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On-line adaptive personalized dynamic thermal comfort (PDTC) model using recursive least square estimation

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Abstract. In this paper, we study the problem of modeling individual differences and dynamic perceptions in thermal comfort. Hardly had any researchers done this work before. In this paper, we propose a method to model the personalized dynamic human thermal comfort, which is different from the traditional thermal comfort research. The proposed model is established based on previous related research, with four personalized parameters to be dynamically estimated. Recursive least square estimation with forgetting factor method is used on-line to learn the personalized parameters. Experiment was operated in an office room with individual thermal perception vote and environment measures. Comparisons with typical black-box model methodology and PMV are performed besides model validation results. The results show that the model has captured the dynamics and individual differences with high accuracy.

Keywords: personalized dynamic thermal comfort model, recursive least square estimation, forgetting factor, Artificial Neural Network

1. Introduction

Modelling human comfort satisfaction, which may relate to not only the physical environment, but also psychology and physiology, is a complex and difficult problem. Intensive studies have been done in this area. Most of existing work was focusing on average thermal comfort models based on data for a group of persons. One line of modelling is based on experimental data. Based on laboratory and climatic chamber researches, P. O. Fanger proposed PMV and PPD model [1]. C.C.Federspiel [2] and Michael A. Humphreys [3] gave the modification, validation and extension of the PMV model. Another line of modelling is based on physiology theory. Gagge [4] developed an easy-to-implement two-layer (core and skin) model of human. At the same time, Stolwijk [5] established multi-segment mathematical model of entire human body. Re-evaluations of the physiological model and further discussions and extensions are still ongoing [6,7,8]. Among these models, Fanger's PMV model received most attention. Effective Temperature (ET*) and Standard Effective Temperature (SET*) are the ASHARE standard [9,10] based on the PMV model.

Very few researches have been done on the models about individual differences and dynamic perception of thermal comfort. Related to this question, the dissertation of M.C. Feldmeier [12] proposed the personalized thermal comfort control concept, whose focus was on the individual thermal devices design and implementations. Liu W.[13] applied artificial neural network to model the individual thermal evaluation model, but it is a black-box model without any physical explanation. The difficulties of dynamic individual thermal comfort model lie in how to capture the individual difference and dynamics in thermal perception while keeping the structure simple and clear.

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This paper focuses on building a personalized dynamic thermal comfort model. The remaining part of this paper is organized as follows. We introduce our model in Section 2. In Section 3, experiment settings and learning algorithms will be given. We will do model validation and comparison in Section 4. We conclude the paper in Section 5.

2. Personalized Dynamic Thermal Comfort Model

We follow Fanger's general framework [1] to regard comfort models as maps from environment to the human thermal perception vote and build our model based on experimental data. But we emphasis the individual differences in thermal perception by noting the fact that the thermal perception is different for different individuals and under nearly the same environment; the same person may have different thermal satisfactory at different time. Classic thermal vote scalar, which ranges from -3 to 3, is utilized in the model.

We use parameterization method to capture the individual differences in thermal comfort perception. Since heat exchange is the main physiological procedure affecting the human thermal perceptions [1], we choose our model structure by identifying key factors related to heat exchange.

Normally, the balance of human body's heat exchange, which is the heat loss equals to the heat production, means the neural thermal perception, i.e. zero vote. The main factors of the heat balance are metabolic heat production M, activity levels W, heat loss due to the respiration and sweating E, the convective heat loss C, and the radiant heat loss R. Notice we can consider R and C together as one item *R*+*C* because it can be interpreted as the effect of the human-clothing system [15]. So, we regard the perception thermal vote as a linear combination of four items, namely *M*, *W*, *E* and *R*+*C*.

We notice that two basic variables P_a, the vapor pressure, and t_a, the air temperature play important roles in the expressions of the respiration and sweating heat loss E [14]:

$$E = 0.42(M - W - 58.2) + 0.0173M(5.867 - P_a) + 0.0014(34 - t_a)$$

To simplify the analysis, we assume that the clothing index is constant as the general working clothes, and the metabolic rate M and the activity level W are constant. We then have the following form for the perception thermal vote.

$$PTV = m_0 + m_1 P_a + m_2 t_a - m_3(R + C) \tag{1}$$

The coefficients $m_i, i = 1,2,3,4$ represent contributions of the related parts to the thermal perceptions. Each individual may have different set of those coefficients, reflecting the individual differences. Note that the contributions of temperature are not only related to m_2 for the reason that P_a, the vapor pressure, is closely related to air temperature while the relative humidity's contribution is only related to m_1.

Since the parameters of PTV in (1) are in fact time-variant due to the dynamic characteristics human thermal perceptions, we further introduce the Personalized Dynamic Thermal Comfort (PDTC) model as follows

$$PDTC(k) = m_0(k) + m_1(k)P_a + m_2(k)t_a - m_3(k)(R + C), \tag{2}$$

where $m_i, i = 0,1,2,3$, are parameters need to be estimated and are functions of k, the moment the vote occurs. Note PDTC can also be formulated as the form used more often in system identification literature:

$$PDTC(k) = \phi(k)X(k)$$

where $X(k) = [m_0(k), m_1(k), m_2(k), m_3(k)]^T$ is the parameter vector, and $\phi(k) = [1, P_a, t_a, -(R + C)]$.

3. Experiments and Data Processing

3.1. Experiment Settings

We selected an office with 5 students and 4 teachers working in it as our experiment platform to collect individual thermal perception votes. Its area is about $5\times 12m^2$. 5 sets of sensors, each of which includes a black ball sensor (radiant temperature sensor), a wind speed sensor, a dry ball sensor (relative humidity sensor), an illumination sensor and a sound level sensor connected together by a data collection box, are evenly distributed. The HVAC system in the office ran normally as usual. Occupants in the room were asked to vote in their computer every one hour during their office time. The thermal sensation vote panel was designed as a scrollbar, with five sensation references. They are extremely hot, warm, neural, cold, extremely freezing. These five levels map to a scalar range from 3 to -3, with neural perception associated with value 0.

3.2. Data Processing

We use recursive least square with forgetting factor [16] to obtain the estimation of parameters in our PDTC model in (2).

Let $\xi(k)$ be the residual at the vote time k, i.e., the difference between the actual vote and the model predicted vote value. Then the estimation problem can be formulated as a minimization problem as follows.

$$\min \sum_{k=1}^{N} \lambda^{N-k+1} \xi(k)^2 \tag{3}$$

where $\lambda \in (0,1)$ is the forgetting factor. Proper selection of λ is striking a balance between the sensitivity and stability. The initial value of the recursive estimation can be obtained from the historical data before certain time, using general least square estimation. Then, as the time going on and new individual thermal votes coming, recursive estimation is performed on line to capture the new dynamics of individual preference.

We performed the experiment from November, 2009 to January, 2010, which is the fall and winter season in Beijing. All the sensors were calibrated before the experiment. Note that the first vote of each day for each person is ignored during the calculations since at the beginning of the day, occupants' first vote will bring more noisy information because of the unstable physiological levels caused by the outside movements during their way to work, such as hiking or riding.

We weigh the vote pre-processed data day by day. In the same day, all the vote values are seen equally, while the past days' data are damped by the forgetting factor. The initial value of the model is estimated with the first half amount of the vote samples, using the general least square error estimation. Then the recursive least square estimation is applied. Forgetting factor is chosen as 0.9, which is the usual choice in estimation and system identification. The left of Figure 1 gives estimation results for two subjects. As can be expected, the four parameters are different for the two individuals from 15th, December, 2009 to 12th, January, 2010. The red circles indicate the dramatic changes caused by dramatic drop of outdoor temperature and high wind speed. For example, around 24th, December, 2009, the outside lowest temperature dropped down significantly from -5 to -14, at the same time, the averaged wind speed jumped from 7km/h to 26km/h. Detailed analysis and validations will be given in the next section.

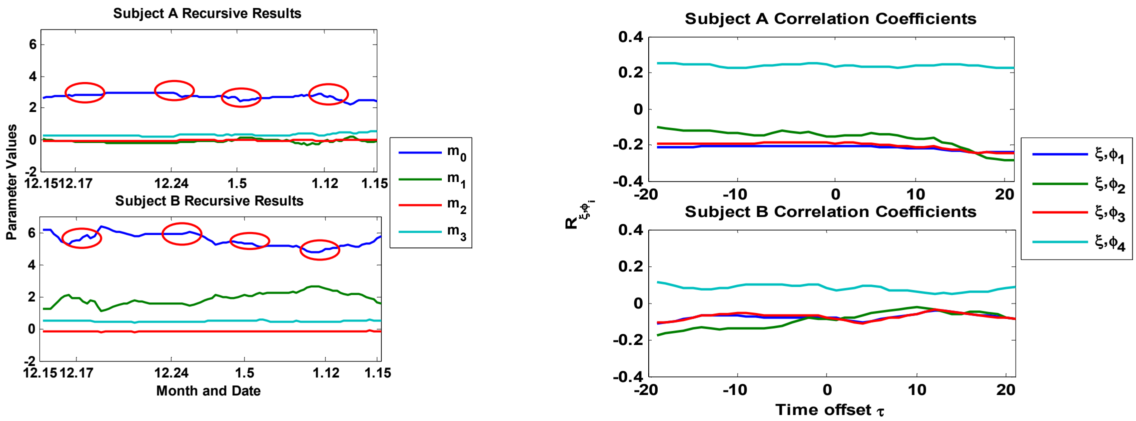

Fig. 1: Left: Two examples of recursive regression results. Right: Residual analysis results.

4. Model Validation and Comparisons

4.1. Model accuracy

Here mean square error is the mean square of the difference between model prediction vote values and the actual individual vote values. In order to make comparison more complete, we also process our data with a black box model, namely, Artificial Neural Network (ANN). Here we first perform a simple ANN with the model structure suggested by [13] (with 5 units in the hidden layer and the transfer function in each layer is tan-sigmoid type). To further improve ANN's accuracy, we also increased the number of units in hidden layer to 15 units. The MSE of all models PDTC, PMV, ANN (with 5 units) and ANN (with 15 units) on 9 subjects are reported in Table I.

It can be seen that the MSE of PDTC is smaller than PMV and PDTC have nearly the same accuracy with the ANN (with 15 units) which can be regarded as a lower bound for the optimal model since it has good approximation ability (it is well known as the number of hidden layer units goes to infinity, ANN can fit arbitrary nonlinear function). For some subjects, the MSE of PMV is much larger, which just reflects the PMV's inability of describing the individual differences, indicating that PDTC can perform quite well for almost all the individuals. We claim that PDTC have advantages over ANN since ANN network is a total black-box model, which has no physical meanings and interpretations. The estimated parameters in PDTC however can be interpreted as the contribution ratios of temperature and humidity to individual thermal comfort.

TABLE I. MEAN SQUARE ERROR COMPARISON FOR FOUR MODELS

Subjects	PDTC MSE	PMV MSE	ANN MSE(15)	ANN MSE(5)
1	0.7820	2.4916	0.7085	0.8705
2	0.7897	3.4994	0.7502	0.7722
3	0.5052	1.2999	0.3645	0.3930
4	0.2685	0.7130	0.2773	0.2846
5	0.3258	0.4633	0.3645	0.3930
6	0.1314	0.5885	0.1001	0.1097
7	0.7246	0.6777	0.4468	0.5171
8	0.2690	0.2640	0.2254	0.3187
9	0.5002	0.4327	0.3367	0.3938

4.2. Residual analysis

In order to validate whether our model's structure is sufficient and reasonable in handling the dynamics of the human perception, we check the independence between the residuals and past inputs. According to the system identification theory [17], such a residual analysis is important in model validation. The "leftovers" from the modelling process—the part of the data that model could not reproduce—are the residuals. It is clear that these bear information about the quality of the model. The independence between the residuals and past inputs means that the information in the residual is independent of the model, reflecting that the model has a sufficient and reasonable structure.

Define $\phi(k)=[1,P_a,t_a,-(R+C)]=[\varphi_1,\varphi_2,\varphi_3,\varphi_4]$, and the correlation coefficient of residual and the inputs can be expressed as

$$R_{\xi\varphi_i}(\tau)=E\xi(t)\varphi_i(t-\tau), i=1,2,3,4 .$$

Where τ is the time offset. Computation results for the same subjects are illustrated in the right part of Figure 1. The absolute values of correlation coefficients are less than 0.3, so are the rest of the subjects' results. These indicate the good independence [17] between residuals and past inputs.

4.3. Discussion of the generalization capability of the model

We also use cross-validation method to test the generalization capability of PDTC. The training set is chosen as the votes at time $2k+1$, the validation set is chosen as $2k$, where $k=1,2,\ldots$. Training set data are used online to train the model, while mean square errors of validation set are calculated. The average MSEs increase but they are still 37.2% smaller than PMV, indicating that our PDTC has good generalization capability.

5. Conclusions

The on-line adaptive personalized dynamic thermal comfort (PDTC) model proposed in this paper captures the individual differences in the thermal perception and the dynamics of the perception for each subjects in our experiments with higher accuracy than the well known PMV model and achieve similar accuracy as black box models such as ANN while has much simpler model structure. Residual analysis shows our PDTC model also provide a sufficient and reasonable structure in capturing dynamics in human thermal perception. Further studies need to be done to quantify various influence factors and their interactions, such as gender, age and living habits, etc..

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