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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

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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 acquisition 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 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.
- The studies are often conducted outside of the test subjects natural working environment.

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- Users suffer from survey fatigue [1] 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 [2].

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 [3]. 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
- Location: In Office - Out of Office

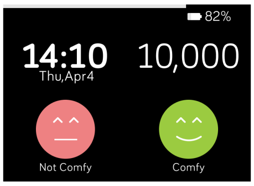

Figure 1: Homescreen

These responses will be grouped 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 at certain hours of the day, random hours of the day, at set time intervals, or at each 1000 steps walked.

2.2. Building Data Labeling

The human comfort feedback can be combined with building sensor data to create a labeled data set of the environment. (perhaps talk more or delete this section)

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 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.

Figure 2: Strap-Pack

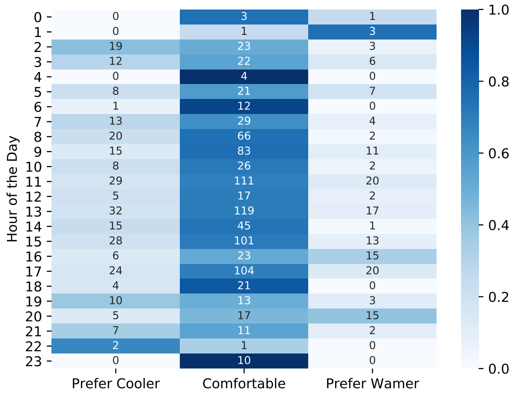

Figure 3: Aggregation of user feedback mapped to the hour of the day that feedback was given. Annotations within the heat-map detail the absolute response value, while the colour gradient relates to the normalised values

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

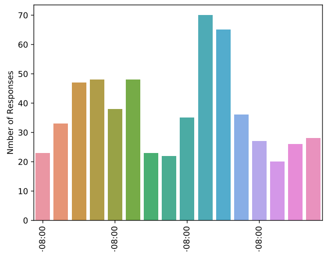

Figure 4: Daily responses during the course of the evaluation period

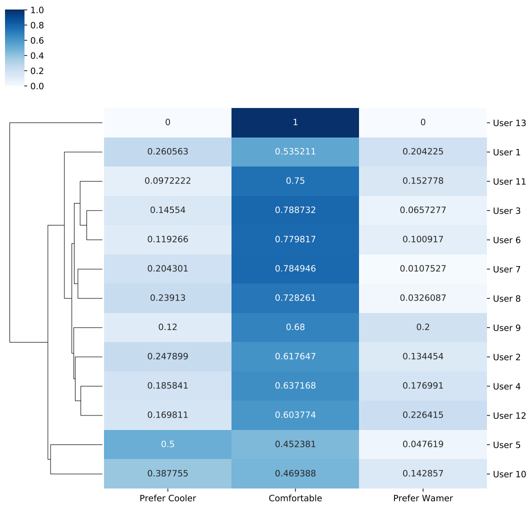

Figure 5: Clustering of user feedback using hierarchal k-means. The results show four distinct clusters.

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.

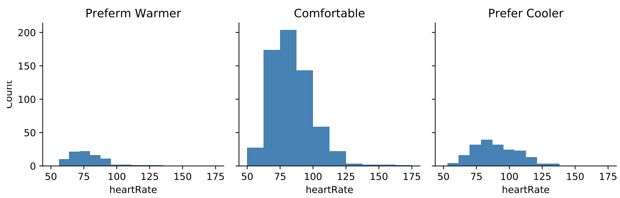

Figure 6: Histogram detailing the influence of heart rate for each thermal response respectively

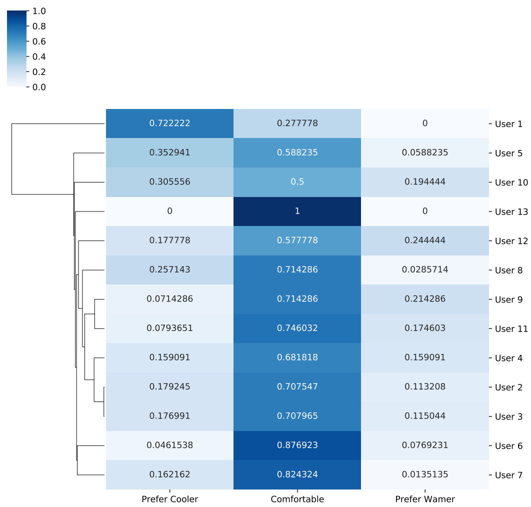

Figure 7: Clustering of user feedback using hierarchal k-means, where heart rate is less than 100 beats per minute

4.3. Influence of Heart-Rate

It is widely known that heart-rate influences metabolic activity, and therefore an occupants comfort preference. Figure 6 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 7.

4.4. Combination with Sensor Data

5. Discussion

5.1. Large Uncontrolled Data vs. Small Controlled Data

Let us take a step back and observe how market analysis was conducted. Traditionally, super markets would call individual households and ask for their feedback about what products they would like to have in stock. In modern times, applications such as facebook mine preference data from users based on what posts they "liked", and use this to generate targeted advertising for each individual.

One can draw these parallels to human comfort surveying. Placing a group of participants in a controlled experimental space and conducting feedback surveys is a trusted 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 slightly warm at temperatures higher than 25.6C °". 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". To further add to this, the uncontrolled method has minimal management overhead, and can be scaled by purchasing more devices, thus providing an even richer data set along the user axis.

5.2. In-situ benefits and limitations

The cozie watch face enables users to be analysed in-situ. By this we mean that the users work in their natural work environment, and give feedback with minimal effort. As introduced in Section 1 this allows the experiments to be conducted and scaled with minimal management overhead; the users don't feel like they are in an experimental setting as they are in their normal office; and finally there is no observable survey fatigue. Figure 4 details the number of responses, including self motivated responses, per day. There is no there is no observable decrease in the feedback given.

The limitation however is the control of the users. Users work from their designated co-working space at their own will, and at their own time. They may decide to work from home, or are at lunch in an outdoor restaurant when giving feedback. This presents a limitation in the context of traditional small controlled datasets. With larger samples however, this uncontrolled situation presents an opportunity to better understand the behavioral characteristics of a user as certain patterns can be derived and interpreted. If the research manager would like to have more control of the experiment they may choose to also add the "In Office / Out of Office" or the "Indoor/Outdoor" question to the list of questions asked.

5.3. 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 technologies such as Steerpath which has recently been installed in buildings at the School of Design and Environment.

5.4. 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.

6. Conclusion

References

[1] S. R. Porter, M. E. Whitcomb, W. H. Weitzer, Multiple surveys of students and survey fatigue, New Directions for Institutional Research 2004 (121) (2004) 63–73.

[2] A. K. Clear, S. Mitchell Finnigan, P. Olivier, R. Comber, ThermoKiosk: Investigating Roles for Digital Surveys of Thermal Experience in Workplace Comfort Management, Proc. of CHI (2018) 1–12doi:10.1145/3173574.3173956.

[3] Fitbit 2018 investor report (2018).
URL `https://investor.fitbit.com`