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Machine learning approaches to predict thermal demands using skin temperatures: Steady-state conditions

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A B S T R A C T

Inefficient controlling strategies in heating and cooling systems have given rise to a large amount of energy waste and to widespread complaints about the thermal environment in buildings. An intelligent control method based on a support vector machine (SVM) classifier is proposed in this paper. Skin temperatures are the only inputs to the model and have shown attractive prediction power in recognizing steady state thermal demands. Data were accumulated from two studies to consider potential use for either individuals or a group of occupants. Using a single skin temperature correctly predicts 80% of thermal demands. Using combined skin temperatures from different body segments can improve the model to over 90% accuracy. Results show that three skin locations contained enough information for classification and more would cause the curse of dimensionality. Models using different skin temperatures were compared. Optimal parameters for each model were provided using grid search technique. Considering the overfitting possibility and the cases without learning processes, SVM classifiers with a linear kernel are preferred over Gaussian kernel ones.

1. Introduction

Widespread in both residential and commercial buildings, heating, ventilation and air conditioning (HVAC) systems consume almost 20% of the world's energy. The benefits from this consumption are not as great as they should be. In a large study, only 11% of buildings met the basic criterion [1,2] that 80% or more of their occupants be satisfied with their thermal environment [3]. Behind the unsatisfactory cases may be ineffective thermal environment control strategies.

Most of the air conditioning systems have temperature/humidity controllers. In some cases such as residential buildings and private offices, occupants tune the set points according to their perception, without a sense of what temperatures could be comfortable or the energy costs associated with the temperatures selected. As a result, the set points are frequently revised and energy is wasted [4]. In other circumstances like conference halls, occupants have little access to the controllers. Temperature is preset based on standard recommended temperatures or on the operators' feelings about what causes the least thermal complaints, which often results in overcooling of the space.

Over the past few decades, many thermal comfort controllers have been proposed [5–7]. The essential idea is to replace the occupants' feedback with thermal sensation prediction based on built-in comfort models or data-driven self-learning methods. The inputs are commonly physical environment parameters such as air temperature, humidity, air velocity and radiation temperature. Measuring these in occupied spaces presents a number of challenges. In addition, clothing insulation and occupant activity level are difficult-to-measure factors that greatly affect comfort model accuracy. To alleviate these problems, one potential approach is to control the thermal environment based on physiological parameters.

The dramatic progress of wearable devices has created technology ready for monitoring body parameters in daily life. Surface body temperature sensors could be attached to watches, clothes and so on. Fiber Bragg grating (FBG) based sensors have made it possible to monitor the skin temperature of different body parts under intelligent clothing [8]. The development of infrared camera technology also makes it possible to capture uncovered skin

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temperatures remotely [9]. However, previous models linking sensation with physiological parameters such as by Fiala [10] and Zhang [11–14] are too complicated to be used in designing practical controllers.

To develop practical ways of using skin temperatures to control heating and cooling systems, Taniguchi et al. [15] proposed an equation to estimate car occupants' thermal sensation based on face skin temperatures. Wang et al. [16] conducted a lab study to explore the hypothesis proposed by Humphreys et al. [17] that finger temperature or an air and finger temperature combination was capable of predicting thermal sensations. They found that the temperature gradient between arm and hand could be a good indicator for cool sensation. To a certain extent, these studies have laid the groundwork for designing intelligent controller based on skin temperatures.

In this paper, we have combined a machine learning algorithm with local steady-state skin temperatures. Different SVM classifiers, model parameters and skin temperature combinations were tried to explore to what extent skin temperatures could go in predicting the thermal states. Exact ways of applying the prediction models to control heating and cooling system were proposed. We collected data from two studies to test the model performance for building areas with either one or more occupants. As the SVM approach needs a process of data learning, we discuss the learning sample sizes needed for certain classifiers to work well automatically, and also examine the performance of preset models for new occupants without training.

2. SVM controlling prototype

As shown in Fig. 1, the SVM approach is a data-driven model. During the learning procedure, data are collected in traditional ways in which occupants adjust the heating and cooling system according to their perception of the thermal environment. Thermal demands and corresponding local skin temperatures are input to the SVM classifiers to study decision boundaries. After that, SVM models predict the thermal demands of occupants based on real-time skin temperature measurements. The application scope of the controller is flexible, including but not limited to HVAC systems and more localized task-ambient conditioning (TAC) systems.

Imagine that one or more local skin temperatures $\boldsymbol{T}$ constitute an m-dimensional space, in which the sample data vectors $(\boldsymbol{T}, y)_i$ $(i = 1,\ldots n)$ are points with corresponding thermal demands y $(y = -1, 0, 1)$. The basic idea behind the SVM classifier here is to construct the optimal hyperplanes in the space that could differentiate the data vectors from others with different thermal demands. As the SVM classifier is basically a two-class method, a one-vs-one (OvO) strategy is adopted in this paper to reduce multiclass classification into a multiple binary problem [18]. Choosing a proper kernel function has always been the largest challenge in using SVM classifiers. In this paper, we compare the performance of linear and Gaussian kernels. Standardization of the dataset was implemented first. As there are two parameters C and Υ for the Gaussian kernel SVM classifier and one parameter C for the linear kernel SVM classifier, we used a “grid search” method on C and Υ to find the proper parameters for the classifiers. Exponentially growing sequences of C ($2^{-2}, 2^{-1}, 2^{0}, \ldots, 2^{10}$) and Υ ($2^{-10}, 2^{-9}, 2^{-8}, \ldots, 2^{4}$) were tried and the ones achieving the best cross-validation accuracy were picked. To grasp a good understanding of the SVM classifier, one can refer to the introductions of Hsu et al. [19] and Noble [20].

3. Experiment 1

This experiment considers the validation of SVM classifiers to learn and predict steady-state thermal demands for a group of occupants in a uniform environment. We place the focus on three basic issues: a. the selection of input features; b. the comparison of classifiers with different kernels; c. tuning parameters for the SVM models.

3.1. Methods

The data were accumulated from a series of tests carried out in the Controlled Environmental Chamber at UC Berkeley to correlate skin temperatures with whole-body sensations for a variety of warm to cool conditions. Sensation votes were obtained at the end of the periods used to acclimatize the subjects to the environmental conditions in the tests. 70 tests were conducted using 11 subjects, with 969 votes collected.

Subjects were first preconditioned to the day's test in a Jacuzzi bath for 15 min. After that, thermocouples were attached to collect local skin temperatures every 5 s. There were totally 28 body locations measured during the tests. Only 13 of them were used in this paper: the forehead, cheek, chest, back, abdomen and 8 extremity skin temperatures on left the side of the body: upper arm, forearm, hand, finger, thigh, shin, calf and foot (Fig. 2). Subjects wore a long-sleeve elastic leotard (0.32clo) and socks (0.02clo) with the thermocouples covered except those at head and hand locations. Whole-body thermal sensation was investigated repetitively by pop-up questionnaires on the computer at varying time steps of 1–3 min. Experimental details are graphically described in previous publications [21,22].

In this study, the first 10 votes in each test were abandoned in order to make sure that the data represent steady-state conditions. The total data set was here split into two subsets: a training set of 80% (774) and a holdout set of 20% (195). The distributions of total data and testing data are shown in Fig. 3.

The sensation scale is similar to the ASHRAE 7-point scale, adding “very hot” and “very cold” (9-point scale: 4- “very hot”, 3-“hot”, 2-“warm”, 1-“slightly warm”, 0-“neutral”, -1-“slightly cool”, -2-“cool”, -3- “cold”, -4-“very cold”). Statistical analysis was implemented in SPSS (IBM SPSS Statistics for Macintosh, Version 22.0). Data were classified into 5 groups based on the thermal sensation votes (TSV): heating demand (TSV < −1.5, cold); slight heating demand (−1.5 ≤ TSV < −0.5, cool); neutral (−0.5 ≤ TSV ≤ 0.5); slight cooling demand (0.5 < TSV ≤ 1.5, warm);

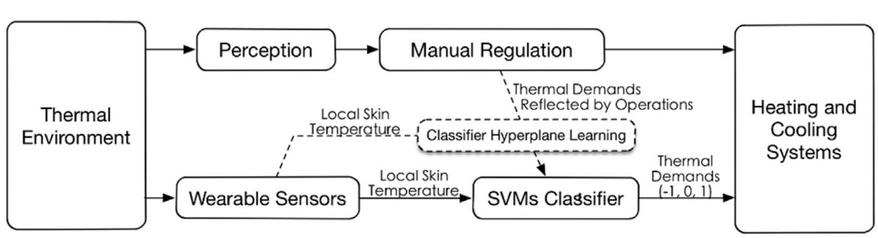

Fig. 1. The controlling concept of SVM classifier based on skin temperature.