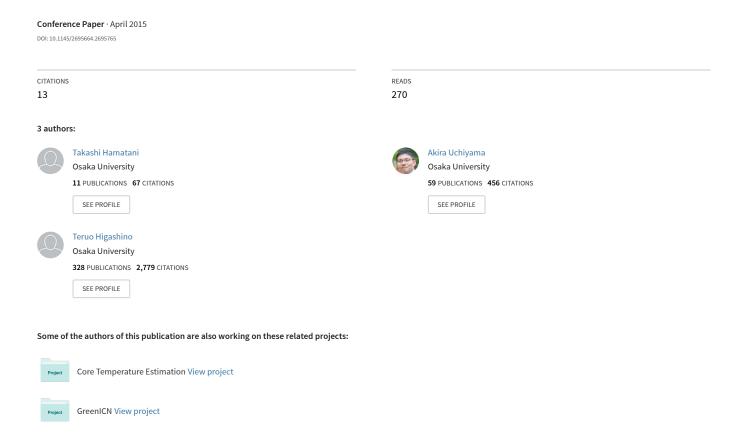
# Estimating core body temperature based on human thermal model using wearable sensors



# Estimating Core Body Temperature Based on Human Thermal Model Using Wearable Sensors

Takashi Hamatani, Akira Uchiyama, and Teruo Higashino Graduate School of Information Science and Technology Yamadaoka 1-5, Suita, Osaka 565-0871, Japan {h-takasi, uchiyama, higashino}@ist.osaka-u.ac.jp

#### **ABSTRACT**

Monitoring body core temperature is important to prevent heat stroke. Core temperature is often measured as rectal or tympanic temperature which is difficult to monitor during activities. In this paper, we propose a method to estimate core temperature based on the two-node human thermal model by using wearable sensors. For accurate estimation, infeasible sets of parameter values representing individual differences are filtered by comparing sensor measurements and simulation results based on the two-node model. The real experiments with 7 subjects have revealed that the proposed method achieves  $-0.07^{\circ}\mathrm{C}$  error in core temperature estimation for 60 minute walking.

## **Categories and Subject Descriptors**

J.3 [LIFE AND MEDICAL SCIENCES]: Health

#### **General Terms**

Design, Experimentation

#### **Keywords**

Healthcare, Heat Stroke, Human Thermal Model, Wearable Sensors

#### 1. INTRODUCTION

Heat stroke becomes an important matter because of rising temperatures caused by global warming and heat wave. Heat stroke is a serious illness that sometimes leads to a severe symptom or death. The main cause of heat stroke is increase of deep body temperature (core temperature) during hard exercise and/or in heat environment. To prevent heat stroke, health manuals for summer exercise are provided by World Health Organization (WHO) [13]. Heat-stress indicator such as Standard Effective Temperature (SET) [4] and Wet-Bulb Globe Temperature(WBGT) [2] are also used to indicate a risk level of heat stroke. These approaches are

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SAC'15 April 13-17, 2015, Salamanca, Spain. Copyright 2015 ACM 978-1-4503-3196-8/15/04...\$15.00. http://dx.doi.org/10.1145/2695664.2695765 helpful to avoid activities when the risk level is high. However, change of core temperature is heterogeneous due to individual variations. For example, core temperature of a person may reach a dangerous level even if the heat-stress indicator is not high. Therefore, core temperature monitoring is of great importance.

Core temperature is often measured as rectal temperature or tympanic temperature, which is difficult to measure due to its invasiveness. Instead, auxiliary temperature or oral temperature is generally used as a reference to core temperature since they are easy to be measured. However, we cannot use these temperature for monitoring during activities because subjects are required to keep rest during measurement when we use a probe for measurement. To directly measure core temperature during activities, CorTemp [8] is an ingestible core body thermometer pill which sends temperature to a receiver for 18 to 30 hours. However, it is disposable and costs \$40. The price of the receiver is also expensive, more than \$2,000. Measurement of skin temperature [7] is alternative to prevent heat stroke by detecting risky skin temperature exceeding a threshold. Nevertheless, skin temperature does not always indicate core temperature because it is sometimes affected by environment conditions such as wind, and solar radiation.

In this paper, we propose a method to estimate core temperature based on the two-node model[18] considering individual variations using wearable sensors. The two-node model is one of human thermal models[3, 17, 19] that simulate change of core and skin temperature by calculating heat exchange with the air and heat production in a body. Given information such as ambient temperature, the activity type, and calories burned, we can estimate change of core temperature based on simulation by using the two-node model. Wearable and ambient sensors can measure or estimate some of the information necessary to conduct simulation. The rest of the necessary information is also given by manual input. However, there are several parameters in the model related to individual variances in response to heat such as a perspiration rate and skin blood flow. Appropriately setting these individual parameters is essential for accurate estimation of core temperature.

Ref. [18] presents a method to calibrate the individual parameters by measuring Hardy and DuBois seven points[5], which are used as a reference to the average skin temperature, under controlled heat environment. However, the following problems still remain: (1) measuring rectal temperature and Hardy and DuBois seven points are difficult to measure during activities, (2) subjects are required to keep

rest for a long time being exposed to various heat stress, and (3) calibrated parameters are not always the best due to different subject conditions on each day.

In contrast, our method eliminates infeasible parameter sets through real-time monitoring of skin temperature, ambient temperature and humidity, and heart rate as activity intensity. The measured values except the skin temperature are input to the two-node model. Then, we conduct simulations of N cases by setting N different sets of individual parameters for each case. The measured skin temperature is compared to the simulated skin temperature and used as the ground truth to judge the feasibility of the individual parameter sets.

Our contributions are summarized as below. First, we design a non-invasive method to estimate core temperature by using commercial off-the-shelf sensors during activities. As far as we know, this is the first approach combining wearable sensors and a human thermal model. Second, we show the effectiveness of the proposed method through real experiments with 7 subjects. The results show that the proposed method achieves core temperature estimation with the average error of  $-0.07^{\circ}\mathrm{C}$  for 60 minute walking. Our method is helpful to notify people of taking a break by estimating near-future core temperature as well as current core temperature.

#### 2. RELATED WORK

For the purpose of human thermal simulation, several human thermal models [3, 17, 19] have been proposed so far. In the models, a human body is composed of multiple nodes and heat exchange between neighboring nodes per unit time is calculated. Gagge's two-node model [3] regards a human body as a combination of the core node and the skin node. In Stolwijk's 25-node model [17], a human body is composed of 25 nodes including four layers of core, muscle, fat, and skin. Ref. [19] further divides the nodes for detailed thermal simulation. There is a trade-off between the granularity of the human body model, computation time, and the simulation accuracy.

Despite a large number of work on the human thermal simulation, only a few papers have applied human thermal models to exercise because the main objective of the human thermal models is evaluation of human thermal comfort in daily life. For example, Ref. [20] has applied a human thermal model to simulate body temperature during cycling exercise. However, as far as we know, none of those work adjusts individual parameters using real-time sensor measurements.

#### 3. PROPOSED METHOD

#### 3.1 Overview

In the proposed method, we assume a user wearing sensor(s) conducts an activity under heat environment. The sensor data is transmitted to a server via wireless networks such as cellular networks and WiFi. The sensor data contains ambient information such as temperature, ambient humidity and solar radiation, and human body information such as skin temperature, sweat rates and burned calories. Some of the collected sensor data are used as the input to the simulation of core temperature based on the two-node model. The other data is used for filtering infeasible sets of

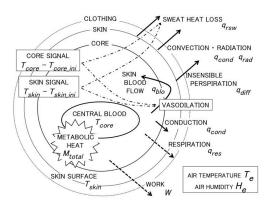


Figure 1: two-node model

parameters representing individual differences. Hereafter, we denote these parameters as individual parameters. If an input value cannot be obtained by sensors, we use a default, estimated or manual-set value. The accuracy of the proposed method is expected to increase when the amount of input values and/or the accuracy of input values increases.

For the accurate estimation of core temperature, our method filters infeasible individual parameter sets that do not generate simulation results similar to the collected human body information. We conduct simulation for all possible cases of individual parameter sets and compare the output value(s) of a human body between simulation and the collected data. Our method regards the average of the current core temperature values of all feasible individual parameter sets after filtering as the estimated core temperature.

#### 3.2 Two-Node Model

#### 3.2.1 Heat Transfer

In our method, we use the two-node model[3] since it is suitable as the human thermal model during activities[16]. As shown in Fig. 1, the two-node model calculates heat exchange between the skin node and the core node per unit time. The temperature change  $dT_{skin}$  of the skin node is

$$m_{skin} \cdot c_{skin} \cdot dT_{skin} = (1)$$

$$(q_{cond} + q_{blo} - q_{diff} - q_{rsw} - q_{conv} - q_{rad}) \cdot A_{body},$$

where  $m_{skin}$ ,  $c_{skin}$ , and  $A_{body}$  denote the mass of the skin node, the specific heat capacity of the skin node, and the body surface area, respectively.  $q_{cond}$ ,  $q_{blo}$ ,  $q_{diff}$ ,  $q_{rsw}$ ,  $q_{conv}$ , and  $q_{rad}$  are heat transferred by conduction, blood, diffusing water vaporized, sweat vaporized, convection, and radiation, respectively. Similarly, the temperature change  $dT_{core}$  of the core node is

$$m_{core} \cdot c_{core} \cdot dT_{core} = (M_{total} - W - q_{res} - q_{cond} - q_{blo}) \cdot A_{body}, (2)$$

where  $m_{core}$ ,  $c_{core}$ ,  $M_{total}$ , and W are the mass of the core node, the specific heat capacity of the core node, total metabolic heat production, and work accomplished, respectively.

The heat  $q_{blo}[W/m^2]$  transferred by blood is defined as

$$q_{blo} = c_{blo} \cdot V_{blo}(T_{core} - T_{skin}), \tag{3}$$

where  $c_{blo}$  and  $V_{blo}$  are the specific heat capacity of blood

and the volume of blood flow.  $T_{core}$  and  $T_{skin}$  are the temperature of the core node and the skin node, respectively. The heat  $q_{cond}$  transferred from the core to the skin by conduction is

$$q_{cond} = K_{min}(T_{core} - T_{skin}), \tag{4}$$

where  $K_{min}$  is the minimum thermal conductance by the skin. The heat  $q_{conv} + q_{rad}$  transferred by convection and radiation is

$$q_{conv} + q_{rad} = h_{total}(T_{skin} - T_{air})F_{cl}, \tag{5}$$

where  $h_{total}$  and  $F_{cl}$  are the combined heat transfer coefficient and efficiency for the passage of dry heat from the skin surface through the clothing to the environment[15]. We let  $h_{conv}$  and  $h_{rad}$  denote the convective heat transfer coefficient and the radiation heat exchange coefficient, respectively. Then,  $h_{total}$  is defined as

$$h_{total} = h_{conv} + h_{rad}. (6)$$

 $F_{cl}$  is also defined as

$$F_{cl} = 1/(1 + 0.155 \cdot h_{total} \cdot clo),$$
 (7)

where clo is clothing insulation.

Normal dampness heat transfer for the skin without sweating  $q_{diff}[W/m^2]$  is defined as

$$q_{diff} = 0.06 \cdot E_{max} \tag{8}$$

$$E_{max} = 2.2 \cdot h_{conv} (P_{skin} - \phi_{air} \cdot P_{air}) F_{pcl}, \qquad (9)$$

where  $P_{skin}$  and  $P_{air}$  are the saturated vapor pressure at skin temperature  $T_{skin}$  and air temperature  $T_{air}$ , respectively.  $\phi_{air}$  denotes relative humidity as a fraction.  $F_{pcl}$  is the permeation efficiency factor for water vapor evaporated from the skin surface through clothing to the ambient air and calculated as

$$F_{pcl} = 1/(1 + 0.143 \cdot h_{conv} \cdot clo). \tag{10}$$

The heat loss  $q_{res}$  by respiration is

$$q_{res} = 0.0023 \cdot M_{total} (44 - \phi_{air} \cdot P_{air}).$$
 (11)

The heat loss  $q_{rsw}$  by evaporation of sweat is given by

$$q_{rsw} = 0.7 \cdot m_{rsw} \cdot 2^{(T_{skin} - T_{skin\_ini})/3},$$
 (12)

where  $m_{rsw}$  and  $T_{skin\_ini}$  are the sweat amount and the initial skin temperature, respectively.

Table 1 shows the values of the constants in the above equations. We describe how we obtain the other inputs in section 3.3.1.

Table 1: Constant Values Skin Specific Heat Capacity  $c_{skin}$ 0.97Core Specific Heat Capacity  $c_{core}$ 0.97Blood Specific Heat Capacity  $c_{vlo}$ 1.163  $\overline{\text{Min. Skin}}$  Thermal Conductance  $K_{min}$ 5.28clothing insulation *clo* 0.6 Convective Heat Transfer Coefficient  $h_{conv}$ 4.3 Radiation Heat Exchange Coefficient  $h_{rad}$ 5.23 Efficiency for the Passage of Dry Heat  $F_{cl}$ 0.53Efficiency for Water Vapor Evaporated  $F_{pcl}$ 0.73

#### 3.2.2 Individual Parameters

We employ the sweat amount  $m_{rsw}$  and the skin blood flow volume  $V_{blo}$  proposed in Ref. [18] since it can represent individual differences.

$$\begin{array}{lcl} m_{rsw} & = & pr7 \cdot (T_{core} - pr1) \\ +pr3 & \cdot & (T_{core} - pr1) \cdot (T_{skin} - pr2) \cdot \frac{1}{1000} \cdot \frac{1}{60} \, (13) \end{array}$$

$$V_{blo} = \frac{pr4 + pr5 \cdot (T_{core} - pr1)}{1 + pr6 \cdot (pr2 - T_{skin})} \cdot \frac{1}{60}$$
 (14)

In the above equations, pr1 - pr7 are the individual parameters. pr1 and pr2 are the initial values of  $T_{core}$  and  $T_{skin}$ . The differences between  $T_{core}$  and pr1, and  $T_{skin}$ and pr2 are calculated by Eq. (13) and Eq. (14). These differences represent the autonomic nerve response: sweating and the increase of the blood flow volume occur with the increase of core and skin temperature. As temperature rises, sweat production and skin blood flow increase. Then, heat is transferred from the body core to the air via the skin by evaporation of sweat and heat gradient. pr3 - pr7 are parameters related to the sweat amount and the blood flow volume. In the above equations, values in each bracket indicate increments based on the initial values. A value in a bracket is regarded as 0 if it is less than 0. pr6 is removed in our method since we assume  $pr2 < T_{skin}$ . According to Ref. [18], we specified the ranges of the individual parameters as shown in Table 2. pr7 is the coefficient of the additional sweat amount during activities and not defined in Ref. [18]. Hence, we define pr7 based on the range of pr3 which is the coefficient of the sweat amount during rest.

Table 2: Range of Individual Parameters

able 2. Italige of Individual Laramete								
pr1	pr2	pr3	pr4	pr5	pr7			
37.7	34.7	100	12.6	150	250			
37.5	34.5	80	10.08	120	200			
37.3	34.3	60	7.56	90	150			
37.1	34.1	40	5.04	60	100			
36.9	33.9	20	2.52	30	50			
36.7	33.7	10	1.26	15	25			
36.5	33.5	5	0.63	7.5	12.5			
36.3	33.3		0.315	3.75				
36.1	33.1		0.1575					
35.9	32.9		0.07875					
35.7	32.7							
35.5	32.5							
35.3	32.3							
35.1	32.1							
34.9	31.9							
Default Value								
36.6	34.1	100	6.3	75	250			

# 3.3 Estimation of Individual Parameters and Core Temperature

#### 3.3.1 Obtaining Input to Two-Node Model

We describe how we obtain the input to the two-node model below.  $A_{body}$ ,  $m_{skin}$ , and  $m_{core}$  are estimated by

height and weight. For the measurement of ambient temperature  $T_{air}$  and humidity  $\phi_{air}$ , we use a portable sensor WBGT-203B[9]. The measured values are used to calculate the saturated vapor pressures  $P_{skin}$  and  $P_{air}$  in Eq. (9) and Eq. (11).

To measure skin temperature, we use a wristwatch sensor Basis B1 [10] which can measure burned calories, wrist skin temperature, wrist perspiration as galvanic skin response (GSR[14]) and heart rate. It can synchronize with smartphones by Bluetooth. We use only the wrist skin temperature measured by Basis B1 although it provides other useful data such as GSR and burned calories. This is because GSR needs conversion to be input to the two-node model and heart rate cannot be measured continuously by Basis B1.

Instead, we use heart rate measured by adidas micoach [6] for estimating exercise metabolism  $M_{ex}$ . We estimate  $M_{ex}$  by using a conversion formula in Ref. [12]. We also estimate basal metabolism  $M_{basal}$  from height, weight, gender, and age. Then, the total metabolic heat  $M_{total}$  in the two-node model is given by

$$M_{total} = M_{basal} + M_{ex}$$
.

If efficiency of work in exercise is  $W_{eff}$ , accomplished work W is

$$W = M_{ex} \cdot W_{eff}.$$

 $W_{eff}$  differs between types of exercise. In our experiment, we use  $W_{eff} = 0.4$  for walking according to Ref. [1].

#### 3.3.2 Individual Parameter Filtering

We let  $T_e^t$  and  $H_e^t$  denote the ambient temperature and the ambient humidity at time t. We obtain the sequence of the ambient temperature  $T_e^t = \{T_e^{\ 0}, T_e^{\ 1}, \dots, T_e^{\ t}\}$  and the sequence of the ambient humidity  $H_e^t = \{H_e^{\ 0}, H_e^{\ 1}, \dots, H_e^{\ t}\}$  from sensor measurement. We also obtain metabolic heat production from exercise  $M_{ex}^t$  at time t by miCoach and the skin temperature  $T_s^t$  at time t by Basis B1<sup>1</sup>.  $M_{ex}^t$  is the sequence of metabolic heat production from exercise, i.e.  $M_{ex}^t = \{[M_{ex}^0, M_{ex}^{\ 1}, \dots, M_{ex}^t\}$ . Given  $T_e^t$ ,  $H_e^t$ , and  $M_{ex}^t$ , we simulate the change of core

Given  $T_e^t$ ,  $H_e^t$ , and  $M_{ex}^t$ , we simulate the change of core and skin temperature according to the two-node model for each set of individual parameter pr1 - pr7. For each set of individual parameter values, the simulation outputs the skin temperature sequence

$$\hat{T_s}^t = \{\hat{T_s}^0, \hat{T_s}^1, ..., \hat{T_s}^t\},\,$$

and the core temperature sequence

$$\hat{T_c}^t = \{\hat{T_c}^0, \hat{T_c}^1, ..., \hat{T_c}^t\}.$$

To filter infeasible individual parameter sets, we define the distance d between the simulated skin temperature and the measured skin temperature as below.

$$d = \frac{1}{t} \cdot \sum_{i=1}^{t} |(T_s^{i} - T_s^{i-1}) - (\hat{T_s^{i}} - T_s^{\hat{i}-1}))|$$
 (15)

We note that the simulated skin temperature is not equivalent to the measured "wrist" skin temperature. Therefore,

Table 3: Experiment Settings

Date	August 13-21, September 1-5 (10 Days)		
Time	1 hour between 13:00-15:00		
Location	Sidewalk around Expo'70 Commemorative Park,		
	Osaka, Japan		
Subject	7 Students (6 males and 1 female)		
Exercise	Walking at 5km/hour		
Measured data	Wrist skin temperature, heart rate		
	core temperature (eardrum)		
	ambient temperature, ambient humidity		

Table 4: Weather Conditions in Experiments

Date	Weather	Avg. temp. [°C]	Avg. humid. [%]
8/13	Cloudy	28.3	67
8/18	Sunny	36.3	53
8/19	Sunny	34.8	50
8/20	Sunny	35.3	49
8/21	Cloudy	33.1	48
9/1	Cloudy	24.1	86
9/2	Sunny	31.8	49
9/3	Cloudy	28.1	64
9/4	Cloudy	28.9	73
9/5	Sunny	31.3	71

we compare the difference of the skin temperature and the difference of the measured skin temperature per unit time assuming the relative temperature is equivalent between skin and a wrist.

An infeasible individual parameter set is defined as a set such that its distance d is larger than a threshold  $\theta$ . We empirically set  $\theta = 0.001^2$ . After filtering, we regard the feasible sets as the individual parameter value sets suitable for a subject.

#### 3.3.3 Core Temperature Estimation

Let  $T_{c_i}^i$  be the simulated core temperature at time t for the i-th feasible set. For N feasible parameter value sets, our method estimates the core temperature at time t as below.

$$\frac{1}{N} \cdot \sum_{i=1}^{N} \hat{T_{c_i}}^t \tag{16}$$

# 4. PERFORMANCE EVALUATION AND DIS-CUSSION

#### 4.1 Environment

We have evaluated the proposed method through real experiments where 52 exercise samples were collected. 7 subjects wore Basis B1 sensor [10] on their wrists and walked outdoors under conditions shown in Tables 3, 4, and 5.

For the ground truth of core temperature, we used tympanic temperature measured by DBTL-2 [11]. In the evaluation, we calculated the difference between measured tympanic temperature and its initial temperature and the difference between the estimated core temperature and its ini-

<sup>&</sup>lt;sup>1</sup>We note that the accuracy of our method is expected to increase if more sensor data and/or more accurate data is available.

 $<sup>^2 \</sup>text{We repeat increasing } \theta$  by 0.0001 if no set is found in the experiments

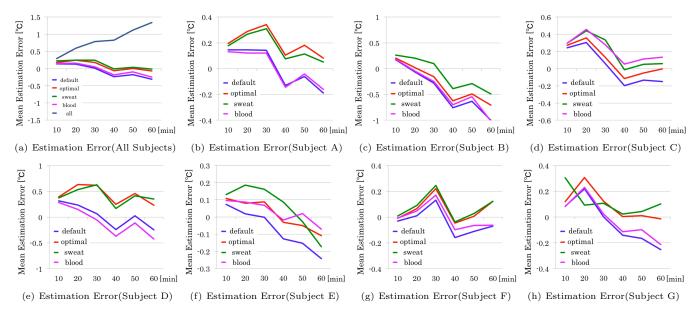


Figure 2: Average Core Temperature Estimation Error

Table 5: Subject Information

ID	Age	Height[cm]	Weight[kg]	Sex
A	23	178	78	Male
В	22	172	80	Male
С	24	163	63	Male
D	22	179	80	Male
E	24	160	48	Female
F	23	177	80	Male
G	23	174	98	Male

tial temperature. Then, we evaluated if the difference of the estimated core temperature is equivalent to that of the measured tympanic temperature. This is because tympanic temperature is usually lower than core temperature. And unit time was set to 1 minutes.

To see the effect of individual parameter sets to be adjusted, we selected four sets: (1) all (pr1-pr7), (2) sweat-related parameters (pr1-pr3), and (pr1-pr3), and (pr1-pr3), and (pr1-pr3), and (pr1-pr3), and (pr3), and (pr3), and (pr3), and (pr3). The empirically optimal parameter set is empirically determined by testing all combinations of individual parameters. (1) - (4) and using default parameter value are called respectively all, sweat, blood, optimal, default under evaluation shown in Figure 2.

Computation time for the simulation may be large since our method conducts simulations for all cases of the individual parameter values. If we adjust all individual parameters pr1-pr7, the total number of combinations is 882,000. We measured the computation time for 60 minute exercise with all individual parameters by a workstation with Intel Xeon 2.66 GHz and 23.6 GB memory. The average computation time was 100 seconds for the all parameter case, which may be slightly long. However, parallel simulation can further speedup the computation time. In other three cases, the computation time was approximately 0.5 seconds. Therefore, the computation time is sufficient for the real-time es-

timation.

## 4.2 Effect of Adjusted Parameter Sets

We compared the accuracy of different individual parameter sets to be adjusted. Figure 2(a) shows mean errors of rising temperature between estimated and measured for all subjects.

The result of the default two-node model tends to be lower than the ground truth especially after 30 minutes. The blood-related parameter set shows the result similar to the default two-node model. This indicates the impact of the blood-related parameters is relatively small.

It is obvious that the case of all parameters does not work well since the error is much larger than the other cases. This is because the number of feasible parameter sets after filtering is much larger than the other sets, leading to the ambiguous estimation. Actually, the number of feasible parameter sets in the all parameter case was 20,253 while they were less than 300 in the other cases.

On the other hand, the other three cases of the proposed method show better results. The error of the optimal parameter set is small especially after 40 minutes when core temperature is high. The estimated temperature of the optimal set tends to be slightly higher than the ground truth. We consider this tendency is acceptable in terms of safety. It is worth noting that the sweat-related parameter set is comparable to the optimal parameter set. This result can be intuitively explained since the sweating is an effective cooling system (i.e. a dominant factor) and different depending on people.

Figures 2(b)-2(h) show the mean errors of core temperature estimation over time for each subject. We can see that the default model shows the best accuracy at 60 minutes for subject D. This is because the default parameter values are appropriate for the subject. In such a case, our method increases the ambiguity since it uses multiple feasible parameter sets for estimation after filtering.

Overall, the optimal parameter set achieves  $-0.07^{\circ}$ C average error at 60 minutes, which is more accurate than  $-0.311^{\circ}$ C

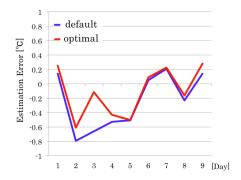


Figure 3: Error on Each Day of Subject E

error of the default two-node model.

## 4.3 Parameter Adjustment on Different Days

Figure 3 shows the estimation error of the optimal parameter set and the default two-node model on each day for subject E. The result is identical each other on some days while the error of the optimal set is smaller on the other days. Therefore, we can conclude that the proposed method can adjust individual parameters that are different depending on days even for the same person.

#### 5. CONCLUSION AND FUTURE WORK

In this paper, we proposed a method to estimate human body core temperature based on the two-node human thermal model using wearable sensors. For accurate estimation, our method filters infeasible parameters representing individual differences by comparing sensor measurements and the simulation output based on the thermal model. The experimental result shows that the proposed method achieves  $-0.07^{\circ}\mathrm{C}$  error in core temperature estimation for 60 minute walking, which is more accurate than the default parameter settings.

Our future work includes evaluation in other environments and exercise type and application of additional sensors to increase accuracy. We are also planning to design a likelihood-based method to estimate individual parameters toward more accurate estimation.

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