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Is your clock-face cozie? A methodology for the in-situ collection of occupant comfort data

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Abstract

A 2012 survey of 52'980 occupants in 251 office buildings found that 50% of all occupants were dissatisfied with their indoor environment [1]. This dissatisfaction can result in a reduction of work performance [2] and be a precursor for future health issues [3].

Significant progress has been made to improve occupant comfort. On one hand, there is the technological advancement of heating, ventilation and air conditioning systems (HVAC). On the other hand, there are advancements in human-building interaction which enables the local environment to adapt to the needs of the occupant [4]. These methods however have one fundamental limitation. They assume that all occupants within a building zone share the same comfort preference. In reality, variations in metabolic rates [5], light preferences [6], and noise tolerance [citation required] presents a challenge when attempting to condition a work-space to meet the requirements of all occupants [7].

Rather than tailoring the work-space to the preferences of the occupants, an alternative approach is to match the individual to a work-space. This requires an understanding of the individuals comfort preferences and a recommendation engine that can suggest a comfortable workspace in real time based on building environmental sensor data.

This paper focuses on the first of these challenges, namely comfort data collection. The state of the art in this field are comfort surveys. Although this works it has three main limitations

- The methodology cannot be scaled to large sample sets due to the administrative overhead in preparing these studies.
- The studies are often conducted outside of the test subjects natural working environment.
- Users suffer from survey fatigue [8] due to the number of data points required to conduct a thorough assessment, and even when willing to participate, they are concerned about how accurate they are responding to them [9]

This paper presents a novel form of occupant comfort data collection, using a wearable health tracker, in this case the Fitbit smartwatch, with 25 million active users [10]. The application is a simple clock-face where the user can state their comfort preference as a binary input "comfy"

or "not comfy". The comfort preferences are mapped to a time series database and linked with sensors that were present in the location of the user at that time.

This proof of concept has been launched with a small sample set of 15 users. Each user has been equipped with a Fitbit, and a wearable environmental sensor from the National Singapore Science Experiment [11]. All data is collected in-situ in the user's natural work environment.

Next steps in this study involve the development of a work-space recommendation engine. This engine will process the data and give each user a unique comfort profile that can be used to recommend work-spaces in real time. This project, known as SpaceMatch will be launched in 2019 at the National University of Singapore.

The clock-face application is available for free download from the Fitbit store for future researchers to conduct their own crowd-sourced comfort studies.

Keywords: Comfort Feedback, Data Collection, Fitbit, Comfort Recommendation, Mood Logging

1. Introduction

In the Maōri legends of old, there was a time when the sun would travel quickly across the sky, leaving people without sufficient light and warmth. Māui, a great hero of the time, observed this discomfort amongst the village and went on a quest to tame the sun. Armed with his magic jawbone of Murirangawhenua and a lot of flax rope, he succeeded in tying down the sun and beating it, until it slowed down to the speeds we have today. What Māui effectively did was categorise everyone in a one-size-fits-all model, and based on this assumption, took action to change the environment he lived in.

The way we control our buildings today, is similar to the way that Māui tamed the sun. We make an assumption of the general population based on a survey of a few people, and change the environment we live in based on these few data points. The issue here is that we assume that all occupants within a building zone share the same comfort preferences. In reality, variations in metabolic rates, light preferences, and noise tolerances presents a challenge when attempting to condition a work space to meet the requirements of all occupants.

From the times of Māui till now, a significant challenge is the aquisition of human comfort feedback data. The state of the art, in attaining human feedback are surveys, either as an online form, or paper based. While this in pricipal works, it presents three major challenges.

- The methodology cannot be scaled to large sample sets due to the administrative overhead in preparing these studies.
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- Users suffer from survey fatigue [8] due to the number of data points required to conduct a thorough assessment. Even when willing to participate, there is a concern about how accurately their responses are [9].

This paper presents cozie, a publically available clock-face designed for fitbit which can be used for tailored human comfort studies, and labeling of building management system data. In this paper, we will show how the watch-face can be easily deployed for a range of tailored scenarios, and be combined with building sensor data to create a high quality labeled data set that can be used to optimise the comfort of the user through spatial recommendation, and provide input training data for the comfort optimisation of the building management system.

The remainder of the paper is organised as follows. The next section outlines the cozie clock-face and how research teams can impliment it for a variety of human comfort related experiments. In Section 3 we detail a preliminary experiment conducted using the cozie clock-face for building comfort optimisation, Section 4 presents the preliminary results from this experiment, and Section 5 discusses our findings and next steps in this project. Finally, Section 6 concludes the paper.

2. The cozie watch-face

Cozie is built as a clock-face for fitbit, a wearable health tracker with 25 million active users [10]. The application is publicly available for download at the following link [insert link]

2.1. Overview

In this section we define "user" as the test participant who is wearing the fitbit, and "manager" as the person coordinating the experiment.

The default status of the clock-face is a simple binary question: "Comfy" or "Not Comfy", as seen in Figure 1. By simply clicking one of the icons, information about the users location (GPS), heart-rate, steps walked since last log, and the comfort data is anonymously sent to an Influx time series cloud database [Ref influx]. Data from this database can be simply queried with an API key that can be provided to the manager.

If the manager is interested as to why the user is feeling discomfort, then there is a range of additional questions that can be configured using the cellphone that the fitbit is paired with. The optional questions include:

- Thermal: Prefer Warmer - Prefer Cooler
- Light: Prefer brighter - Prefer Dimmer
- Noise: Prefer Louder - Prefer Quieter
- Mood: Happy - Neutral - Sad
- Location: Indoor - Outdoor

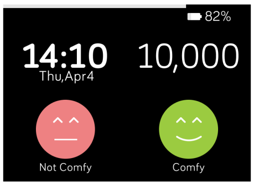

Figure 1: Homescreen

These responses will be bundled with the afore mentioned data, and stored in the Influx time series database. The manager is invited to contact the authors if they have further tailored questions that they would like to add.

A unique user-id for each user, and a unique experiment-id can be configured by the manager using the cellphone that the fitbit is paired with.

The watch-face also has the ability to prompt the user with a 3 second vibration, and force them to provide comfort feedback. This may be triggered using time intervals, certain hours of the day, random hours of the day, or at each 1000 steps walked.

2.2. Building Data Labeling

While the cozie watch-face can provide subjective in-situ human comfort feedback, the true value of the application arises when combined with building sensor data.

(Expand more here about the sensors used etc)

An example of this in practice will be introduced in the next section.

3. Methodology

An experient was conducted at the SDE4, a new built net-zero energy building, at the National Unviersity of Singapore. 20 participants who work in the co-working spaces of the level 6 design studio were recruited for the experiment and equiped with a fitbit watch. The watch settings were set to also request thermal preference (prefer warmer, prefer cooler, comfy), and the set to force request feedback at the hours of 9:00, 11:00, 13:00, 15:00, and 17:00

The watch was further complimented with IoT connected on-body and environmental sensors shown in Figure 2. The onbody sensor consists of a temperature and light sensor from mbientlabs, with bluetooth connectivity to raspberryPi gateways [ref]. The working space on level six is retrofitted with three WiFi connected environmental sensors from SenSING that measure temperature, humidity, light, noise, presence, CO_2, and VOC. All data is automatically synced to the Influx time series cloud database.

4. Results

The experiment consisting of 15 users each equipped with a fitbit over a month, produced a dataset of [INSERT NUMBER HERE] data points. Each data point is effectively a survey of the

Figure 2: Strap-Pack

user at a particular time. The results presented in this section is intended as a demonstration of the type of analysis that can be conducted using data acquired from the cozie watch-face.

4.1. Evaluational of User Comfort Over Day

Figure 3 details a simple heat-map where the user comfort feedback is mapped to the hour of the day. Users appear to be comfortable on average [INSERT NUMEBR HERE] % of the time, and there are no statistically significant trends during working hours (9:00 - 17:00). Variations in user comfort feedback during the day can be used to infer faulty building operation.

It is interesting to note that there is on average [INSERT NUMBER HERE] times more responses in the hours of 9:00, 11:00, 13:00, 15:00, and 17:00 which is when the occupant is buzzed and asked to give feedback. Nevertheless there are still significant amounts of responses made outside these times which had been done from the motivation of the participants themselves. Figure 4 details the daily responses from the participants. Interestingly, there appears to be no trace of survey fatigue as the number of responses during the month, which includes the self-motivated responses does not decrease.

4.2. Influence of Individual Users

Individual user feedback can be clustered using un-supervised learning techniques. In this example, we use a hierarchal k-means clustering based on euclidean distance using the Nearest-Point-Algorithm. The results, shown in Figure 5, show four distinct clusters of users. Users that are comfortable 100% of the time, users that are comfortable 60-80 % of the time, those that are comfortable 50% of the time and generally would prefer it cooler, those that are comfortable 50% of the time and would prefer it both warmer and cooler. Understanding and defining these differences in user preferences can be used to recommend spaces that may better suit the needs of the occupant. For example, User 5 and User 10 can be recommended working spaces that are on average cooler. User 13 on the other hand appears to have a broad comfort spectrum.

It is important to note here that the data is not entirely representative of a single building space, as the user may have given feedback while having lunch outside. As seen in Figure 3, there are even feedback results outside of working hours. Conclusions such as "Building Zone A was comfortable 80% of the time" can therefore not be made. This will be further discussed in Section 5.

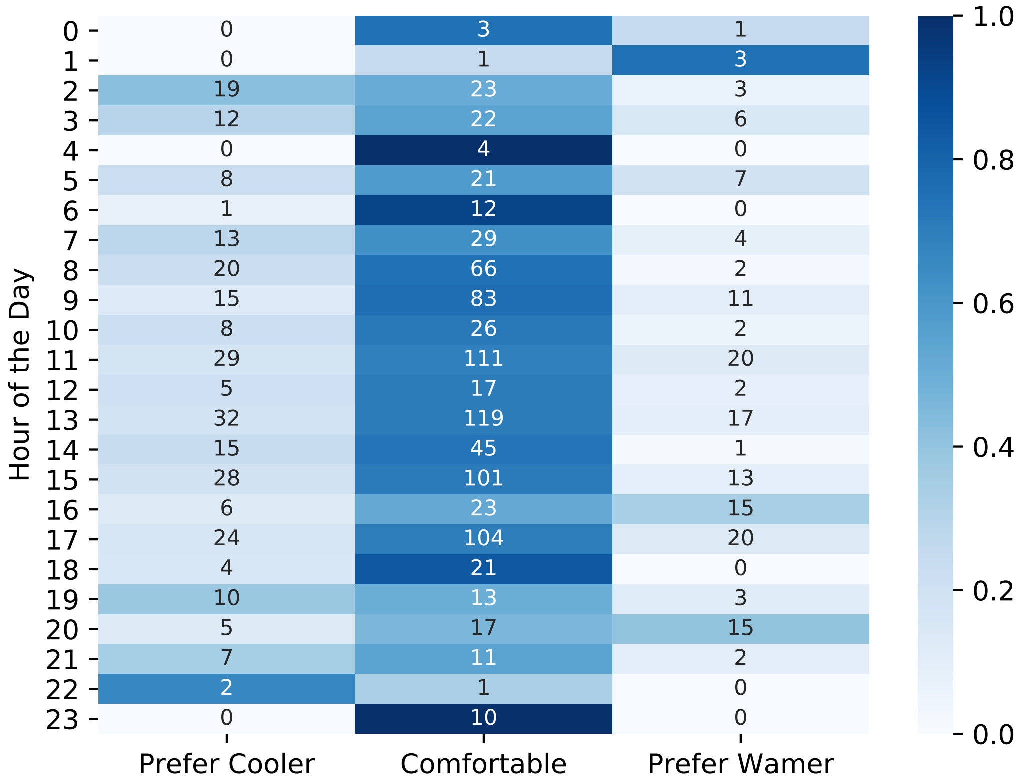

Figure 3: Aggregation of user feedback mapped to the hour of the day that feedback was given. Annotations withing the heat-map detail the absolute response value, while the colour gradient relates to the normalised values

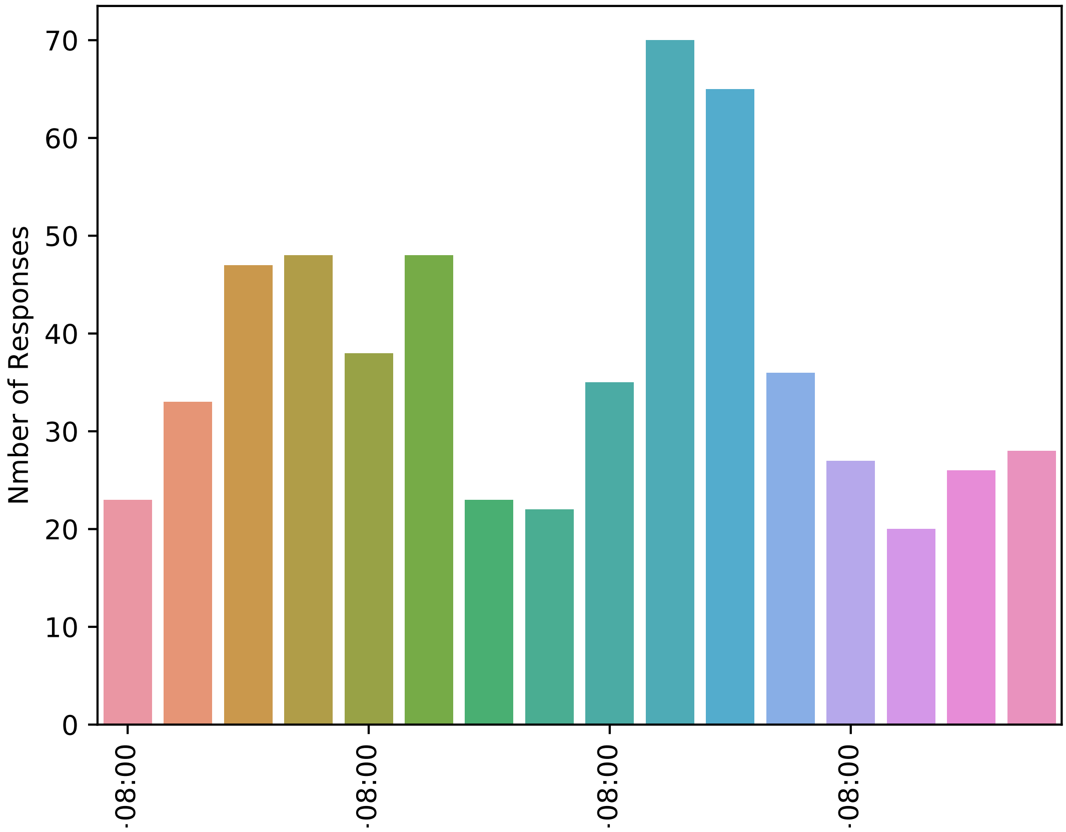

Figure 4: Daily responses during the course of the evaluation period

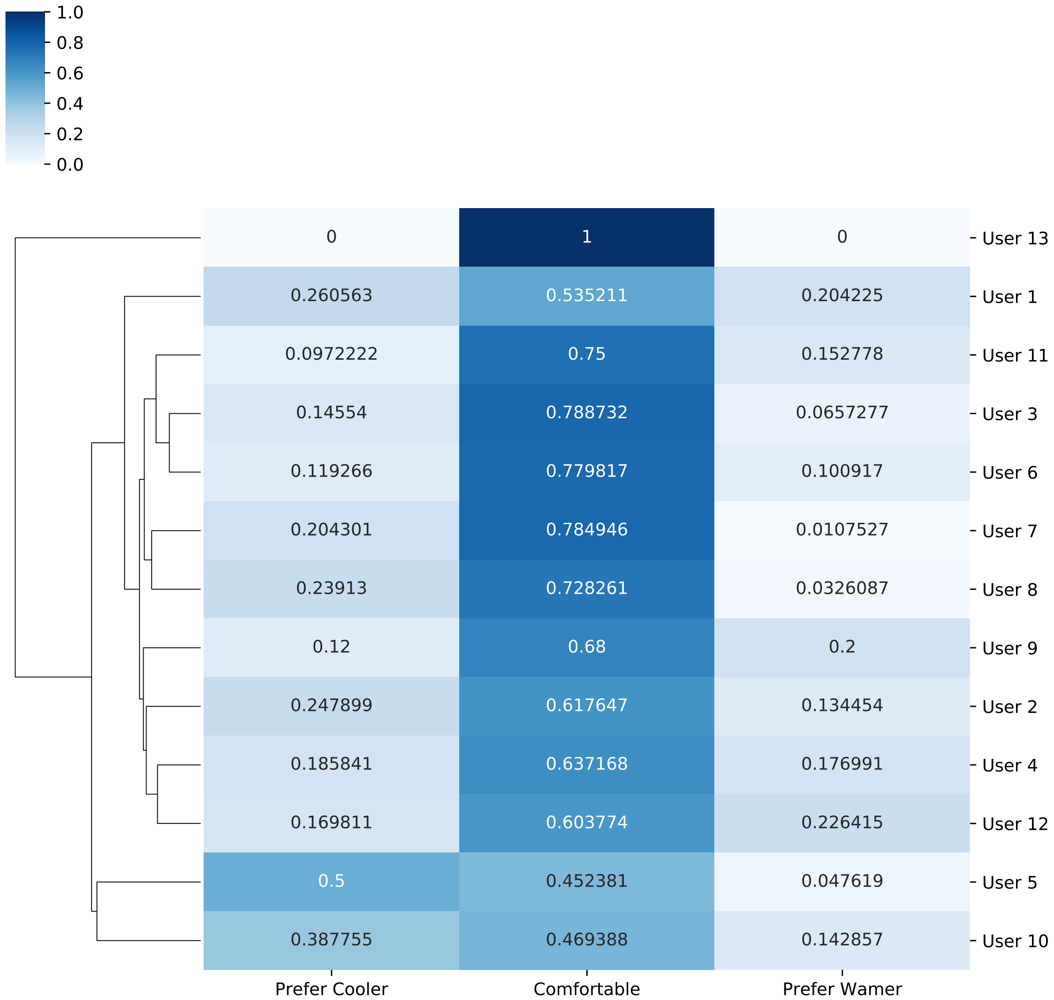

Figure 5: Clustering of user feedback using hierarchal k-means. The results show four distinct clusters.

4.3. Influence of Heart-Rate

4.4. Combination with Sensor Data

5. Discussion

5.1. Large Uncontrolled Data Sets vs. Small Controlled Experiments

One method commonly employed in comfrot research involves placing a sample of participants in a controlled space and conducting surveys during this time. In this methodology, users are under no control. They are generally asked to work from the SDE4 building, however no direct restrictions are placed, and they are free to move as they like. (talk more about statistical significance of larger datasets and types of results infered)

5.2. Indoor Localisation

The clock-face collects GPS data from the fitbit, however GPS data indoors is not always reliable, and often is not accessible. Other indoor localisation techniques such as pattern matching of noise data to indoor sensors [CITE JUN] are proven methods that may improve the results. Alternatively, the research institution may consider investing in indoor localisation technology such as Steerpath which has recently been installed in buildings at the School of Design and Environment.

5.3. Problems Encountered

During the course of the experiment two fitbits were lost by the users. Fortunately, one was found again, however two weeks of data was lost during this process. The other fitbit was not found.

5.4. Future Recommendations

6. Conclusion

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