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

P Jayathissa [1], M Quintana[1], T Sood[1], N. Narzarian[2], C. Miller [1 4]
[1] Building and Urban Data Science Group, Department of Building, Singapore
[2] University of New South Wales, Australia

E-mail: p.jayathissa@nus.edu.sg

Abstract.
This paper presents a methodology for the collection of occupant human feedback data using a fitbit smart watch. The clock-face application can be downloaded, free of charge on the fitbit store, and tailored to fit a range of occupant comfort related experiments. 15 users were given a fitbit for one month, where they were prompted to give feedback on their thermal preferences. In one month, with minimal administrative overhead [insert number here] of responses were collected. This paper demonstrates how these large datasets of human feedback can be analysed to reveal a range of results from building anomalies, occupant behaviour, occupant personality clustering, and general feedback related to the building. The paper also discusses limitations in the approach and next design stages.

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.

However understanding the preferences of individuals presents a significant challenge, both the times of Māui and now. The state of the art of human comfort data collection is in the form of surveys, either as an online form, or paper based. While this in principal works, it presents three major challenges.

- The methodology cannot be scaled to large sample sets due to the administrative overhead in preparing these studies.

[4] Present address: Department of Building, National University of Singapore, 4 Architecture Drive, Singapore

- 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. Even when willing to participate, there is a concern about how accurately their responses are [9].

This paper presents cozie, a publicly available clock-face designed for fitbit which can be used for tailored, scalable, in-situ human comfort studies. We will show how the watch-face can be deployed for a range of tailored experimental scenarios, and be evaluated using modern data analytics to infer behavioral patterns of the test participants. This information can be used to optimise human comfort through spatial recommendation, or combined with building sensor data to create a labeled data-set 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 implement 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 2. 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. Further documentation can be found on the cozie website [insert link].

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 preference, light preference, noise preference, indoor/outdoor, mood, and whether the user is in office. These settings, along with 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 and force them to provde feedback at custom intervals set by the manager.

3. Experimental methodology

An experient was conducted at co-working spaces at the National Unviersity of Singapore. 15 participants 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. The onbody sensor consists of a temperature and light sensor from mbient-labs that had been modified to fit the watch strap with a custom 3d printed case. An off body sensor measuring

Figure 2: Using the fitbit mobile application to design a survey flow

temperature and humidity was attached to the participants bag. The sensors communicate via bluetooth to raspberryPi gateways that had been positioned throughout the working space.

Data from the cozie watch face, and the environmental sensors were aggrigated in an Influx cloud time-series database, which served as a platform for data aquisition and fault detection. Source codes can be found here [ref aurek-data-crunch repo].

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

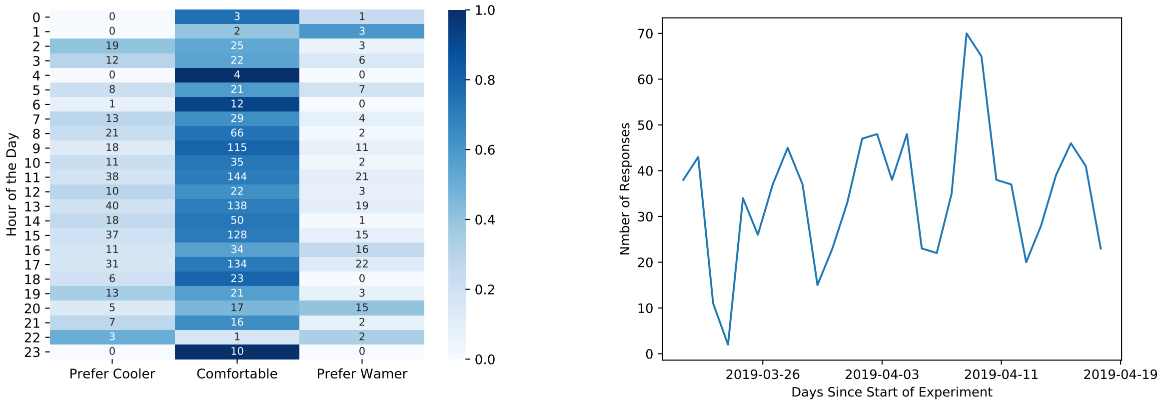
4.1. Evaluational of user comfort over a day

Figure 3a 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 an issue within the building.

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 when the occupant is buzzed and forced to give feedback. Nevertheless there are still significant amounts of responses made outside these times through the motivation of the participants themselves. Figure 3b details the daily responses from the participants, and no observable decrease in responses can be made. Dips in responses naturally occur during the weekend.

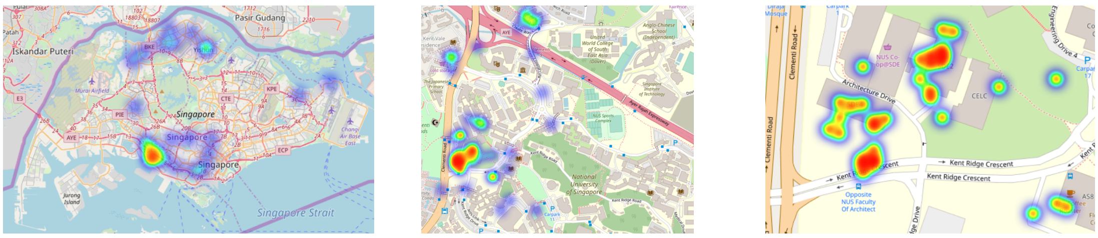
4.2. Influence of Individual Users

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 8, show four distinct clusters of users. 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



(a) (b)

Figure 4: (a) Aggregation of user feedback mapped to the hour of the day that feedback was given. Annotations within the heat-map detail the absolute response value, while the colour gradient relates to the normalised values (b) Daily responses during the course of the evaluation period. The dips in the graph are weekends



(a) (b) (c)

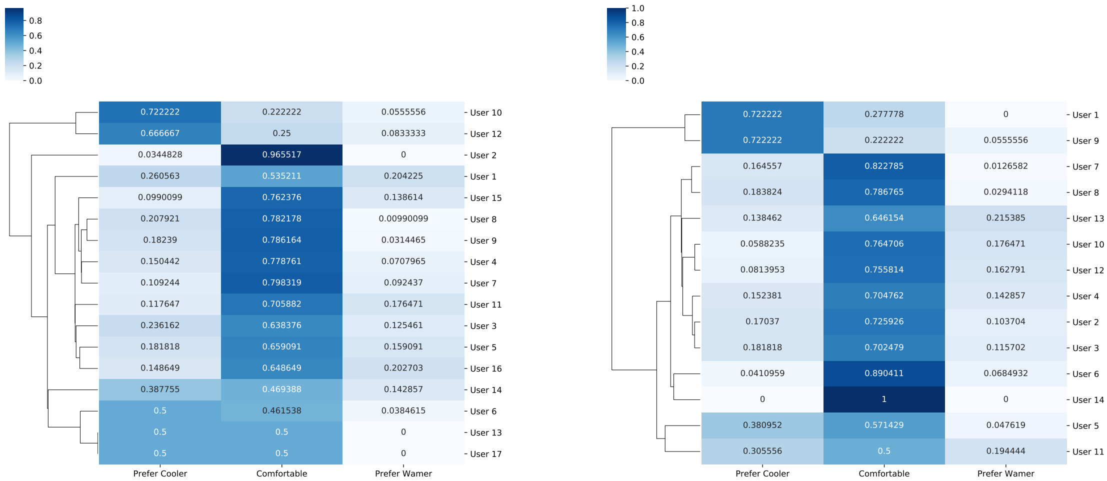
Figure 6: Map of responses. From left to right, the city of Singapore, National University of Singapore, and the School of Design and Environment. The experiment was conducted at co-working spaces at the school of design and environment, however responses are seen throughout Singapore. Note that these results only show 172 of the [INSERT NUMBER] total responses as GPS localisation often failed indoors.

recommended working spaces that are on average cooler. User 13 on the other hand appears to have a broad comfort spectrum.

It is importat to note that the data is not representative of a single space. As shown in Figure 6, responses were made throughout Singapore. GPS data can support in localising responses to individual buildings, but also comes with issues which will be discussed in Section 5.3.

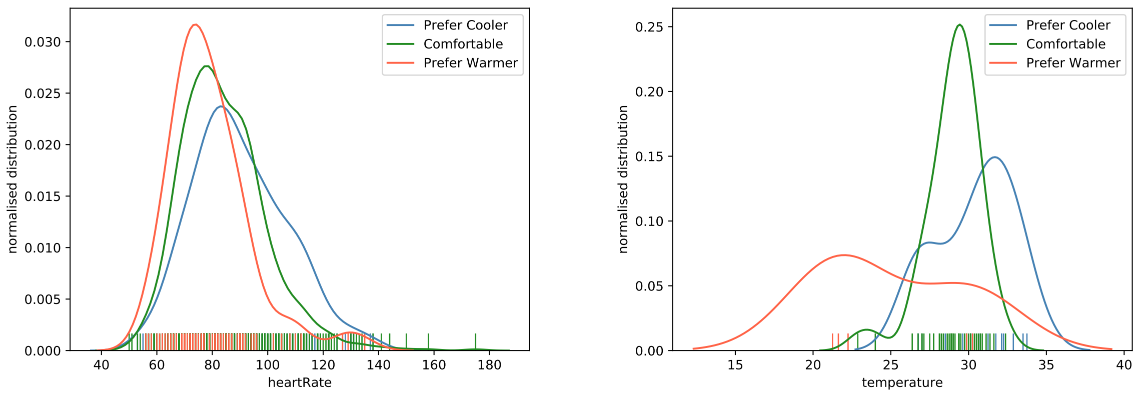
4.3. Influence of Heart-Rate

It is widely known that heart-rate influences metabolic activity, and therefore an occupants comfort preference. Figure 9a details the number of responses for each thermal response based on the heart rate. [INSERT NUMBER HERE] % of "Prefer Cooler" responses occurred during higher metabolic activity when the heart rate was greater than 100 beats per minute. If we filter out these responses,and apply the same algorithms detailed in Section 4.2, we see a slightly different response and clustering pattern, as shown in Figure 7b.



(a) (b)

Figure 8: Clustering of user feedback using hierarchal k-means. (a) The full results show four distinct clusters, (b) filter by heart rate that is less than 100 beats per minute



(a) (b)

Figure 10: Normalised distribution of the response type based on (a) heart rate (b) temperature. Note that the normalisation for "prefer warmer" is skewed due to the lack of responses of this type

4.4. Combination with Sensor Data

Combining the cozie watch face, with the "strap-pack", an environmental sensor addition to the watch face opens another dimension of analysis. User responses are mapped to the environmental condition at which they are exposed to, which can provide a high quality labeled data set for training data driven models. Figure 9b detail the temperatures at which responses were mapped. Note that the temperature of the strap sensor is on average 0.8 °C warmer than the surrounding environment due to the influence of body temperature.

5. Discussion

5.1. Large Uncontrolled Data vs. Small Controlled Data

Placing a group of participants in a controlled experimental space and conducting feedback surveys is a trusted traditional method for human comfort surveys. Giving each participant a smart watch, and analysing the patterns of hundreds of data points per user would be more akin to modern data analytics employed in industries outside the building sector.

While they both work, the types of conclusions that can be derived are different. The traditional method can derive conclusions such as "4 of the 20 users felt warm at temperatures higher than 25.6 °C". Whereas the uncontrolled, large data method can draw conclusions such as "4 of 20 users can be catergorised as a user type that prefers cooler working environments".

5.2. In-situ benefits and limitations

Uncontrolled experiments have minimal management overhead, which means that it can be easily scaled to larger groups by purchasing more devices. Furthermore, the users are analysed in their natural work environments and give feedback with a simple click on their watch. This reduction of effort results in no fatigue in the number of volantary responses given as shown in Figure 3b.

While users generally work from their office, they sometimes work from home, or at a local cafe. This presents a limitation in the context of traditional small controlled datasets. Large enough datasets therefore need to be obtained to filter out these scenarios and interpret meaningful results.

5.3. Indoor Localisation

The clock-face collects GPS data from the fitbit, however GPS data indoors is not always reliable, and often not accessible. Out of the [INSERT NUMBER OF DATAT POINTS] only 347 were tagged with GPS data. This presents a limitation in its current form.

The team are currently investigating other methods of localistion, which includes a continuous logging of GPS data to infer an entry and exit of a building space, bluetooth based localisation from Steerpath, integration with the SpaceMatch application [CIT SpaceMatch], and pattern matching of wearable sensor data to indoor sensors [CITE JUN]

5.4. Problems Encountered

During the course of the experiment two fitbits were lost by the users. One was lost permanently, and the other was found at a later date. There were also some issues with the collection of the enviornmental sensor data, resulting in only [79] matching points of the comfort feedback to the sensors, where as we expected approcimatly 200 matching points.

6. Conclusion

First trial runs of the cozie application for occupant comfort data collection have prooven successful. Within just four weeks [INSERT NUMBER] data points of thermal comfort were obtained from the 20 test participants, with minimal administrative overhead. This rich data set provides new opportunities in analysing occupant comfort behaviour through data driven methods. Within this paper, we have demonstrated how the data can be manipulated and clustered to group people into various comfort profiles. In our case there were [INSERT NUMEBR HERE] distinct groups, which can be then recommeneded spaces that better suit their comfort profile. The data can also be clustered via time to display building defects, or annomylies in occupant behaviour. Finally, we demonstrate how the app can be combined with wearable environmental sensors to cross reference a users preference to the environment that they were in.

The watch-face is publically available for download at this link, and we strongly encourage the readers to contact the authors if they have any questions or recommendations.

Next steps in this research involve using cozie for the exploration of occupant clustering and spatial recommendation. We will explore elements of sound, light, and thermal comfort to determine whether spatial recommendation can serve as an alternative to individualised adaptive buildings control. Furthermore, the developement of a "strap-pack", a smart-watch environmental sensor that can be adapted to the watch strap is underway.

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