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A fuzzy neural network model for predicting clothing thermal comfort

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Abstract

This paper presents a Fuzzy Neural Network (FNN) based local to overall thermal sensation model for prediction of clothing thermal function in functional textile design system. Unlike previous experimental and regression analysis approaches, this model depends on direct factors of human thermal response — body core and skin temperatures. First the local sensation is predicted by a FNN network using local body part skin temperatures, their change rates, and core temperature as inputs; then the overall sensation is predicted. This is also performed by a FNN network. The FNN networks are developed on the basis of the Feed-Forward Back-Propagation (FFBP) network; the advantage of using fuzzy logic here is to reduce the requirement of training data. The simulation result shows a good correlation between predicted and the traditional experimental data.

Keywords: Thermal sensation; Functional textile design; Fuzzy neural network; Feed-forward back-propagation; Clothing thermal comfort

1. Introduction

Today numerous consumers consider thermal comfort to be one of the most significant attributes when purchasing textile and apparel products, so there is a need to develop a functional garment CAD system. In recent years, many textile thermal function models and simulation systems have been developed [1–3]. They can simulate human thermal physiological status and clothing heat and moisture transfer processing for designated arbitrary garment constructions and thermal environments.

Because the human–clothing environment is a transient and non-uniform thermal environment, up to now there has been no appropriate thermal comfort model to evaluate clothing thermal comfort. The existing literatures on human thermal sensation and comfort are generally focused on steady-state and uniform conditions. Representatives are Fanger's PMV (Predicted Mean Vote) model [4] and Gagge's two-node model with its indices of TSENS (Thermal Sensation) and DISC (Thermal Discomfort) [5]. They are the basis of ASHRAE *Standard* 55-1992 and ISO EN 7730 *Standard*. There are also works addressing transient and non-uniform conditions separately [6,7]. The above models are usually aimed at representing relationships between environment conditions and human thermal responses. In

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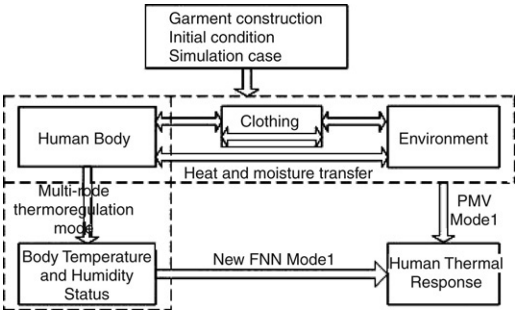

Fig. 1. System structure.

order to develop a model under both transient and non-uniform conditions, Zhang explores the relationship between human body physiological status (skin and core temperatures with their change rates) and thermal response [8]. Zhang's model explains many phenomena concerning comfort adaptation and asymmetrical experiences, but its mathematical model is not practicable as it is limited by having too many coefficients, and because of the experiment's limitation, the regression analysis result cannot be assured either.

The statistical methods in this research have several limitations; these include difficulty of coping with complex non-linear relationships with so many variables, lack of adaptive ability, and difficulty of gathering undisturbed psychological sensation and comfort vote data. On the other hand, neural networks and fuzzy logic show tremendous success in many fields. Artificial Neural Networks (ANN) and fuzzy logic have been widely used in many fields related to the thermal environment and comfort. Hamdi develops a fuzzy comfort model which is deduced from Fanger's PMV equation [9]; Wong proposes an ANN model to predict an overall comfort perception from 10 individual sensory perceptions [10]. These works have shown good applicability of ANN for studying neurophysiology and psychology processing.

Fuzzy Neural Networks (FNN) provide us with a very human–machine friendly knowledge representation scheme for acquiring, representing and using the knowledge of the domain expert. This is a significant advantage for thermal comfort areas where the exact system transfer functions cannot be well modeled and adequate training data sets are not available. In this paper, we developed a FNN thermal comfort model for evaluating human thermal comfort in a functional textile design system. The knowledge bases and rules are mainly from the literature, especially Zhang's experiment [8]. The following sections present the model description, the FNN design, training and simulation result analysis.

2. Model description

2.1. Functional textile design system

Li et al. developed an integrated model for simulating interactive thermal processes in a human–clothing system [1], in which Stolwijk's multi-node model is modified by considering the sweat accumulation on the skin surface, and is applied to simulate the human physiological regulatory response. Then the human model is interfaced with a coupled heat and moisture model of clothing materials in which the adsorption of water vapor in the fibers is taken into consideration. In addition, a multi-layer clothing system is also developed and integrated with the human model. On the basis of this, a clothing thermal function evaluation model is needed to complete the thermal functional textile design system. Unlike current ASHRAE or ISO standards, the new model is a physiological model which reflects the relationship between body temperatures and thermal response. Fig. 1 shows the system structure.

2.2. Sensation and comfort

According to Zhang, the local body parts' thermal perception cannot be ignored for reflecting human thermal comfort under a transient and non-uniform environment; therefore the model includes local sensation, local comfort, overall sensation and overall comfort. However, the proposed new model only addresses thermal sensation. Thermal comfort, which is generally defined as the condition of mind which expresses satisfaction with the thermal

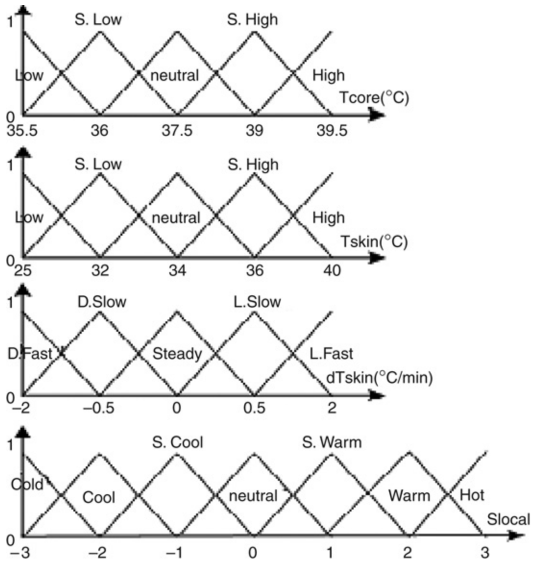

Fig. 2. Input variable membership functions.

Table 1
List of linguistic expressions

v-name	Linguistic terms	Exact value range	Unit
T_c	(low, slightly low, neutral, slightly high, high)	[35.5, 39.5]	°C
T_s	(low, slightly low, neutral, slightly high, high)	[25, 40]	°C
$\mathrm{d}T_s/\mathrm{d}t$	(fast decrease, slow decrease, steady, slow increase, fast increase)	[−2, 2]	°C min^{-1}
S_l	(cold, cool, slightly cool, neutral, slightly warm, warm, hot)	[−3, 3]	–

environment, is an emotional experience which may be described as "pleasant" or "unpleasant" [11]. It is difficult to exactly predict comfort, since there are so many factors. Here we have developed the local and overall sensation model to reflect the whole-body thermal state under a transient and non-uniform environment; the physiological parameters (skin and core temperatures, rate of change of the skin temperature) are given as inputs.

2.3. Local sensation model

The local sensation model is used to investigate every local body thermal sensation according to body core and local skin temperature data. Local sensation is directly linked with skin temperature and its change rate. The target is to reflect the adaptive characteristics of the thermoreceptors. Zhang's model uses a set point, which is floating with the body temperature. This is not a practical method. Furthermore, the statistical function has difficult coping with complex non-linear relationships between body temperatures and sensation. In a human being's thermoregulatory system, core temperature will be influenced by the change of skin temperature. In other words, core temperature can reflect the accumulated effect of skin temperature changes, i.e. adaptation. Therefore, the local sensation (S_l) is a function of core temperature (T_c), skin temperature (T_s) and its change rate ($\mathrm{d}T_s/\mathrm{d}t$), as in Eq. (1).

$$S_l = f(T_c, T_s, \mathrm{d}T_s/\mathrm{d}t). \tag{1}$$

Each particular body part has its own local sensation model (same FNN structure, different weights). In a FNN, the fuzzy membership function's coefficient is determined by the neural network; the definitions of the linguistic variables and supposed triangular membership functions for the variables are as shown in Table 1 and Fig. 2 respectively.

The inference rules are extracted from the literature [8] and life experiences. Example rules are as follows (for the hand):

if T_{core} is neutral and T_{skin} is low and $\mathrm{d}T_{skin}$ *is steady, then the hand sensation is cold*;

if T_{core} is slightly high and T_{skin} is low and $\mathrm{d}T_{skin}$ *is steady, then the hand sensation is cool*.

Table 2
Body groups by thermal impact weight

Variable name	Body group	Body part
S_{big}	Big impact	Back, thigh (left, right)
S_{middle}	Middle impact	Chest, abdomen; upper arm, calf (left, right)
S_{small}	Small impact	Forehead; forearm, hand, foot (left, right)

2.4. Overall sensation model

In a uniform condition, the definition of overall sensation is obvious; it means the whole body's global warm or cold feeling. However in a non-uniform environment, the different local sensations exist simultaneously. Therefore it is necessary to integrate all local sensations. To decrease the difficulty of training the network, we simplify the input variables by grouping body parts based on the thermal impact weight (imitating the mean skin temperature calculation [12]) for the whole body. Table 2 shows the grouping details.

The local sensation is chosen as the input value for this group if it has the biggest deviation from the weighted mean sensation in its group. The calculation equations are as follows:

$$\bar{S}_l = \sum_i W_i S_{li} \Big/ \sum_i W_i \tag{2}$$

$$S_g = \bar{S}_l + \max(S_{li} - \bar{S}_l) * \operatorname{sgn}(S_{li} - \bar{S}_l) \tag{3}$$

where the parameters are defined as:
$\bar{S}_l$: weighted mean sensation.
S_l: local sensation.
W: weight of local sensation.
S_g: sensation deviation value of group.
Note: In Eq. (3), the sign function is used to restore the original value affected by the absolute value calculation.

The chosen three groups' sensation values are inputs for the overall sensation. Here all input and output variables are thermal sensations; their linguistic definitions and the membership functions are the same as in the local sensation model. An example inference rule is as follows:

If S_{big} *is neutral and* S_{middle} *is neutral and* S_{small} *is cold, then the overall sensation is cool*;
If S_{big} *is cool and* S_{middle} *is cool and* S_{small} *is cold, then the overall sensation is cool*;
...

3. FNN design and implementation

The essence of neural networks lies in the distributed memory of knowledge and processing, in massive interconnections and interactions, and in learning and self-organization. Neural networks are considered as universal approximators; they provide a generic framework for a wide range of problems. Multi-layer feed-forward networks with sigmoid transfer functions can approximate any continuous multivariate function arbitrarily well, if properly designed. While training the network requires a training data set which must be large enough and properly distributed to represent the whole data range, fuzzy neural networks can decrease the training data set requirements by incorporating expert knowledge with the fuzzy concept. Moreover, a NN based model is highly flexible and is easy to implement on computers.

The FNN of local and overall sensations are both four-layer feed-forward back-propagation networks, as shown in Fig. 3. The number of input units is same as that of input variables; the first hidden layer represents the fuzzy subsets of the inputs, and the second hidden layer represents the fuzzy subsets of the output; the fourth layer is the output layer with just one unit related to the one output. The sigmoid functions are chosen as input activation functions, and linear functions for other layers. Thus the complex non-linear map is achieved and the output range is unlimited.

The network is trained in Matlab®. On the basis of fuzzy membership functions and inference rules, the exact input–output value pairs are obtained as the training data set. Network training is in a supervised manner with a highly

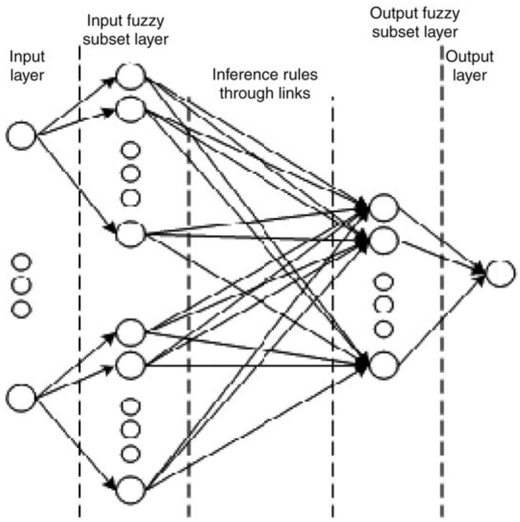

Fig. 3. FNN structure.

Table 3
Simulation cases

Case	Condition (as PMV model's inputs)
Warm steady	$T_a = 30$ °C, $T_{\mathrm{mrt}} = 30$ °C, $V_{\mathrm{air}} = 0.01$ (m/s), RH = 50%, $M = 1$ (Sedentary), Clo = 0.0.
Cold steady	$T_a = 15$ °C, $T_{\mathrm{mrt}} = 15$ °C, $V_{\mathrm{air}} = 0.02$ (m/s), RH = 50%, $M = 1$ (Sedentary), Clo = 1.0.
Transient	First in warm steady, 10 min later, switch to cold steady (20 min).

popular algorithm known as the error back-propagation algorithm. After the training is completed, a C++ module is developed to represent the network structure and trained link weights, and used to predict clothing thermal function.

4. Simulation results and discussion

The model developed was tested using the temperature data which were generated from the integrated human–clothing simulation system [1]. Because Zhang's mathematical model was not published, we chose two typical simulation cases under steady conditions as the initial conditions for the simulation system, and compared the prediction results between our models and Wyon's EHT model. We also gave both transient and non-uniform simulation cases and used our model to predict the thermal response. The simulation cases and prediction results are shown as Table 3 and Figs. 4–6 respectively.

This is a typical scenario in early winter: the people go outdoors with thin clothing, barefoot. Fig. 4 shows under warm steady conditions the temperatures and thermal sensation predictions for six body parts and the core (overall), comparing with the EHT prediction. Fig. 5 shows the cold steady case. The predicted results are very close for the two models, proving the feasibility of using the FNN model. In Fig. 6 the foot temperature and thermal sensation prediction are illustrated, as well as the overall sensation at the same time. We can see that the result agrees with life experiences very well.

Up to now there have been no suitable experimental data for validating the FNN model; here we have just given simple cases. The fuzzy initial function and inference rules also need to be improved to assure the correctness of the final prediction. Comparing with the previous static approach in thermal perception research, "*The static models are based on extensive and rigorous laboratory experiments and yield fairly consistent, reproducible results between climate chambers. The question is whether the simplistic cause-and-effect approach embodied in these laboratory-derived models can be applied, without modification, to describe the real-world thermal perception*" [13]. The FNN model can contribute in two respects: to solve the difficult of the regression analysis in such multivariable physiology, neurophysiology and psychology thermal response process by the human-like fuzzy neural system; and to point out an

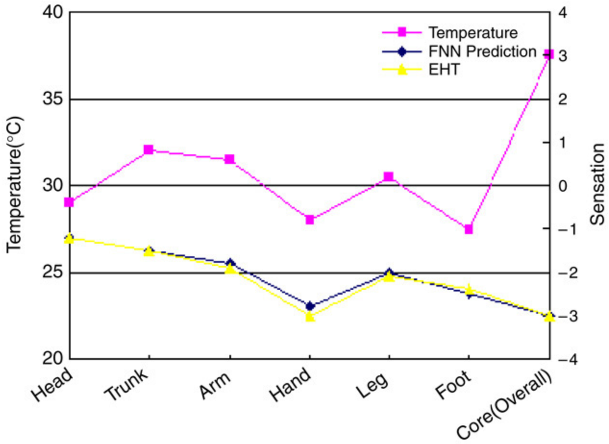

Fig. 4. Temperature, sensation comparison under cold steady condition.

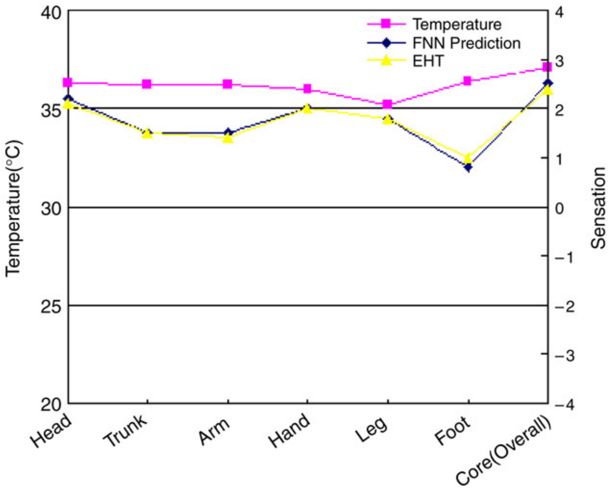

Fig. 5. Temperature, sensation comparison under warm steady condition.

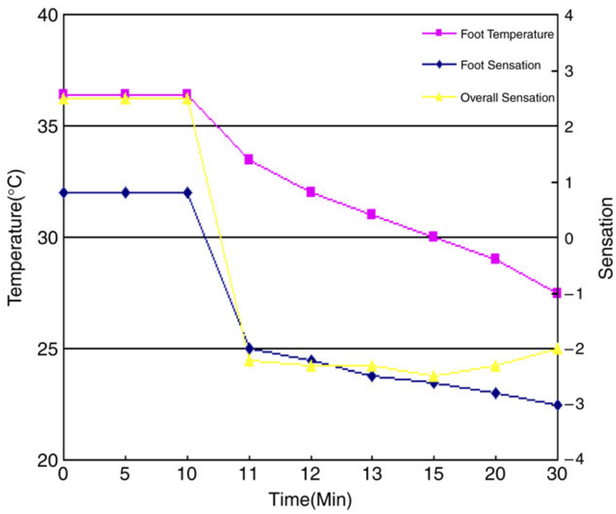

Fig. 6. Temperature, local sensation of foot and overall sensation.

easy and reliable experiment plan by following the limited fuzzy rules; thus it not only avoids the rigorous laboratory environment disturbance but also avoids obtaining adequate varied data.

5. Conclusions

A fuzzy neural network model for clothing thermal function evaluation in a dynamical and non-uniform environment is developed, and tested in a functional textile design system. This model predicts a human's local and overall thermal sensations according to physiological parameters including core and local body part temperatures and the rates of temperature changes. The test results for simulation data verified the reliability of this human-like approach. Our next step is to improve the fuzzy initial functions and inference rules by thorough experiments, and to add the humidity affect into this model.

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