A data-driven model on skin temperature and dynamic thermal sensation under step-change solar radiation

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Abstract

Under dynamic thermal conditions, especially solar radiations, thermal psychological and physiological response changes may have a time discrepancy with thermal climates. To predict thermal psychological and physiological responses accurately, the paper proposed a data-driven model based on the long short-term memory (LSTM) model, which considers the previous thermal influence. The predicted skin temperature is in accordance with experiment data with RMSE below 0.05 while the predicted thermal sensations have a significant difference with original data. However, for the test dataset, the performance is quite well in predicting thermal sensations. Compared with thermophysiological models (DTS), the LSTM model has a better prediction accuracy on thermal sensations. Skin temperatures have a strong relationship with the exposed thermal environment following the heat transfer theory. People may have adaptations or thermal expectations of the thermal environment, which could lead to discrepancies between thermal sensations and the thermal environment.

Highlights

• A time-series data-driven model for predicting dynamic thermal sensation and skin temperature was put forward.
• Prediction accuracy of the LSTM model and DTS model were compared.
• The prediction accuracy discrepancy between thermal sensation and skin temperature was analyzed.

Introduction

Outdoor thermal comfort under dynamic conditions

Humans engaging in outdoor activities are more likely to be exposed to frequent spatiotemporal step changes in outdoor thermal conditions, as opposed to constant thermal conditions staying indoors. Understanding pedestrians’ thermal responses to such dynamic thermal environments helps enhance outdoor thermal comfort by providing spatiotemporal variations in thermal conditions.

Human thermal load, as a thermophysiological parameter, was applied to evaluate outdoor thermal comfort under steady and unsteady conditions (Shimazaki et al., 2011). Similarly, a relationship between human-body exergy and thermal sensation was explored in an unsteady state(Schweiker et al., 2016). Furthermore, based on the dynamic two-node IMEM model(Hoppe, 1993), human thermophysiological parameters were simulated under unsteady conditions. Human thermophysiological and thermal sensation responses were analyzed under rapid and simultaneous sun and wind exposures(Li, Niu, and Mak, 2022). Thermal psychological responses were investigated under step-change phases in outdoor environments (Li et al., 2022). Thus, thermal physiology and psychology have a strong inter-connection and can be explained by each other to some extent.

In real-world environments, solar radiation is highly variable. Moreover, the amount of solar radiation exposure people receive due to outdoor activities is also changing. In the 1920s, people realized that there were a lot of problems in the field of biochemistry that could not be explained by classical thermodynamics. The British thermodynamicist Uberlord officially started the research of bio-thermodynamics and proposed its original concept, such as local entropy decrease. In the process of instantaneous heating, non-Fourier heat conduction may play an important role in living tissue, which is often used in treatment with high-intensity heat sources, such as concentrated laser, ultrasound, or radiofrequency ablation. For example, during thermal therapy, thermal relaxation of the tissue can delay the onset of temperature peaks, resulting in a reduction in thermal dose (Shih et al., 2005). The non-uniform internal structure of biological tissue leads to non-Fourier behavior in its heat transfer process (Davydov et al., 2001). For example, temperature oscillations and fluctuations in biological tissue have been observed in experiments (Roemer, Oleson, and Cetas, 1985). Subsequently, Mitra et al. conducted experiments on meat under 4 different thermal loading boundary conditions and observed the thermal wave phenomenon(Mitra et al., 1995).

The frequency of changes in the dynamic environment should be less than the frequency of changes in human physiology or psychology. From the above research, it can be seen that when the ambient temperature suddenly changes, the thermal sensation response time is very fast. In the first 2 minutes of the ambient temperature sudden change, the thermal sensation transcendence phenomenon is the most obvious(Liu et al., 2014), while there was a delay of several minutes for physiological parameters (skin temperature and core temperature). For solar radiation, the amount of surface solar radiation does not change on the minute scale, but due to the relative movement between people's activities and buildings and...
greenery, the human body's exposure to solar radiation on the minute scale is relatively large. Therefore, the physiological and psychological responses of the human body under this dynamic solar radiation exposure are quite different from those under steady-state solar radiation exposure.

**Data-driven model for predicting thermal comfort**

The most widely used model for exploring the relationship between subjective and objective parameters is the linear regression model. This kind of model can explicitly describe the variance of thermal sensation (a representative vote) with thermal environment parameters. However, this model can hardly express the individual influence with only mean results.

Now more and more non-linear regression models have been utilized in many thermal comfort models with a good prediction performance. Ordered probability and logistic models are two representative models. These models take thermal sensation as an ordered categorical variable, and the regression was based on probability, which explains the relationship from the view of probability. And these two models are classification models, based on a prediction model, e.g., logistic function (or called sigmoid function) for ordered logit model. No matter in linear models and regression models, most researchers trained all data to work out a model which can probably be used to explain the existing data but is not suitable for prediction outside the knowledge of the existing range. Such models can be called the interpretive model.

These models are widely used in steady state, however, under dynamic climate conditions, the factor of time takes an important role in prediction models. Time-series data is high-dimensional and complex with unique properties that make them challenging to analyze and model. Time-series regression model can describe relationships between multi-variables, taking concerning on time factor. Having more than two parameters in the forecasting model that are interacting in a multi-variant manner make the linear methods such as ARIMA may not be efficient in the prediction. A robust approach such as Long short term memory network (LSTM) and regression models, most researchers trained all data to work out a model which can probably be used to explain the existing data but is not suitable for prediction outside the knowledge of the existing range. Such models can be called the interpretive model.

In general, thermal physiological and psychological responses may have a time discrepancy with thermal environment variations under dynamic thermal conditions. Therefore, this paper put forward a data-driven prediction model on skin temperature (physiological) and thermal sensation (psychological) under the condition of dynamic solar radiation, attempting to provide a quick and accurate method for generating skin temperatures and thermal sensations.

**Methods**

**Dataset acquisition and Experimental validation**

A field experiment on thermal physiological and psychological responses under step-change solar radiation was conducted in June 2022. A total of 15 subjects were recruited in this study, including 7 males and 8 females, who were healthy and well-proportioned. During the experiment, the subjects wore uniform clothing. Intermittent solar radiation exposures were designed in the field experiment. A five-minute solar exposure followed by a five-minute shadow stay for three loops was set. The experimental site was selected on the square near a semi-open space, where respondents could switch between solar exposure and non-solar exposure quickly. In each experiment, two subjects participated, eight groups of experiments were conducted, and a total of 15 experiments were conducted. Before each experiment, subjects were kept in a still state to keep the physiological conditions stable.

Considering the influences of solar radiation intensity and outdoor stay time on physiological parameters, the outdoor thermal environment parameters (solar radiation intensity, air temperature, relative humidity, and wind speed) were tested every 10 seconds automatically. At the same time, the human body's physiological parameters (skin temperature, heart rate, blood pressure, etc.) are continuously monitored. Skin temperatures were measured at five points, which are the forehead, back, abdomen, back of the hand, and calf. Thermal responses including thermal sensation were collected through questionnaires.

**Multi-variable time series model——LSTM**

Long short term memory network (LSTM) is a special variant of recurrent neural network (RNN), which has a “gate” structure. Whether data is updated or discarded is determined by the logic control of the gate unit, which overcomes the shortcomings of over-large influence RNN weight, gradient disappearance, and explosion, enables the network to a better and faster convergence, and effectively improves the prediction accuracy.

**Data pre-processing**

Data transformation is important for neural network training, which can accelerate the training speed with a good performance. One good data transform suggests the transformation of data to be within the same range as the output of the activation function that is used in the model training. The Rectified linear unit (ReLU) is the most widely used activation function in the training of the neural network. It is provided by default from the PyCharm environment, and its derivative values are between 0 and 1. A good scaling for the data is to transform it to fall within the same range. The MinMaxScaler function provided by the sklearn pre-processing library is used for this.

The data are then transformed into supervised data (input and output patterns). The previous observations of the previous time step are used as input to the network at the current time step. The data are then transformed into supervised data (input and output patterns). The previous observations of the previous time step are used as input to the network at the current time step.

**LSTM model configuration**

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Before training the LSTM model, some hyper-parameters should be determined by tests, such as the number of hidden layers, and the number of neurons at each hidden layer. These model parameters are set to several values empirically and then select the most stable parameters through experiments, which means that the training error changes a little after a specific setting.

Five-fold cross-validation was applied to test the performance and stability of each parameter setting where the value of one parameter is changed within a specific range and the others are kept fixed. The fold that generates the best accuracy will use its configuration as the optimal choice for the investigated parameter. The k-fold cross-validation is a re-sampling method that divides the original dataset into k groups, and each sub-dataset will be used as a validation set. The model is trained and tested in different subsets of data to evaluate the model performance on the validation set. The model parameters are given in Table 1.

**Table 1 LSTM model configuration.**

<table>
<thead>
<tr>
<th>Network Parameter</th>
<th>Configuration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of hidden layers</td>
<td>2</td>
</tr>
<tr>
<td>Number of neurons at each hidden layer</td>
<td>50</td>
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</tbody>
</table>

The LSTM model training process was conducted in the Tensorflow package in Python.

**Results**

**Predicted skin temperature model based on LSTM model**

Here we adopted the LSTM model to establish a prediction model on skin temperatures. Applying thermal environmental parameters (air temperature, relative humidity, wind speed, and global solar radiation) as model inputs to predict skin temperature, and the five-fold cross-validation results are given in Figure 1. The predicted skin temperatures are in accordance with experiment data with RMSE ranging from 0.038 to 0.050. The LSTM-based model has a good performance in predicting skin temperatures.

<table>
<thead>
<tr>
<th>Number of epochs</th>
<th>500</th>
</tr>
</thead>
<tbody>
<tr>
<td>Learning rate</td>
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<td>Activation function</td>
<td>ReLU</td>
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<td>Weight initialization</td>
<td>Normal distribution</td>
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<tr>
<td>Loss function</td>
<td>RMSE</td>
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</tbody>
</table>

The LSTM model training process was conducted in the Tensorflow package in Python.
**Predicted thermal sensation model based on LSTM model**

Thermal sensations under dynamic solar exposure are predicted through the LSTM model. The four thermal environmental variables are model inputs here as well. However, here only 2/3 of the original data were trained with the LSTM model. The left data were used to validate the model's accuracy. The model performance is shown in Figure 2. Although RMSEs ranging from 0.699 to 1.027 show a significant error, the predicted thermal sensation has a similar trend with experiment data. A lack of database or inappropriate inputs may lead to the result. Besides, unlike the strong theoretical relationship between skin temperature and the thermal environment (Heat transfer between the human body and thermal environment follows the Fourier laws), thermal sensation may be also influenced by human thermal adaptation. This may aggravate the error between the predicted and the original data.

To test the model accuracy, three original sub-datasets are compared with predicted thermal sensations shown in Figure 3. RMSEs between predicted and validated data are 0.084, 0.175, and 0.263, which has a quite good performance. This may be caused by model overfitting or data distribution discrepancy between test and validated data. To solve the above problem, model parameter
adjustments and database expansion may improve the model performance.

\[
DTS = 3 \times \tanh \left( a \cdot \Delta T_{sk,m} + F_2 + \left( 0.11 \frac{d^2 T_{sk,m}}{dt^2} \right) + 1.91 e^{-0.681t} \cdot \Delta T_{sk,m} \cdot \frac{1}{1 + F_2} \right) \tag{1}
\]

Where \( a \) is regression coefficient, \( \Delta T_{sk,m} \) is the error signal of mean skin temperature, \( ^\circ C \), \( F_2 \) represents the influences of thermal strain caused by body core, \( T_{sk,m} \) is the mean skin temperature, \( ^\circ C \).

Based on measured skin temperatures, DTS can be generated. The comparisons between DTS and LSTM-predicted thermal sensation are shown in Figure 4.

As Figure 4 shows, the LSTM model has a better performance in predicting dynamic thermal sensation compared with the DTS model. DTS model has an obvious time lag with real thermal sensations. This is maybe caused by non-Fourier heat transfer in skin tissues, which would lead to a time lag in skin temperature. As Equation (1) shows, DTS is determined by skin temperatures. Thus, DTS would have a time lag between thermal sensations and real sensations.

**Comparison between the thermophysiological model and LSTM model**

Fiala developed a dynamic thermal sensation model (DTS), which is derived from a relationship between time series of thermal sensation votes from experiments with dynamic physiological parameters predicted by the Fiala multi-node thermoregulation model (Dusan Fiala, 2003). The regression was performed taking into account the nonlinear trend of measured sensation votes when thermal sensation approaches asymptotically the lower and upper limit of the ASHRAE 7-point scale. DTS can be calculated by Equation (1):
Conclusions
Based on the LSTM model, a skin temperature prediction model, and a thermal sensation prediction model were established. The predicted skin temperature has an accordance with experiment data with RMSE below 0.05 while the predicted thermal sensations have a significant difference from original data. However, for the test dataset, the performance is quite well in predicting thermal sensations. Compared with thermophysiological models (DTS), the LSTM model has a better prediction accuracy in thermal sensations.

Skin temperatures have a strong relationship with the expose thermal environment following the heat transfer theory. People may have adaptions or thermal expectations of the thermal environment, which could lead to discrepancies between thermal sensations and the thermal environment.

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References