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Accurate Non-Contact Body Temperature Measurement with Thermal Camera under Varying Environment Conditions

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***Abstract*—Non-contact measurement of body temperature is preferred due not only to the convenience it provides but also to the necessity for preventing medical staffs and patients from infection and safety risk. For non-contact body temperature measurement, thermal cameras have been used to measure the temperature of facial skins. However, the problem is that temperature of facial skins varies according to varying environmental conditions such as outside temperature, subject activities prior to measurement, etc. Efforts to compensate the temperature of facial skin locations that are least affected by environmental conditions have shown only a limited success, leaving further improvement in accuracy as necessary. This paper presents a deep learning approach to body temperature prediction based on thermal camera facial skin images that provides highly accurate body temperature under varying environmental conditions. We achieve high accuracy by measuring temperature distributions of several Region-of-Interests (ROIs) on facial skins and learning the relationship between the ground truth body temperatures and the temperature distributions on ROIs. The results indicate that we can obtain around 0.2°C average error in body temperature estimation despite that subjects are exposed to hot and cold temperature, engaged in different physical activities.**

***Index Terms*—Deep Learning, Face Detection, Facial Parts Detection, Body Temperature Prediction, External Environment Prediction**

I. Introduction

When treating patients, medical staff are likely to be exposed to infectious diseases. To protect the medical staff, it is necessary to identify infectious diseases that the patients may have. [1]. To do this, previous methods used a device with a built-in infrared temperature sensor to measure the temperature inside of the ear, wrist, and forehead. However, this requires physical contact, which may infect the staff. This possibility necessitates the existence of non-contact body temperature measurement systems. [2]. Blood flow affects skin temperature of each body part. When using corneal temperature to predict body temperature, a correlation between the two measurements were found. Based on this correlation, a method for predicting the corneal temperature to maintain body temperature has been proposed [3]. Since skin temperature is changed by the external environment, observations of changes in body temperature and skin temperature in varying environments have been reported [4]. A body temperature prediction method that uses the correlation between body temperature and the collected environment data was proposed, as well as a method using regression model based on body part temperature were also proposed [5]. A method utilizing the thermal camera has been proposed to measure body temperature in a non-contact system [6]. Recently, the emergence of deep learning methods have led to the proposal of a face recognition method, which trains a deep learning network with thermal image. In this study, the body temperature was predicted by measuring between the eyebrows, the part of the facial skin with the highest temperature [7]. As of recent, You-Look-Only-Once (YOLO) which is developed based on Convolutional-Neural-Network (CNN) is mainly used to detect image features. A double network built with two CNNs is proposed because a single network detects parts of object in region of outside the object. This double network recognizes the object in the first network and cuts the detected coordinates from the original image. In the second network, parts of object are detected in the cropped image. So the detection of object parts in the area outside the object can be prevented [8].

In this paper, face and face parts are detected using Cascaded-YOLO designed with two YOLOs. After obtaining the coordinates of each ROI, temperatures are measured with the thermal camera. A deep learning model is proposed to predict body temperature from the measured ROI temper-

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atures. In this paper, a system that combines a Cascaded-YOLO for detection face and face parts from thermal image and a deep learning model for body temperature prediction is proposed. We measure the ROIs temperature of the subject's face with a thermal imaging camera. The facial parts which show information about the exposed external environment were determined as ROIs.

II. Problem Definition

Accurate body temperature measurement based on non-contact measurement of skin temperatures, e.g., facial skins, is of high practical value for the purpose of health care and medical diagnosis in real-world applications. However, skin temperatures are easily influenced by a number of internal and external conditions, such as personal activity, outside temperature, clothing, etc., other than body temperature itself. This makes it difficult to accurately predict body temperature from skin temperatures. For instance, we measure the temperature distribution of facial skins by a thermal camera at room temperature, as shown in Fig. 1. It shows a wide temperature distribution ranging from 33.7°C to 25.9°C as the highest and lowest temperatures, respectively, despite the fact that the actual measured body temperature is 36.7°C. To address this problem, there have been proposed approaches to compensating the temperature of a particular facial skin area that shows a least temperature variation to the change of external conditions, e.g., forehead and inner canthi. The proposed compensation approaches are based either on radiometric regression or black body based offset compensation [9]. However, these approaches are yet to provide the accuracy of less than 0.2°C that is required for health care and medical diagnosis. For example, the radiometric regression of forehead temperature shows over 0.3°C average error up to over 1°C maximum, while the black body offset compensated inner canthi temperature shows over 0.5°C average error up to over 1°C maximum error.

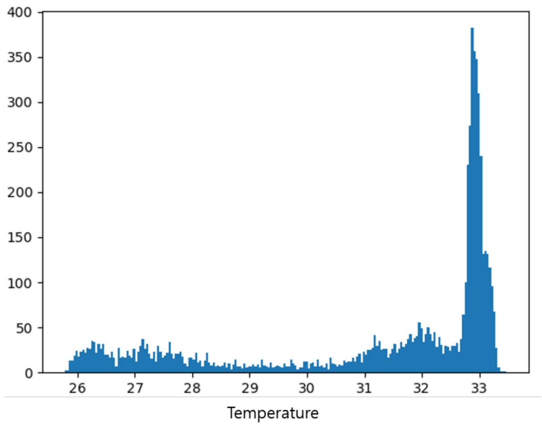

Fig. 1. Facial Skin Temperature Distribution

We verified the error distribution of the black body based error compensation approach by actual experiment, as shown in Fig. 2.

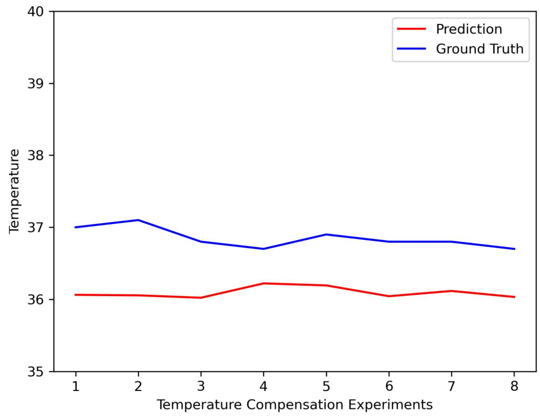

Fig. 2. Skin Temperature Compensation Result

In this paper, we solve the problem of accurately predicting body temperature based on non-contact facial skin temperature measurement by a thermal camera. Specifically, we aim at achieving around 0.2°C average error as well as maximum error under wide variations of external conditions including personal activity and outside temperature.

III. Thermal Image and Temperature Data Collection

A. Thermal Image Data Collection in Each Environments

Thermal image data consisting of types hot, normal, cold and exercise were collected. As shown in Fig. 3, The left image was taken in a hot environment, the middle in a room temperature environment, and the right image in a cold temperature environment. Nose and cheek are brightened and darkened by the external environment, and inside eye was not significantly affected. Thermal image data were collected by capturing thermal frame after exposing the body to each environments.

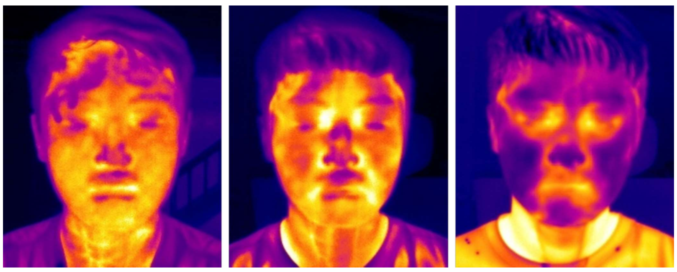

Fig. 3. Face Thermal Images in Each Environments

B. Skin Temperature Data Collection in Each Environments

The nose and cheek have thick skin that reflects the external environment and the inside eye has the most similar temperature with body temperature in common among several people, so these three parts were selected as the ROIs. The body temperature data was collected by ear thermometer. The temperature data of the inside eye, nose, and cheek were collected by thermal camera. Data hot type and cold type were collected after exposing the body to a room with internal temperature of 90°C and 5°C for 15 minutes, respectively. Exercise type data were collected after high-intensity exercise. Normal data were collected non-regularly multiple times. Temperature data were collected in a room temperature that followed the exposure of the body to each environment. Table I shows collected data in varying conditions.

TABLE I
THERMAL DATA COLLECTION FROM THREE EXPERIMENTERS

	The Number of Collected Data					
External Types	Body Temp.	Inside Eye	Nose	Cheek	External Temp. (c)	Exposure Time (m)
Hot	100	100	100	100	90	15
Exercise	40	40	40	40	25	-
Normal	100	100	100	100	25	-
Cold	100	100	100	100	5	15

The inside eye was measured the highest temperature in the region. Nose and cheek data were measured average temperature in each region to collect the general temperature.

C. Correlation of Collected Temperature Data

The collected data as a graph in the order of hot, exercise, normal, and cold, as shown in Fig. 4. ROI temperatures change according to body temperature trend. The temperature of inside eye is the best representative of body temperature. The temperature of nose and cheek is changed under the influence of the external environment.

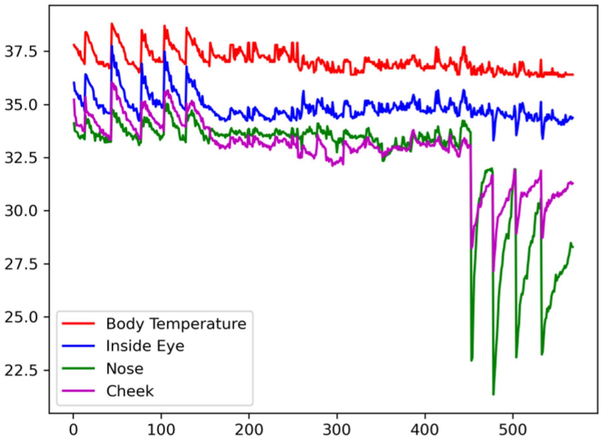

Fig. 4. Data Collection in Each Environments

A visual representation of correlations between the four collected data is shown in Fig. 5. The temperature of inside eye has a characteristic of having a linear relationship with body temperature. Nose and cheek are more susceptible to external environment, because the skin is thicker than the skin of the inside eye, so nose and cheek temperatures are changed a lot by outside condition even though the body temperature is maintained. Data collected after exercise shows a different trend from other data collected after exposure to external environments.

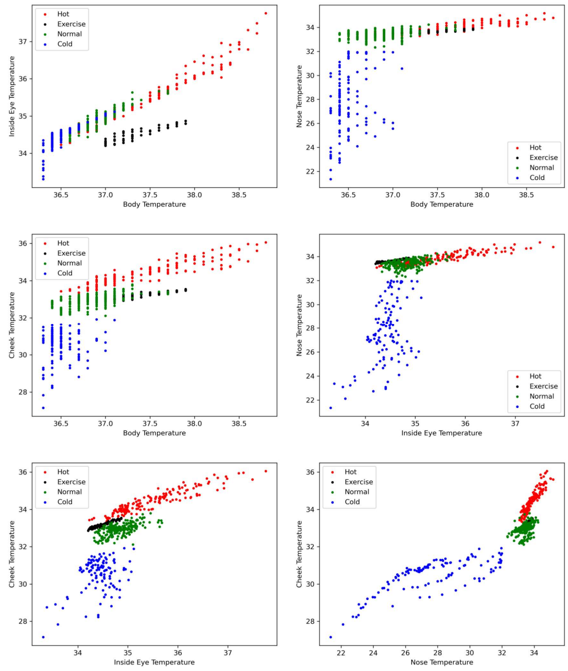

Fig. 5. Correlation of Temperature Data

IV. PROPOSED SYSTEM FOR NON-CONTACT BODY TEMPERATURE PREDICTION

A. Face Parts Detection Method

The YOLO V.3 network was used for object detection in thermal image. When using a single network, there is a problem that face parts are detected outside the face. To solve with this problem, Cascaded-YOLO network is adopted. This network is built with two YOLO V.3 networks. The first network is trained to detect face and detected face region is cropped from original image. The second network is trained to detect face parts from cropped face image, as shown in Fig. 6. Face label is created from collected original data and ROI label is created from cropped face image.

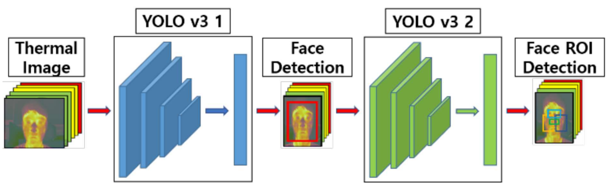

Fig. 6. Cascade-YOLO for Face Parts Detection

B. Deep Learning Model for Body Temperature Prediction

A deep learning model is designed to predict body temperature based on measured ROI temperatures. The designed model consists of several fully connected layers. All of the layers, except the last layer, use ReLu as activation function. The structure of prediction model has a dimension that increases and decreases as it passes through the layers. It receives three measured temperatures and the output is the predicted body temperature, as shown in Fig. 7. Since the model receives one temperature value per one ROI, each ROI is expressed as one temperature value.

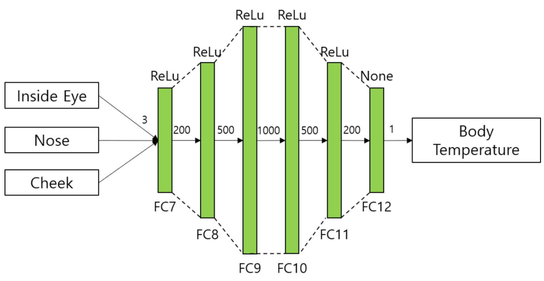

Fig. 7. Body Temperature Prediction Model

Skin temperature is affected by the body state and the external environment, so it has different characteristics following the environment. Based on this characteristics of skin temperature, environment recognition model was designed to predict the external environmental information, as shown in Fig. 8. This model is used to improve the performance of the body temperature prediction model by providing the predicted information of external environment.

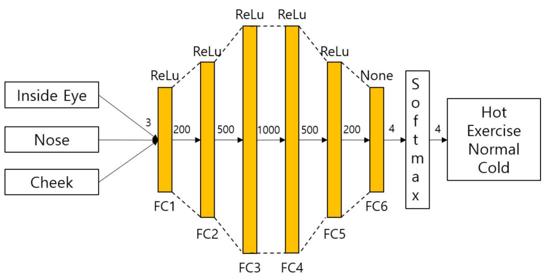

Fig. 8. Environment Recognition Model

The environment recognition model predicts environment information as four values in vector format. The output is converted into probability that sums to 1 by equation (1). Each converted values indicate a probability of each environment. Cross-entropy is used to train the environment recognition model, which is a classification model.

$$Softmax(x_i) = \frac{exp(x_i)}{\sum_j exp(x_j)} \quad (1)$$

In order to improve the accuracy of the body temperature prediction model, a method is proposed to combine the environment recognition model with the body temperature prediction model, as shown in Fig. 9. Measured ROI temperatures are used to predict external environment and together with predicted environment is used to predict body temperature.

The prediction result error is calculated using Reduce Mean Square Error(RMSE). In (2) $\hat{y}_i$ indicates predicted body temperature and y_i indicates ground truth. This error function is used to train the body temperature prediction model.

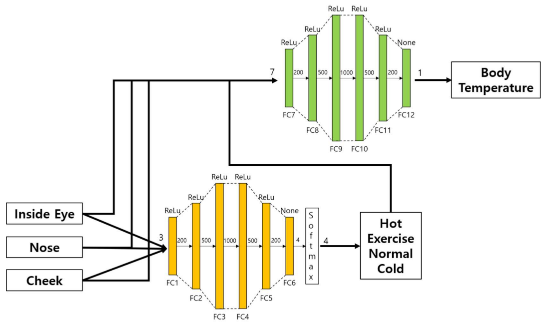

Fig. 9. Body Temperature Prediction Coupling Model

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \quad (2)$$

C. Combined System of Face Parts Detection and Body Temperature Prediction Coupling Model

The non-contact body temperature prediction system proposed in this paper obtains coordinates of ROIs in real-time using Cascaded-YOLO, and predicts body temperature using the body temperature prediction coupling model based on measured ROI temperature, as shown in Fig. 11. The Cascaded-YOLO is trained to recognize four types of inside eye, nose, left cheek, and right cheek. In this system, cheek ROI temperature is measured of the larger of left cheek or right cheek. The detected cheek and nose regions includes unnecessary parts such as the outside of the face and eyes. To cope with this problem, a method measuring center of detected region is used. In this way, it is possible to accurately measure facial skin and it can avoid measuring the necessary region. In Fig. 10, color bounding boxes indicate each detected ROI and black bounding boxes indicate temperature measurement region. The temperature of inside eye is determined by measuring the entire detected area.

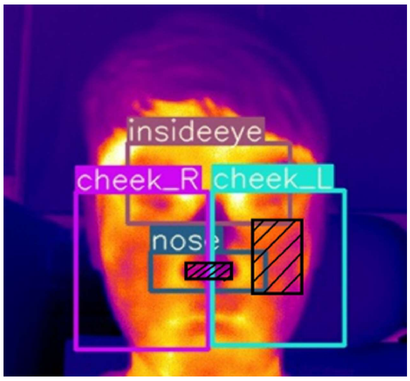

Fig. 10. Temperature Measurement of Detected Region

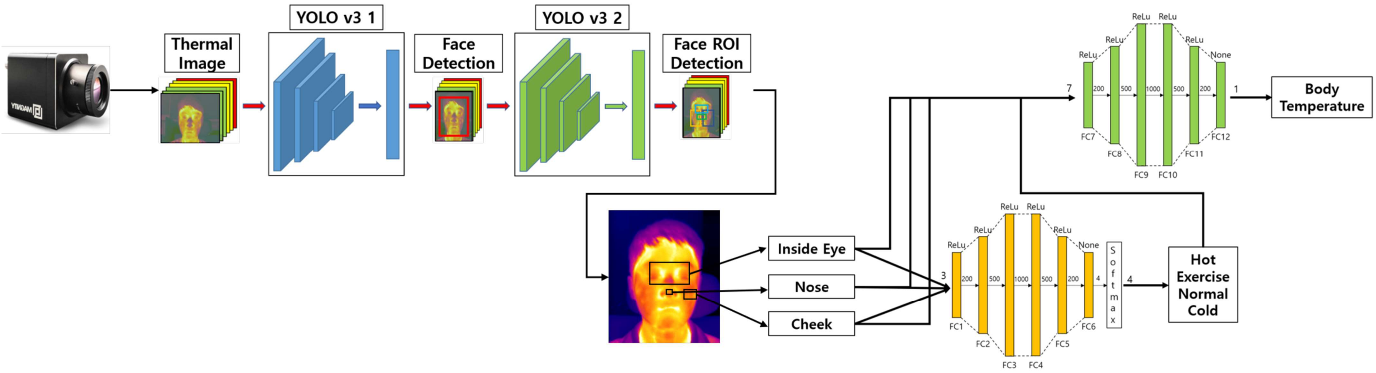

Fig. 11. Structure of The Proposed Non-Contact Body Temperature Measurement System

V. Experiment Verification

A. Performance of Body Temperature Prediction

A model with good performance is obtained from experiments of each models. The result of an experiment that exclusively utilizes the body temperature prediction model, without the environment recognition model, shows poor performance. Most of the points with poor results are observed in data collected after exercise, as shown in Fig. 12. Since the exercise data has different feature from other data, as shown Fig. 5, prediction performance without environment information includes error for exercise data.

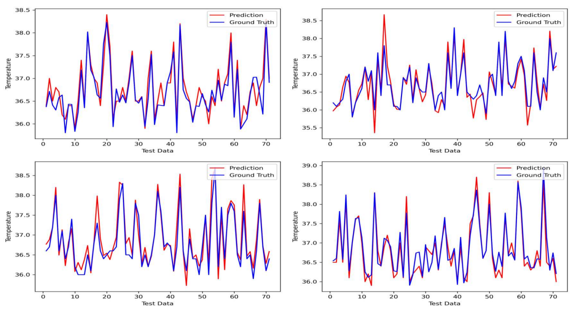

Fig. 12. Experiment Results without Providing Environment Information

A method of providing environment information predicted is proposed to improve the performance of the body temperature prediction model by adding an environment recognition model. Two experiments were conducted in which environment recognition model provided information in the form of scalar or vector. The method of providing in scalar form predicts each environment as 0, 1, 2, or 3 and this is combined with measured ROI temperatures, and then 4 values are provided to the body temperature prediction model. The prediction results of exercise data were improved by proposed method, as shown in Fig. 13. In this experiment, the environment recognition model does not include classifier and softmax layer and the number of output is one.

The method of providing in vector form predicts each environment as a probability that exist between 0 and 1 and sum to 1. This predicted vector is combined with measured ROI temperatures, and then 7 values are provided to the body temperature prediction model. This experiment, which provides in vector form, offers more precise results than the method providing in scalar form, as shown in Fig. 14. In this experiment, the number of output of the environment recognition model is four and it includes classifier and softmax layer.

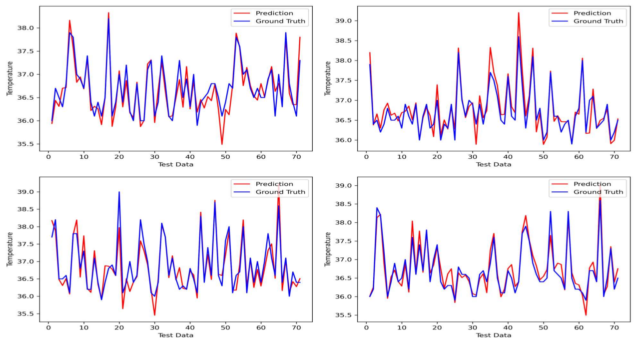

Fig. 13. Experiment Results with Providing Environment Information in Scalar

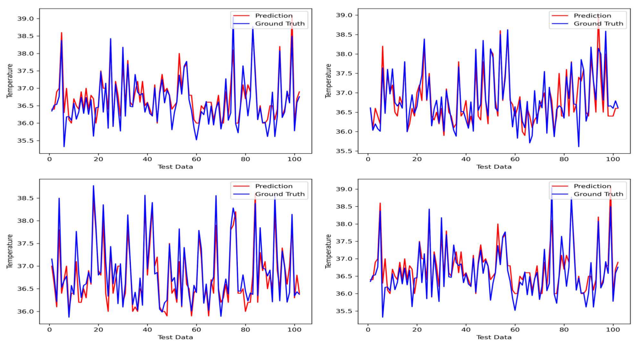

Fig. 14. Experiment Results with Providing Environment Information in Vector

All experiments are conducted with randomly selected 10 percent as test data of the collected data and the rest was used as training data. Each type of experiment was performed 4 times to obtain general RMSE. The comparison of experimental results is shown in Table II.

TABLE II
COMPARISON OF EXPERIMENTAL RESULTS

	Fig.12	Fig.13	Fig.14
Test1	0.3102	0.2885	0.2208
Test2	0.3079	0.2934	0.2226
Test3	0.3113	0.2697	0.2176
Test4	0.3057	0.2851	0.2288
Avg. RMSE	0.3087	0.2841	0.2224

B. *Performance of Proposed System in Real Environment*

A real-time body temperature prediction experiment was conducted with the proposed system in the real environment by preparing the trained Cascaded-YOLO and the trained body temperature prediction coupling model. In order to accurately evaluate the performance of the system, three people participated as the experimenters. Fig. 15 shows the real-time ROI detection of three people.

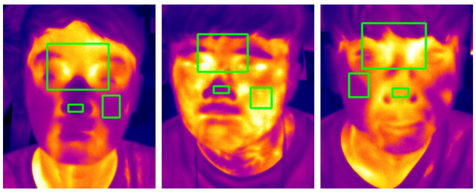

Fig. 15. Face Parts Detection of Three People

The real time experiment was conducted at room temperature for subjects. The performance was evaluated through a total of 30 experiments. The prediction result was compared with the real body temperature measured inside ear, as shown in Fig. 16, and RMSE was obtained as 0.1053.

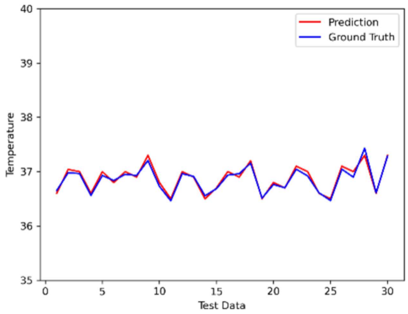

Fig. 16. Experiment Results of The Proposed Non-Contact Body Temperature Measurement System in Real Environment

VI. CONCLUSION

This paper presents a method of accurately predicting body temperature under varying environmental conditions based on non-contact thermal facial skin temperature measurement. To this end, we propose a deep learning approach to body temperature prediction based on distribution as well as context of temperatures at multiple ROIs on facial skins from thermal images. More specifically, we achieve high accuracy by learning the relationship between the temperatures at ROIs on facial skins and the ground truth body temperatures, as well as by classifying the environmental conditions associated with subject activities from the temperature distribution on ROIs. We use Cascaded-YOLO V.3 for real-time ROI detection and tracking, and a two-track fully connected network for activity classification and temperature regression. The results indicate that we can obtain around 0.2°C average error from the ground truth temperature measured by ear thermometer, despite of diverse environmental conditions including hot and cold external temperatures as well as such subject activities as exercise and bathing. In the future, we plan to continue extending and improving the current results by taking into consideration wider variations of environmental conditions.

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