Unsupervised Personal Thermal Comfort Prediction via Adversarial Domain Adaptation

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ABSTRACT

Personal thermal comfort models aim to predict an individual's thermal comfort response, instead of the average response of a large group. However, conducting large-scale experiments to develop such models for general occupants of a building is time and resource-intensive. At the same time, the developed models for experimental subjects do not always generalize to other building occupants. In this work, we propose a transfer learning framework, using Adversarial Domain Adaptation (ADA) to develop personal thermal comfort predictors for target occupants in an unsupervised manner. We also discuss inherent assumptions governing domain adaptation in this application and relevant future works.

CCS CONCEPTS

• **Computing methodologies → Machine learning**.

KEYWORDS

Thermal Comfort, Domain Adaptation, Transfer Learning

ACM Reference Format:
Hari Prasanna Das, Stefano Schiavon, and Costas J. Spanos. 2021. Unsupervised Personal Thermal Comfort Prediction via Adversarial Domain Adaptation. In *The 8th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation (BuildSys '21), November 17–18, 2021, Coimbra, Portugal.* ACM, Coimbra, Portugal, 2 pages. https://doi.org/10.1145/3486611.3492231

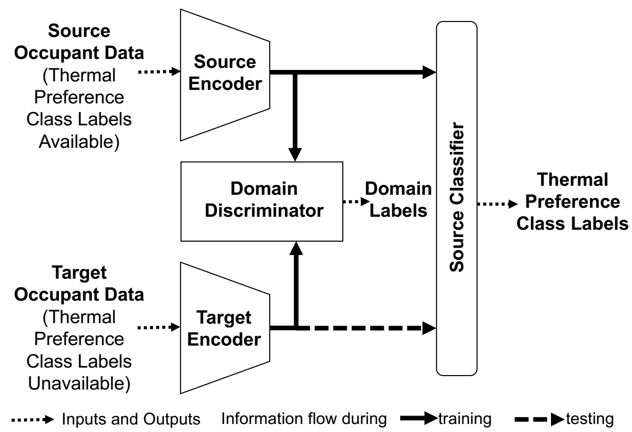

Figure 1: Schematic diagram of the proposed method

1 INTRODUCTION AND RELATED WORKS

Humans spend more than 90% of their day indoors, where their well-being, performance and energy consumption are demonstrably linked to thermal comfort. But, study shows that only 40% of commercial building occupants are satisfied with their thermal environment [2]. There has been significant amount of research done to develop models to accurately predict thermal comfort metrics for occupants in a building. Contrary to conventional group-based thermal comfort models, personal thermal comfort models [3] focus on developing thermal comfort predictors at a building occupant level. They have proved efficient in human-centric cyber-physical systems to efficiently regulate the building control systems, as well as to understand the correlation between human factors affecting comfort. The general process is to conduct experiments with human subjects and collect their physiological signals along with other environmental parameters, and thermal sensations and preference, to develop models to predict them. In general, such labels are hard to obtain for general occupants in a building. At the same time, the above developed models for experimental subjects do not generalize very well to others, as we will show later in the experiments. We propose an adversarial domain adaptation based method to transfer the knowledge from subjects with thermal preference labels available (hereby referred as the *source*) to those without the labels available (hereby referred as the *target*) and develop a thermal comfort model for the target occupant in an unsupervised manner.

Transfer learning for thermal comfort prediction has been studied at a city-level in [1]. Authors in [4] study transfer learning for personal thermal comfort, but do not focus on underlying assumptions on domain relatedness or few-shot learning cases. Adversarial domain adaptation has been extensively studied in various spaces, such as computer vision and smart buildings [5].

2 METHODOLOGY

The objective of this work is to improve the generalization capability of a personal thermal comfort classifier across multiple occupants without collecting labeled data for target occupant(s). Without loss of generalization, take the case of two domains, a single source occupant a single target occupant. We start by training the source encoder and classifier end-to-end using supervised data from source. For transfer learning, we embed the data from both the domains

BuildSys '21, November 17–18, 2021, Coimbra, Portugal

ACM ISBN 978-1-4503-9114-6/21/11.
https://doi.org/10.1145/3486611.3492231

into a common feature space, and align the target encoder with the source via ADA, in a completely unsupervised manner. At equilibrium, the target and source encoders are aligned, so the previously trained source classifier can be used along with the target encoder for testing in the target domain. The schematic is illustrated in Fig. 1, and the training steps are summarized below.

Step 1: Suppose N_s samples X_s with labels Y_s are collected in the source domain with L possible classes. Train a source encoder M_s and a source classifier C_s

$$\min_{M_s, C_s} -\mathbb{E}_{(x_s, y_s)\sim(X_s, Y_s)} \sum_{l=1}^{L} \left[\mathbb{I}_{[l=y_s]} \log C_s(M_s(X_s))\right]$$

Step 2: Train a target encoder M_t with X_t unlabelled target samples and fine-tune the source encoder M_s adversarially with a domain discriminator D. Discriminator loss:

$$\min_{M_s, M_t} \max_{D} \mathbb{E}_{x_s\sim X_s} \left[\log D(M_s(x_s))\right] + \mathbb{E}_{x_t\sim X_t} \left[\log(1 - D(M_t(x_t)))\right]$$

Encoder loss for M_s (similarly for M_t with target data X_t):

$$\min_{M_s} -\mathbb{E}_{x_s\sim X_s} \left[\log D(M_s(x_s))\right]$$

With aligned target encoder, thermal comfort prediction for the target domain can be done using the target encoder + C_s.

3 EXPERIMENTAL STUDY

In our previous work [3], we conducted an experiment to collect physiological signals (e.g., skin temperature at various parts of the body, heart rate) of 14 subjects (6 female and 8 male adults) and environmental parameters (e.g., air temperature, relative humidity) for 2–4 weeks (at least 20 h per day). The subjects also took an online survey, where they reported their thermal sensation (on a scale of -3 to +3) and thermal preference (Warmer, Cooler, No Change) among other parameters.

For this work, we developed deep learning based thermal preference classifier for 7 of the subjects, specifically using fully-connected neural networks for the encoder and classifier blocks. We consider permutations of subjects as source and target, i.e. (source,target) = $(i, j), i, j \in \{1, 2, \cdots, 7\}, i \neq j$, to test the extent of transfer learning between the subjects. We start by training a classifier for the source subject, and then align encoders for source and target as described in Sec. 2, finally performing testing in target domain using the aligned target encoder and previously trained source classifier. As a baseline, we directly test the source classifier in the target domain, without any knowledge transfer between the domains. The thermal preference classification accuracy is summarized in Fig. 2. We observed that for majority of the source/target pairs, the classification accuracy improves after there is transfer learning between the domains, and we are able to design a thermal comfort predictor in the target domain without using any labels. But, for some source/target pairs, the accuracy diminishes.

Target Subject ID \ Source Subject ID	1	2	3	4	5	6	7
1	68.35	44.60/53.24	54.68/53.24	53.24/53.24	53.96/53.24	28.78/33.81	44.60/53.24
2	42.62/52.32	66.67	53.59/56.12	56.12/56.12	29.54/56.12	25.74/19.83	51.48/56.12
3	63.54/69.10	60.76/68.06	85.42	69.10/69.10	30.90/69.10	23.61/13.54	64.58/69.10
4	63.64/88.48	86.67/88.48	81.21/88.48	89.09	50.91/88.48	5.45/6.06	81.82/5.45
5	55.24/51.75	48.25/51.75	50.35/51.75	51.75/51.75	72.73	23.78/4.90	53.15/51.75
6	36.08/48.10	30.38/31.65	18.35/18.35	18.35/18.35	32.28/18.35	64.56	18.99/18.35
7	37.07/12.36	62.93/65.64	59.85/65.64	65.64/65.64	42.47/16.60	24.32/11.97	80.69

Figure 2: Comparison of thermal preference classification accuracy on target data using a trained source encoder+classifier vs a transfer learning based target encoder+source classifier. Green/Red blocks: Accuracy increases/decreases after ADA.

4 DISCUSSION AND FUTURE WORK

While aligning multiple domains, there is an inherent assumption that the domains share the same set of features at a common feature space. The objective is to obtain a space in which the domains are close to each other while maintaining good performance on the source labeling task. For the above case, the thermal comfort at a personal level depends on a wider range of feature variations. Under such scenario, it is not guaranteed that models developed for a specific subject/occupant of a building can be adapted to be used for any other occupant. This is empirically proved by the diminishing accuracies for some source/target pairs. The underlying closeness between various subjects at a common feature space must be established before adapting thermal comfort classifiers.

This work has a number of future directions, summarized below.

- Thermal comfort datasets are inherently class-imbalanced. Since adapting personal thermal comfort model of one subject to another does not necessarily lead to improved performance, we conducted a comparison for accuracies. A similar comparison can be done for metrics that reflect imbalance, e.g. F-1 score.
- Domain adaptation can be studied at a group level as source to person level as target and vice-versa.
- Few-shot transfer learning, where few of the target samples are labeled, improving target classification model can be studied.
- Domain adaptation can be studied for cases where only some of the features have labels available, e.g. publicly available features such as room temperature etc.

5 ACKNOWLEDGMENTS

This research is funded by the Republic of Singapore's National Research Foundation through a grant to the Berkeley Education Alliance for Research in Singapore (BEARS) for the Singapore-Berkeley Building Efficiency and Sustainability in the Tropics (SinBerBEST) Program. BEARS has been established by the University of California, Berkeley as a center for intellectual excellence in research and education in Singapore.

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