle [3, 4].

To solve these problems, previous studies have been developing optical non-invasive measurement methods to detect and monitor diabetes [5]. For example, the surface plasmon resonance-based method has advantages in accuracy and high sensitivity for minute changes of blood glucose level that relates to diabetes [5, 6]. However, the optical non-invasive method that implements the surface plasmon resonance-based method cannot be applied in daily screenings because this method requires a large size device and a long calibration time [5]. From these problems, it is considered that a non-invasive method with short measurement time and small size device is required. Thus, we have been developing a non-invasive diabetes detection method that does not require large optical devices.

In our previous study we have developed a non-invasive diabetes detection method using a skin surface temperature measurement based on metabolic heat conformation (MHC) technology [7]. The MHC technology is a methodology to predict the glucose level based on the correlation between the glucose level and the heat dissipated from a human body [5, 8-10]. The MHC technology can be implemented by simple temperature measurement [8]; thus, the MHC technology-based device does not require long measurement time and large size device. For example, our previous method could implement a MHC technology-based device in handheld size [7, 11, 12]. However, our previous method using only MHC technology could not detect diabetes in some participants because MHC technology was affected by environmental conditions including air temperature [5, 7]. It is therefore necessary to develop a novel non-invasive diabetes detection method using additional bio-signal with a goal to accurately detect early diabetes.

Heart rate is considered as an additional bio-signal which can be measured by a non-invasive device because several previous studies reported that there is a relation between heart rate and diabetes [13-15]. Furthermore, heart rate can be measured by small non-invasive commercial products such as pulse oximeters [16, 17]. From previous studies, it can be concluded that the combination of MHC technology and heart rate can be used for non-invasive early diabetes detection.

The objective of this study is to propose a novel non-invasive diabetes detection method using both MHC technology and heart rate.

PROPOSED METHOD

Figure 1 shows a block diagram of the proposed method to detect diabetes using MHC technology and heart rate. The proposed method detects diabetes by machine learning technique using features obtained from MHC technology-based skin surface temperature measurement and heart rate. The machine learning technique is applied in the proposed method since this technique proved to be useful in many previous studies that relate to diabetes [18-20].

Figure 2 shows two measurement devices used in the proposed method. The skin surface temperature is measured by a custom-made device consisting of thermal array sensors (AMG8853, Panasonic Co. ltd, Japan) and a Raspberry Pi 4 (Raspberry Pi Foundation, UK.) single board computer with 1 Hz sampling rate implemented.

As shown in Figure 2, the skin surface temperature can be measured without contact. Heart rate in the proposed method is measured by a commercially available pulse oximeter (YK-80C, Xuzhou Yongkang Electronic Science Technology Co. ltd, China). The necessary measurements can be completed in less than 1 minute.

Heat radiation (hr) and heat convection (hc) are calculated to be used as MHC technology-based features. Both features are calculated as follows:

$$hr = \rho \cdot \sigma \cdot (T_s^4 - T_r^4) \quad (1)$$

$$hc = h \cdot (T_s - T_r) \quad (2)$$

where hr is heat radiation, hc is heat convection, T_s is the skin surface temperature measured by thermal array sensors, T_r is the room air temperature, ρ is the reflection coefficient of the skin surface, σ is the Stefan-Boltzmann constant, and h is the heat transfer coefficient. Both equations are based on Stefan-Boltzmann law.

Heart rate and two variable parameters of heart rate are also used as features in the proposed method. A ratio between the current heart rate and the initial heart rate and a ratio between the current heart rate and the heart rate of previous sample are calculated as the two variable parameters of heart rate.

The proposed method detects diabetes by logistic regression using the abovementioned features that relate to MHC technology and heart rate. Logistic regression [21] was selected as a machine learning technique because this algorithm exhibited the best performance in our previous study [7].

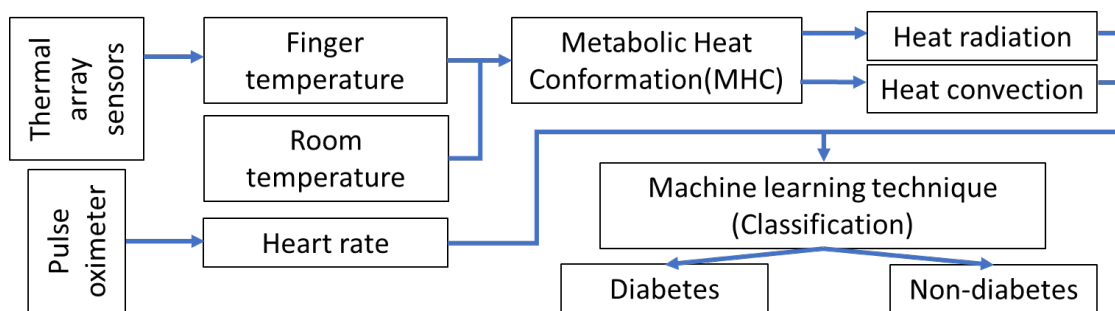


Figure 1. Block diagram of the proposed method

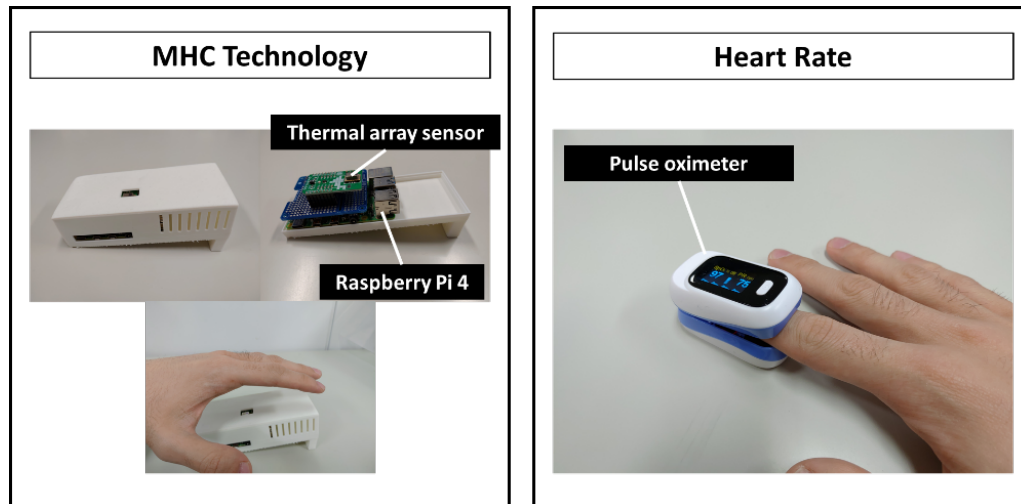


Figure 2. Measurement device for the proposed method

Experiment

In the experiment, we evaluated whether the proposed method could detect diabetes by the combination of MHC technology and heart rate. Also, the performance of the proposed method was compared to our previous method [7].

Participants

Table 1 shows the participants data. The participants were 4 males and 1 female including two type 2 diabetes patients. All participants provided their verbal informed consent to the experiment.

Table 1: Participants data

Participant	Gender	Age [years]	Height [m]	Weight [kg]	Label
A	Male	72	159	59	Diabetes
B	Female	62	161	86	Diabetes
C	Male	26	179	69	Non-diabetes
D	Male	23	165	52	Non-diabetes
E	Male	26	179	78	Non-diabetes

Experimental Procedure

The skin surface temperature and heart rate in the proposed method experiment were measured during 3 hours after a meal. The measurement was performed every 10 minutes, and features of 19 samples were calculated for each participant. As a result, features of 95 samples in total were obtained from all participants. These features were used as a dataset for the evaluation of the proposed method.

DATA ANALYSIS

The proposed method and our previous method were compared by using the dataset obtained in the experiment. The logistic regression was applied as a machine learning technique for both the proposed method and our previous method. Training and testing of the methods were performed via 10-folds cross validation. Accuracy, precision, recall, and F-measure were

calculated as the performance indices each by confusion matrix obtained from 10-folds cross validation. The indices were calculated as follows:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} * 100 \quad (3)$$

$$\text{Precision} = \frac{TP}{TP+FP} * 100 \quad (4)$$

$$\text{Recall} = \frac{TP}{TP+FN} * 100 \quad (5)$$

$$\text{F-measure} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} * 100 \quad (6)$$

where TP is true positive, TN is true negative, FP is false positive, and FN is false negative. It is considered that accuracy and recall of diabetes are important indices for screening of diabetes. The indices of the proposed method and of our previous method were evaluated and compared.

RESULTS

Table 2 shows accuracy, precision, recall, and F-measure of the proposed method and of our previous method. Table 3 and Table 4 show confusion matrices of the proposed method and our previous method.

The results show that accuracy, precision, recall, and F-measure of the proposed method were all greater than in our previous method. Accuracy of the proposed method was higher than 90 %. In addition, precision, recall, and F-measure of the proposed method were higher than 75 % in both diabetes and non-diabetes participants. On the other hand, the accuracy of our previous method was less than 80 %. Furthermore, recall and F-measure of diabetes participants were less than 50 % in our previous method.

Table 3 shows that the proposed method could almost perfectly detect data of both diabetes and non-diabetes participants accurately. On the other hand, Table 4 shows that our previous method could not detect more than half of the data of diabetes participants.

Table 2. Accuracy, precision, recall, and F-measure

Method	Accuracy[%]	Precision [%]		Recall[%]		F-measure[%]	
		Diabetes	Non-diabetes	Diabetes	Non-diabetes	Diabetes	Non-diabetes
Proposed method	90.5	89.2	91.4	86.8	93.0	77.5	85.0
Our previous method	75.8	85.7	73.0	47.4	94.7	40.6	69.1

Table 3. Confusion matrix of the proposed method

		Predict	
		Diabetes	Non-diabetes
Actual	Diabetes	33	5
	Non-diabetes	4	53

Table 4. Confusion matrix of our previous method

		Predict	
		Diabetes	Non-diabetes
Actual	Diabetes	18	20
	Non-diabetes	3	54

DISCUSSION

The results show that the proposed method could detect diabetes with accuracy higher than 90 % and recall for diabetes higher than 85 %. In addition, confusion matrix of the proposed method shows that the proposed method could almost perfectly detect diabetes. The results indicate that the proposed method could detect diabetes accurately. Furthermore, the performance of the proposed method using both MHC technology and heart rate was significantly better than our previous method using only MHC technology [7]. These results suggest that the combination of MHC technology and heart rate was effective to detect diabetes. Therefore, it is considered that the proposed method using both MHC technology and heart rate can be applied for non-invasive early diabetes detection. In comparison, our previous study could not detect more than half of diabetes data. These results show that our previous study using only MHC technology cannot be applied for diabetes detection because MHC technology was affected by environmental conditions including air temperature [5, 7].

The limitation of this study is that the proposed method was evaluated only for 4 males and 1 female. In addition, the measurement conditions of the experiment were limited to after a meal. In the future, the proposed method needs to be tested on a wider specter of participants and in various conditions. After usefulness of the proposed method is confirmed via further studies, we plan to develop an application for screening diabetes using the proposed method. The application will be implemented on common devices which can be used in daily life such as smartphones. In our previous study we were able to implement a prototype of smartphone application for screening and monitoring of diabetes [11].

CONCLUSION

In this study, we proposed a non-invasive diabetes detection method using a combination of MHC technology and heart rate. The experimental results showed that the proposed method can detect diabetes with accuracy higher than 90 %. The presented results indicate the possibility for the proposed method using both MHC technology and heart rate to be applied for non-invasive early diabetes detection. In the future, we will evaluate the proposed method on a wider range of participants and in various conditions. Furthermore, the proposed method will be implemented as an application for screening and monitoring of diabetes.

References

- [1]. Zhou, B., et al., Worldwide trends in diabetes since 1980: a pooled analysis of 751 population-based studies with 4· 4 million participants. *The Lancet*, 2016, 387(10027): p. 1513-1530.
- [2]. David, C, Why screen for type 2 diabetes?. *Diabetes research and clinical practice*, 2016, 121: p. 215-217.
- [3]. So, C.F., et al., Recent advances in noninvasive glucose monitoring. *Medical Devices (Auckland, NZ)*, 2012, 5: p. 45.
- [4]. Yasuhiro, U., et al., Noninvasive blood glucose measurement. *Nutritional and Therapeutic Interventions for Diabetes and Metabolic Syndrome*, 2018, p. 489-504.
- [5]. Villena, G., et al., The progress of glucose monitoring-A review of invasive to minimally and non-invasive techniques, devices and sensors. *Sensors*, 2019, 19(4): p. 800.
- [6]. Li, D. C., et al., Glucose measurement using surface plasmon resonance sensor with affinity based surface modification by borate polymer. 2015 Transducers-2015 18th International Conference on Solid-State Sensors, Actuators and Microsystems (TRANSDUCERS). 2015, p. 1569-1572.
- [7]. Ryo, T., et al., Non-Invasive Diabetes Prediction Method Based on Metabolic Heat Conformation Theory and Machine Learning. *Journal of Mechanical and Electrical Intelligent System*. 2021, 4(1): p. 42-19.
- [8]. Kit, S.Y.H., et al., Non-invasive blood glucose measurement using temperature-based approach. *Jurnal Teknologi*, 2013, 64(3): p. 105-110.
- [9]. Cho, O.K., et al., Noninvasive measurement of glucose by metabolic heat conformation method. *Clinical chemistry*, 2004, 50(10): p. 1894-1898.
- [10]. Tang, F., et al., Non-invasive glucose measurement by use of metabolic heat conformation method. *Sensors*, 2008, 8(5): p. 3335-3344.
- [11]. Ryo, T., et al., Proposal of Blood Glucose Control and Exercise Therapy Support System Using Non-invasive Blood Glucose Meter. *Pertanika Journal of Science & Technology*, 2020, 28(S2): p. 13-24.
- [12]. Ryo, T., et al., Proposal of Blood Glucose Prediction Method Based on MHC Theory. *The 8th IIAE International Conference on Industrial Application Engineering 2020*, 2020, p. 44-49.
- [13]. Thomas, B., et al., Heart rate variability in type 2 diabetes mellitus: A systematic review and meta-analysis. *PloS one*, 2018, 13(4): p. e0195166.
- [14]. Rosa, E.A-C., et al., Heart rate variability as early biomarker for the evaluation of diabetes mellitus progress. *Journal of diabetes research*, 2016, 2016: p. 8483537.
- [15]. Kudat, H., et al., Heart rate variability in diabetes patients. *Journal of international medical research*, 2006, 34(3): p. 291-296.
- [16]. El-Amrawy, F., et al., Are currently available wearable devices for activity tracking and heart rate monitoring accurate, precise, and medically beneficial?. *Healthcare informatics research*, 2015, 21(4): p. 315-320.
- [17]. Cheatham, S.W., et al., Concurrent validity of resting pulse-rate measurements: a comparison of 2 smartphone applications, the polar H7 belt monitor, and a pulse oximeter with bluetooth. *Journal of sport rehabilitation*, 2015, 24(2): p. 171-178.
- [18]. Kavakiotis, I., et al., Machine learning and data mining methods in diabetes research. *Computational and structural biotechnology journal*, 2017, 15: p. 104-116.
- [19]. Pronab, G., et al., A Comparative Study of Different Machine Learning Tools in Detecting Diabetes. *Procedia Computer Science*, 2021, 192: p. 467-477.
- [20]. Dagliati, A., et al., Machine learning methods to predict diabetes complications. *Journal of diabetes science and technology*, 2018, 12(2): p. 295-302.
- [21]. Le, C.S., et al., Ridge estimators in logistic regression. *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, 1992, 41(1): p. 191-201.