HeatWatch: Preventing Heatstroke Using a Smart Watch

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***Abstract*—In this paper, we present a novel application, HeatWatch, which predicts heatstroke and prevents heatstroke by ensuring users breaking and water intake. The application estimates user's core temperature based on human thermal model and vital sensors equipped with smart watches. We also designed the application tracks user's water intake by assuming to apply existing activity recognition technique to acceleration sensors inside a smart watch. We have discussed how to detect heatstroke sign and evaluated its performance through a real data set over 100 hours. Finally, the result showed that our method is able to instantly notify high temperature states with more than 0.9 recall and 0.53 precision by allowing early/late notification within 6 minutes.**

I. Introduction

Heatstroke is a growing matter all over the world because of global warming and heat wave. The major factor of heatstroke is higher core temperature, however core temperature cannot be measured during exercise because we have to measure rectal temperature, tympanic temperature or esophagus temperature that require invasive measurement to insert a probe. To prevent heatstroke, World Health Organization (WHO) provides health manuals for exercise in heat environment [1]. Besides, WBGT(Wet Bulb Globe Temperature) is widely used as an index to evaluate a risk level of heat stroke [2]. However, it is still insufficient to consider heterogeneous changes of core temperature of individual subjects.

In our previous study [3], [4], we have proposed a method to estimate core temperature based on a human thermal model, a wearable sensor and environmental sensors. We also confirmed our method successfully estimates core temperature with mean absolute error 0.30 !n through over 100 hours of real experiments including walking, running and tennis. Currently, we are developing HeatWatch application to notify the individual heatstroke warning based on a heatstroke risk index derived from integration of core temperature rising and water intake context estimated by wearable sensor measurement. There are many studies of activity recognition in daily life by using accelerometer, thus we employ these techniques and optimize them to suit wrist-mounted sensors. As a first step to detect core temperature rising, we have discussed and developed a prototype of a heatstroke alerting system. An individual user will receive heatstroke warning when his/her core temperature exceeds a threshold. According to notification, users can decrease their core temperature by taking a break and/or ingesting enough water to avoid heatstroke.

Our contributions are summarized as below.

1) We proposed HeatWatch, a more effective approach than observing just an environmental heat index such as WBGT. It tracks user's core temperature during sports with a commercial-off-the-shelf smart watch for heatstroke prevention.
2) We collected a real exercise data set over 100 hours through 13 participants and analyzed it to determine an appropriate threshold for notification.
3) Our prototype of a heatstroke alerting system showed moderate precision and recall even for complicated exercise data sets including walking, running and cycling with interval breaks.

From the evaluation results, we confirmed that our method successfully notifies high core temperature with 0.314 precision and 0.948 recall in cycling, 0.779 precision and 0.720 recall in running and walking. When we allowed 5-minute error of notification, precision and recall rose to 0.514 and 1.0 in cycling, 0.965 and 0.899 in walking and running, which shows the feasibility of HeatWatch.

II. Related Works

A. The Study of HeatStroke

In recent decades, heatstroke has received considerable attention because of global warming and catastrophic heat waves [5]. The mechanism of heatstroke is described in [6], where core temperature rise is a fundamental factor. If core temperature rises, cerebral, skin and gut blood flow rate changes and they cause several symptoms. In summary, monitoring core temperature is the most important task to prevent heatstroke. In addition, reference [7] reports that all the measured temperatures of heatstroke patients were over 39.5 !n. It also infers that "over 39.5 !n core temperature" can be regarded as a cause of heatstroke, however lower temperature can be a positive diagnosis of heat stroke. Another major factor of heatstroke is dehydration which makes the cardiovascular system difficult to suppress rise of core temperature. A study [8] revealed that core temperature rises 0.3 !n for every 1% of fluid lost during exercise. Severe dehydration also causes a failure of sweating, the most important heat emission function.

B. Heat Index for Preventing Heatstroke

For quantifying risk of heatstroke in daily life, WBGT, a measure of the heat stress taking into account temperature, humidity, wind speed and solar radiation is widely used [2]. According to WBGT, there are many guidelines for outdoor

TABLE I
GUIDANCE FOR ATHLETIC TRAINERS [9]

WBGT(!n)	Alert Level	Recommendation
> 31	Stop Exercise	No outdoor excercise
> 28	Strict Warning	Avoid hard exercise
> 25	Warning	Frequent breaks and water intake
> 21	Attention	Make sure water intake in the intervals
< 21	None	Usually safe

exercise. For example, Japanese Ministry of the Environment introduces recommendations based on WBGT as shown in Table I. However, many people work or participate in sports during daytime even though many days in summer reach higher or the highest alert level in subtropical and tropical countries (e.g., Osaka, Japan observed 43 days with alert "Stop Exercise" or "Strict Warning" (WBGT>28 !n) in 2015). Moreover, environmental index cannot take individual difference of response to heat environment and hard exercise into account. For example, core temperature of a person is possible to reach a dangerous level in spite of lower heat index if he/she is not accustomed to heat environment. Therefore, monitoring individual core temperature is an urgent task for preventing heatstroke.

C. Heatstroke Sensing

There are some studies of heatstroke sensing. Reference [10] proposes a sensor-equipped headgear to monitor in-hardhat temperature. It shows relationship between temperature inside headgear and core temperature. Nevertheless, the system can be applied to limited sports which require headgears. In contrast, our approach uses only a smart watch which can be used in many sports. Several studies proposed heatstroke alert applications for smartphones [11]. They are suitable for almost all situations. However, they depend on temperature and humidity measured by smartphones, thus it does not solve the problem of the environmental heat index described in Section II-B.

Another study [12] proposes a wearable shirt with integrated e-textiles to prevent heatstroke for firefighters. It integrates heartrate with the air temperature and humidity. It is also suitable for various situations, however our advantage is direct estimation of core temperature. Our approach can achieve more accurate estimation because core temperature rise is the key factor of heatstroke.

There are also some sensors which can accurately measure core temperature. CorTemp[1] is a wireless ingestible thermometer to measure core temperature intracorporeally. However, we must dispose of the thermometer after each measurement and the receiver is expensive, thus it leads to a considerable cost. 3M SpotOn System[2] can also indirectly measure core temperature by a probe attached on a forehead, although it is not appropriate to exercise since it requires a wired control unit.

[1] http://www.hqinc.net/cortemp-sensor-2/

[2] http://multimedia.3m.com/mws/media/878163O/spoton-system-brochure.pdf

III. APPLICATION DESIGN

A. Overview

As a straightforward approach to prevent heatstroke, we propose HeatWatch which directly estimates core temperature and alerts when user's core temperature reaches a higher level. In our previous study [3], [4], we have proposed a core temperature estimation method based on integration of a human thermal model called Gagge's two node model and wearable and environmental sensors. We have also proposed an individual-parameter optimization method which is applicable during exercise for more accurate estimation. The result of real experiment through over 100 hours of walking, running and tennis shows that our method successfully estimates core temperature with mean absolute error less than 0.30 !nThe detail of our method is briefly summarized in section IV. In this paper, we use our method proposed in [4] for core temperature estimation. In addition, we have designed HeatWatch considering water intake which is another important factor for preventing dehydration by employing existing works such as [13] for drinking activity recognition. Our final goal is to combine rise of core temperature and water intake context for deriving a heatstroke risk index, and to notify each player when his/her index exceeds a threshold.

In this paper, we discuss a fundamental indicator using rise of core temperature. We also briefly describe a core temperature estimation method in section IV and discuss a fundamental indicator through evaluation by real data sets in section V.

B. System Architecture

The architecture of HeatWatch is shown in Figure 1. The overall platform consists of three devices: (1) a smart watch to measure subject's heartrate, skin temperature and acceleration continuously, (2) an environmental sensor deployed in the exercise field to measure the ambient air temperature and humidity and (3) a smartphone which receives and processes sensor measurement via wireless communication (e.g., Bluetooth).

HeatWatch inputs measured heartrate, skin temperature, air temperature and humidity into the two node model to simulate core temperature. In the simulation process, the two node model calculates user's core and skin temperature at time t based on both the temperatures at time $t-1$ and sensor input collected at time t. By repeating time-sequential calculation, the model obtains sequences of skin and core temperatures. Now we intend to combine user's water intake context with estimated core temperature. During "drink water" activities, people usually raise their arm and keep high place for water ingestion. Therefore, we consider "drink" estimation is easily carried out by a simple algorithm because "drink" act may show abnormal acceleration of earth gravity for each axis and lower variance for acceleration and gyroscope.

After that, HeatWatch combines estimated core temperature and context of water intake into one indicator (i.e. heatstroke index). Based on this indicator, HeatWatch notifies heatstroke

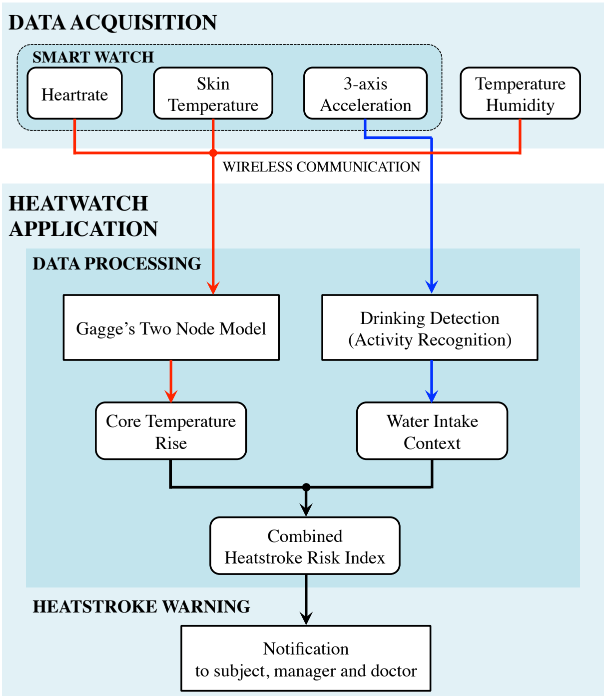

Fig. 1. HeatWatch Architecture

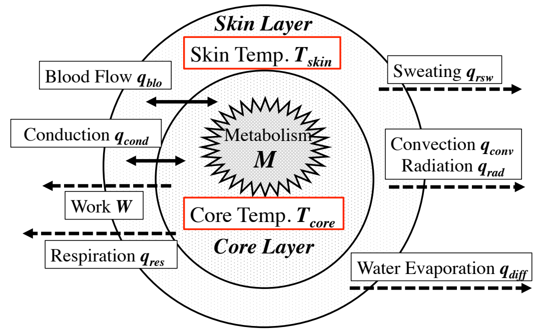

Fig. 2. Gagge's two node model

warning to user (players, managers or doctors). We note that our prototype in this paper only observes core temperature rise as our initial discussion.

C. Requirement

HeatWatch requires a user to wear a smart watch to measure his/her skin temperature and heartrate for core temperature estimation. We also have to input environmental information (i.e. temperature and humidity) into the core temperature estimation algorithm. Both of the sensors should be able to connect to a smartphone via wireless communication. For a smart watch, we use Microsoft Band[3] which can measure heartrate, skin temperature and acceleration. There are a few programmable environmental sensors which measure air temperature and humidity, however it is easy to develop an environmental sensor with a wireless capability by using a sensor platform such as Arduino[4]. The core temperature estimation algorithm also requires initial core temperature for each subject, thus we measure actual core temperature by using an infrared tympanic thermometer such as OMRON Gentle Temp 510[5] before starting exercise. Measured core temperature is manually given to HeatWatch application.

IV. Core Temperature Estimation Using Wearable Sensors

We have proposed a method for core temperature estimation and confirmed that estimation error is less than 0.30 !nthrough multiple exercise data sets in our previous studies [3], [4]. The method estimates core temperature based on thermal simulation using Gagge's two node model [14]. Two node model approximates a human body as a sphere composed of the skin layer and the core layer as shown in Figure 2. For temperature simulation, the model repeats calculation of the heat transferred between the skin layer, the core layer and the ambient air per unit time. To start simulation, we input initial skin temperature and initial core temperature. We also manually input subject's information: height, weight, resting heartrate, maximum heartrate, clothing insulation and an exercise type. After that, we continuously measure heartrate, the ambient air temperature and humidity to calculate the heat exchange per unit time. We convert heartrate into metabolism according to maximum heartrate and resting heartrate.

In the core layer, some amount of heat is always produced by metabolism. Then, some of the metabolic energy is consumed by exercise and the rest is transformed to heat energy. The heat is transferred to the skin layer by blood flow and direct conduction and emitted to the ambient air by respiration. The skin layer receives the heat transferred from the core layer, then the layer emits the heat by water diffusion, perspiration, radiation and convection on the skin surface. For details, readers may refer to reference [3].

In the two node model, sweating and blood flow increase, that are the most important mechanisms for thermoregulation, are calculated based on rise amount of core and skin temperature compared to their initial values. This means both of sweat production rate and blood flow increase rate depend on core and skin temperature rising. For more accurate core temperature simulation, four parameters representing individual difference of sweating and blood flow increase are proposed in [15]. Moreover, our study [4] proposes additional two parameters to consider the delay of human thermal response. We optimize these six parameters by applying a fitting algorithm to a few samples of core temperatures measured during breaks.

We have evaluated the method through over 100 hours of real experiments of walking, running and tennis. From the result, we have confirmed mean absolute error is less than 0.30 !n. In the next section, we discuss heatstroke warning based on this method.

[3] https://www.microsoft.com/microsoft-band/en-us
[4] http://www.arduino.cc.
[5] http://www.healthcare.omron.co.jp/product/mc/mc-510.html

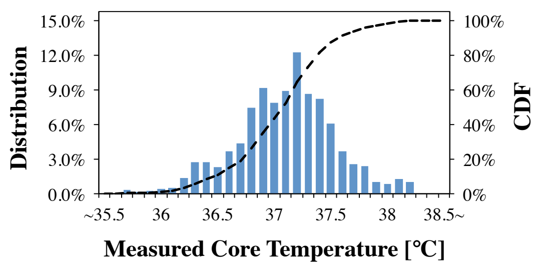

Fig. 3. Distribution of Core Temperature (Ergometer Dataset)

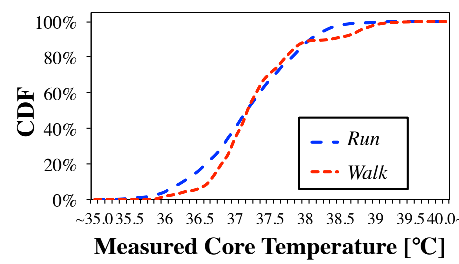

Fig. 4. Distribution of Core Temperature (Run&Walk Dataset)

V. Discussion and Evaluation

A. Dataset

In our previous study, we collected two real datasets through (1) ergometer exercise and (2) running and walking. Tables II and III summarize each experiment. In ergometer exercise, we collected over 40 hours data from seven participants and the exercise intensity changed between 2.4[W] and 7.2[W] every five minutes. We note that the ergometer data set does not include breaks but it includes core temperature changes due to exercise intensity change. In the running and walking experiment, we collected over 60 hours data from six subjects in heat environment. They could choose either running (4 runs + 3 breaks) or walking (3 walks + 2 breaks) according to their conditions. Note that these datasets include interval breaks between runs or walks. In the following evaluation, we analyze the difference between cycling, running and walking.

TABLE II
Ergometer Exercise Settings

Date	Jan 14-30, 2015 (15 Days)
Subject	6 males and 1 female
Time	1 hour
Location	Air-conditioned room
Exercise	Cycling with an ergometer Intensity: $2.4[W] \rightarrow 4.8[W] \rightarrow 7.2[W] \rightarrow 4.8[W] \rightarrow 2.4[W] \rightarrow \cdots$
Measured data	Initial skin temperature, Heartrate, Core temperature (tympanic) Ambient temperature, Ambient humidity
Temperature	26.9 ± 0.9 [!n] (Mean±SD)
Humidity	25.5 ± 4.8 [%] (Mean±SD)

TABLE III
Running & Walking Experiment Settings

Date	July 28 - September 2, 2015 (10 Days)
Subject	6 males
Time	110 minutes between 12:00-15:00
Location	Sidewalk around Information Science Technology building in Osaka University, Suita, Japan
Exercise	7.5 km walking at 5km/hour & 10 km running at 8km/hour with 2 × 10-minute breaks (walking) & 3 × 10-minute breaks (running)
Measured data	Skin temperature, Heartrate, Core temperature (tympanic) Ambient temperature, Ambient humidity
Temperature	33.3 ± 2.9 [!n] (Mean±SD)
Humidity	45.6 ± 15.7 [%] (Mean±SD)

B. Heatstroke Warning Algorithm

According to [7], core temperature more than 39.5 !n is a reliable indicator for heatstroke. However, our goal is not detecting heatstroke patients but preventing users from heatstroke. Thus, we initially analyze core temperatures in the datasets. Figures 3 and 4 show the core temperature distributions of ergometer exercise and running and walking exercise, respectively. In the ergometer exercise, only 2.2% of all the samples are greater than 38.0 !n. Also, in the running and walking exercise, 11.9% of all the samples exceed 38.0 !n. According to this result and World Meteorological Organization (WMO) recommendation for outdoor workers [16], we set a threshold for heatstroke warning to 38.0 !n. We note that this threshold should be optimized based on the feedback from users (e.g., a higher threshold may be suitable for well-trained athletes). In the following sections, we evaluate precision and recall of heatstroke warning that arises when the core temperature exceeds 38.0 !n.

C. Result

TABLE IV
Contingency Table
(Ergometer)

Notification	True Warning		
	Yes	No	Sum
Yes	55	120	175
No	3	2384	2387
Sum	58	2504	2652

TABLE V
Contingency Table
(Run&Walk)

Notification	True Warning		
	Yes	No	Sum
Yes	311	88	399
No	121	3085	3206
Sum	432	3173	3605

In order to evaluate precision and recall, we manually classified all the estimated core temperature and measured core temperature into two categories: (1) 38.0 !n or greater and (2) less than 38.0 !n. We show classification result for both the datasets in Table IV and V where the rows mean show the number of warnings produced by our algorithm and the columns show the number of true warnings. We note that the numbers on the tables are the total time duration in minutes when core temperature is 38.0 !n or greater / less than 38.0 !n. Table IV shows core temperature in the ergometer data set is over the threshold for only 58 out of 2652 minutes. This is because the room temperature was not so high ($< 30°C$) and there was no solar radiation which constantly heats up human body in outdoor. The result represents our prototype system can alert with very high recall (0.948 = 55/58), however the precision is still low (0.314 = 55/175). The reason for low precision is that our method tends to estimate core temperature higher than the actual temperature. Actually, there are data occur 81 false positives where estimated core temperature is much higher than the actual temperature.

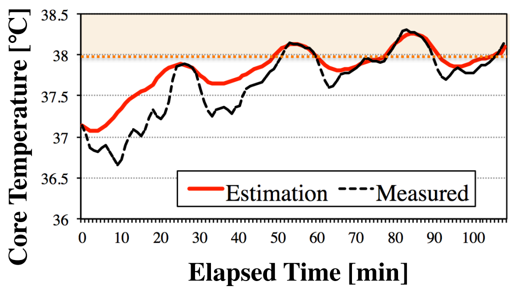

Fig. 5. An Example of Core Temperature Estimation

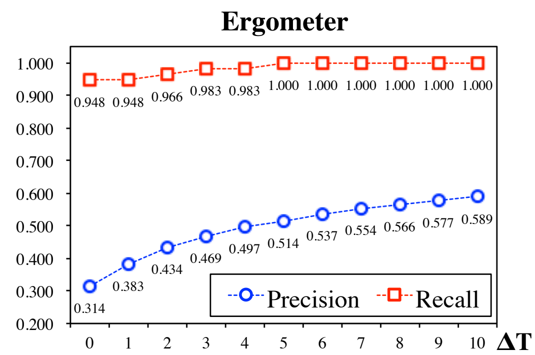

Fig. 6. Precision and Recall with ΔT

Table V shows the result of running and walking datasets, where precision and recall are 0.779 (=311/399) and 0.720 (=311/432). Although our method achieves moderate performance, our application requires higher recall for human safety. The major reason of low recall is core temperature estimation error up to 0.30 !n. Another reason is the fact that there are some subjects whose actual core temperature exceeds 38.0 !n for only a few minutes. In that case, correct notification becomes more difficult due to estimation error. We consider exceeding the threshold for a moment is not so dangerous, thus we ignore the samples such that temperature once exceeds 38.0 !n and returns to under the threshold within five minutes. As a result, we removed 20 false negative samples in Table V. Figure 5 is an example of core temperature estimation and heatstroke alert. It shows core temperature estimation is still challenging, namely reproducing actual response is a difficult task. On the other hand, the estimation result is useful for detecting whether the temperature reaches 38.0$°C$ or not. In this case, our algorithm can correctly alert it with a few false positives.

D. Result with acceptable error ΔT

We consider some error of timing should be acceptable because core temperature estimation is still difficult by limited sensors and we assume the threshold must be much lower than 39.5 !n (dangerous level) for safety. Therefore, we introduce acceptable error ΔT and evaluate precision and recall while changing the range of ΔT. For example, $\Delta T = 3$ means that we regard warnings which error of warning timing within three minutes as correct. Figure 6 depicts the relationship between precision, recall and acceptable error ΔT for the ergometer data set. If no error is accepted ($\Delta T = 0$), precision is 0.314 and recall is 0.948 as described in the previous result. On the other hand, precision gradually improves over 0.5 and recall reaches 1.0 even with ΔT = 5. Finally, we confirmed 0.589 precision and 1.0 recall when we allowed 10-minute error of alert timing ($\Delta T = 10$). Precision is still challenging, however we believe that we can improve accuracy of notification by considering continuous alerts (i.e. raise warning in the case that the algorithm continuously detects high temperature) because our current algorithm detects high-core temperature at that moment.

The upper row on Figure 7 depicts the overall result for the running and walking datasets. In each figure, precision and recall rise with the increase of ΔT. We also found notification in running is still challenging compared to walking since precision is high while recall is low, which means estimated core temperature tends to be lower than the actual temperature. This is because reproducing human body response in complicated exercise is difficult. Nevertheless, precision and recall in running improve with the increase of ΔT and exceeds 0.9 with $\Delta T = 8$. This indicates our method is helpful for detecting core temperature rise over the threshold. However, there are still some false negatives which seriously drop reliability. To solve this problem, we add some offset to the estimated core temperature for safer warning. Adding offset decreases precision (i.e. increase of false alarms), however false positives are much better than false negatives.

The lower row on Figure 7 represents precision and recall after we added 0.1 !n as a minimum offset to estimated core temperature. The result shows recall of both the exercises exceeds over 0.74 even in the case that no error is accepted ($\Delta T = 0$). Although precision decreases compared to the results without the offset, it is still high (> 0.8) if we allow 2-minute error of notification timing. Overall recall increases by adding 0.1$°C$ offset and reached 0.984 with $\Delta T = 10$. This means 1.6% false negatives is still undetected. Nevertheless, all the false negatives occurred in one experiment case. The false negatives are observed just before finishing the experiment due to sudden rise of core temperature. If we could continue the experiment, our method can possibly alert heatstroke. As a consequence, it is better to estimate core temperature with some offset for safety although we have to accept some false alarms. However, precision is still higher than 0.9 with $\Delta T = 6$.

VI. Conclusion

In this paper, we presented HeatWatch, a novel application for smart watches, to prevent heatstroke by ensuring users breaks and water intake. The application continuously estimates user's core temperature without any invasive sensors and notifies when the core temperature exceeds a threshold. We discussed our algorithm to detect high temperature exceeding

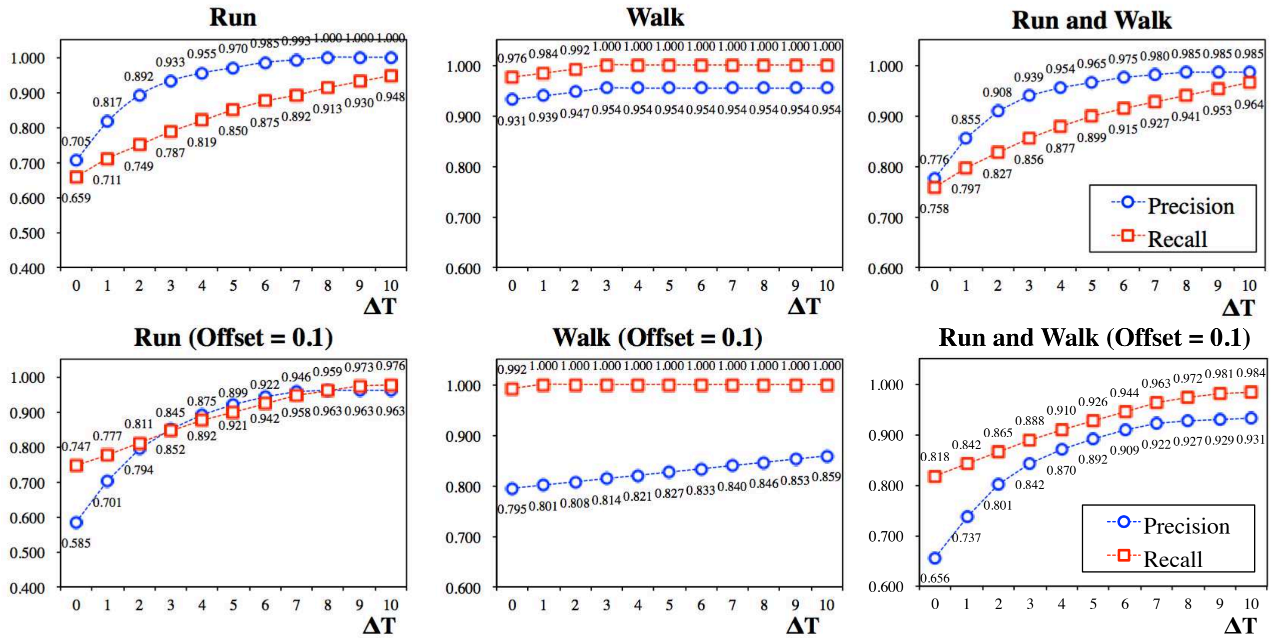

Fig. 7. Precision and Recall with ΔT

the threshold and evaluated it through over 100 hours of real dataset.

The results have revealed our method can instantly detect high temperature exceeding 38.0 !n with over 0.7 recall. The result also showed precision and recall dramatically increase when we accept some error of warning timing. In the future, we are planning to develop HeatWatch with a real-time warning algorithm and drinking activity recognition. To detect drinking activities, we intend to employ acceleration and gyroscope equipped with a smart watch and make an activity recognition model based on the features such as difference of gravity for each sensor axis and variance for acceleration and gyroscope. We are also planning to validate the appropriateness of alarms based on the users' feedback through real experiments.

REFERENCES

[1] C. Koppe, S. Kovats, G. Jendritzky, B. Menne, D. J. Breuer, and D. Wetterdienst, *Heat waves: risks and responses*. Regional Office for Europe, World Health Organization, 2004.

[2] Y. Epstein and D. S. Moran, "Thermal comfort and the heat stress indices," *Industrial health*, vol. 44, no. 3, pp. 388–398, 2006.

[3] T. Hamatani, A. Uchiyama, and T. Higashino, "Estimating core body temperature based on human thermal model using wearable sensors," in *Proceedings of the 30th Annual ACM Symposium on Applied Computing*. ACM, 2015, pp. 521–526.

[4] T. Hamatani, A. Uchiyama, and T. Higashino, "Poster: Core temperature estimation during exercise using wearable sensors," in *Proceedings of the 14th Annual International Conference on Mobile Systems, Applications, and Services Companion*. ACM, 2016, p. 29.

[5] U.S. Environmental Protection Agency, "Climate change indicators in the United States, 2016. Fourth edition." 2016, http://www.epa.gov/climate-indicators.

[6] L. R. Leon and B. G. Helwig, "Heat stroke: role of the systemic inflammatory response," *Journal of Applied Physiology*, vol. 109, no. 6, pp. 1980–1988, 2010.

[7] Y. Shapiro and D. Seidman, "Field and clinical observations of exertional heat stroke patients." *Medicine and science in sports and exercise*, vol. 22, no. 1, pp. 6–14, 1990.

[8] E. F. Adolph *et al.*, "Physiology of man in the desert." *Physiology of Man in the Desert.*, 1947.

[9] Japanese Ministry of the Environment, "Precautions for exercise," http://www.wbgt.env.go.jp/pdf/envman/3-3.pdf.

[10] J. B. Mitchell, K. R. Goldston, A. N. Adams, K. M. Crisp, B. B. Franklin, A. Kreutzer, D. X. Montalvo, M. G. Turner, and M. D. Phillips, "Temperature measurement inside protective headgear: comparison with core temperatures and indicators of physiological strain during exercise in a hot environment," *Journal of occupational and environmental hygiene*, vol. 12, no. 12, pp. 866–874, 2015.

[11] Y. Xue, S. Hosokawa, S. Murata, S. Kouchi, and K. Fujinami, "An on-body placement-aware heatstroke alert on a smartphone," in *Computer Applications for Communication, Networking, and Digital Contents*. Springer, 2012, pp. 226–234.

[12] G. Florea, R. Dobrescu, D. Popescu, and M. Dobrescu, "Wearable system for heat stress monitoring in firefighting applications," in *Recent advances in computer and net-working. Proceedings of the 2nt international conference on information technology and computer networks (ITCN !¢13), Antalya*, 2013, pp. 8–10.

[13] Y.-J. Hong, I.-J. Kim, S. C. Ahn, and H.-G. Kim, "Mobile health monitoring system based on activity recognition using accelerometer," *Simulation Modelling Practice and Theory*, vol. 18, no. 4, pp. 446–455, 2010.

[14] A. Gagge, "An effective temperature scale based on a simple model of human physiological regulatory response," *ASHRAE TRANSACTIONS*, vol. 77, no. 2192, pp. 247–262, 1971.

[15] S. Takada, H. Kobayashi, and T. Matsushita, "Thermal model of human body fitted with individual characteristics of body temperature regulation," *Building and Environment*, vol. 44, no. 3, pp. 463–470, 2009.

[16] G. McGregor, P. Bessemoulin, K. Ebi, and B. Menne, "Heat waves and health: Guidance on 7 warning system development 8," *WORLD METEOROLOGICAL ORGANIZATION*, vol. 14, p. 15, 2010.