Can a building read your mind? Results from a small trial in facial action unit detection

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Abstract.
In the last few decades, the energy consumption of individual buildings has been steadily improving. As a result, research efforts are shifting towards acquiring a deeper understanding of occupant comfort, health, and well-being in the built environment. However, existing techniques used to measure and predict the comfort of occupants have seen little change since Fanger. New research attempts are hence focusing on methods to gather more data, more frequently, and less intrusively. A little explored source of data is the one gathered from real-time videos of occupants, the so-called facial action units (FAU), which is the focus of this paper. These are the facial movements and positions that constitute the basic elements of emotions. Using software developed in the realm of affective computing, seven building occupants were monitored for a period of 2 weeks, whilst also completing surveys that gathered information about the office environment, and their work and personal life. Results found that participants that were happy with their office space showed significantly higher average values of the Cheek Raiser (AU06) and Lid Tightener (AU07) facial action units. These findings show the potential of using FAUs to assist in the control and design of buildings in a human-centric manner.

1. Introduction

Climate change is firmly on the agenda, and could well be humanities 'greatest threat in thousands of years' said David Attenborough [1]. With 40% of the total energy used in the EU attributable to buildings, the built environment accounts for 36% of its total CO_2 emissions, making it the largest contributor to climate change [2]. Although building and environmental regulations, together with research, standards, and technologies, are continuously helping enhance buildings' performance, the fact that they are increasing in number to accommodate the predicted 2.5 billion people migrating to urban areas by 2050 dampens these improvements [3]. This is causing green areas in cities to be slowly eroded away in favour of new developments [4], to the detriment of citizens' health and well-being [5]. In parallel, the cost of renewable energy and storage is plummeting, with Swiss Investment Bank UBS analysts predicting effectively free electricity by as early as 2030 [6]. Research efforts are therefore shifting towards acquiring a deeper understanding of occupant comfort, health, and well-being in the built environment, and putting a value on these metrics can help to have a positive impact on businesses worldwide, where over 90% of costs can be attributed to staff (Figure 1) [7].

New standards, such as WELL and Fitwell, are further spearheading this trend, creating ratings on the premise that a building's design has the potential to positively impact the health and well-being of its occupants. Yet, the more established building standards, namely LEED

and BREEAM, are now also welcoming the idea, incorporating elements of comfort, health, and well-being to their more traditional energy and sustainability components [8]. All these are part of a much wider movement, triggered by an increasing interest of consumers in their own health and well-being and evidenced by the popularity of smart watches and fitness classes, amongst others [9].

Despite the positive role of standards, techniques used to measure and predict the comfort and satisfaction of occupants with respect to their environment have seen little change since Fanger [10]. The same can be said about post-occupancy evaluations (POE), whereby both indirect and direct feedback is collected from a building and its occupants. Examples of these include, but are not limited to, environmental measures and models to predict occupants comfort (indirect), and surveys or focus groups (direct). Some of their main drawbacks is that they provide infrequent data and can be extremely disruptive. Thus, new research attempts are not only focusing on finding new methods to gather more data, but also on acquiring it more frequently and less intrusively. These new data types could not only help to move towards a more effective control of the next generation of smart, tailored, connected buildings, but also, to inform future building's design. This paper briefly examines these traditional methods and newer physiological techniques, before setting out a framework and evaluating a small trail in facial action unit (FAU) detection, a technique which uses video data in an attempt to capture occupants comfort, health, and well-being.
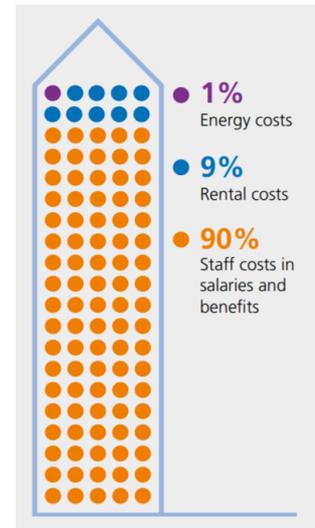

Figure 1. WGBC report shows typical business operating costs [7].

2. Existing Data and Models for Buildings

There are three main stages in the development of comfort models in buildings. The first, devised by Fanger [10], is the predicted mean vote (PMV), which uses data from chamber experiments to predict thermal comfort. The second, the adaptive comfort model, takes the outdoor temperature as a reference to establish an acceptable range of indoor temperatures [11]. And finally, the personal comfort model, steps away from the previous two methods, both established on the basis of average values, to create a model that predicts an individual's response using data acquired from personal comfort systems (PCS), such as a heated chair, environmental data, and building system settings [12].

POE are another popular way to gather data, combining information from environmental sensors and occupant surveys in an attempt to optimise a building. This data can also be gathered in-use, allowing building managers to adjusts settings and fine-tune performance, and providing the opportunity to inform future designs and control strategies [13].

Physiological measurements - such as heart rate, galvanic skin response, and electrical brain impulses - can also help to give a more detailed picture of occupant comfort and well-being. Yet, a potential drawback is their intrusiveness. A clear example is the electroencephalogram (EEG), which despite providing interesting data on cognitive performance under a research setting, requires a large headset to be worn by the user [14]. Other, less intrusive physiological measurements are of course possible, with smartwatches being a great example of these. They are able to measure numerous factors, including heart rate, location, skin temperature, perspiration, and activity [15], making them a widespread tool in research studies [16, 17, 18, 19].

3. Why Faces?

The face offers an unexplored opportunity for capturing data. In his book *The Expression of the Emotions in Man and Animals* (1972), Darwin examined emotions as discrete entities with

a major focus on the face [20]. Much later on, Ekman [21] established six basic emotions: anger, disgust, fear, happiness, sadness, and surprise, which were slightly different in concept to the 4 pairs of opposites proposed by Plutchnik [22]: joy-sadness, anger-fear, trust-distrust, surprise-anticipation. More recent studies on monkeys and apes further suggest that facial expressions are less voluntary than manual gestures, which in themselves are less voluntary than language [23]. All these have paved the way for Affective Computing, which often uses real-time videos of occupants to capture the so-called facial action units (FAU), or the facial movements and positions that constitute the basic elements of emotions.

Affective computing was defined by Picard [24] as 'computing that relates to, arises from, or influences emotions'. In the same paper she further ventured to state that computers '[are] beginning to acquire the ability to express and recognise affect, and may soon be given the ability to have emotions', implying that their recognition and interpretation of affect may grant computers the ability to interact with humans in a more intelligent and natural fashion [25]. The prolific installation of sensors and control mechanisms in buildings are converting them into giant computers, but the next step is yet to be taken: using personal comfort models to understand occupants and deliver, through automated processes, optimum conditions promoting their health and well-being.

The number of cameras used worldwide is staggering, with CCTV security cameras commonplace in commercial buildings, providing a potential source of occupancy data [26]. But it is their use in autonomous vehicles [27] or in Japanese vending machines [28] which is really opening up this new machine-user paradigm. Despite some questionable claims on the misuse of facial recognition to identify homosexuals [29], the advantages outweigh the disadvantages. For instance, assisting doctors in identifying psychological conditions, namely depression [30] and suicidal tendencies [31].

A motion detecting surveillance kit is set up using a Raspberry Pi Zero W, running MotionEyeOS, and a Pi camera, both encased within a standalone Octopus case (Figure 2). When an occupant is detected, 5-minute videos are recorded at a resolution of 320 x 240 pixels and a rate of 5 frames/second (fps), offering a good trade-off between data size and quality. These videos are then uploaded to the cloud, where they are automatically processed with OpenFace, a FAU software and then deleted.

Figure 2. Octopus.

OpenFace is an OpenSource 'state-of-the art tool intended for facial landmark detection, head pose estimation, facial action unit recognition, and eye-gaze estimation' [32]. It is able to recognise the presence and intensity of the following action units (AUs): 1, 2, 4, 5, 6, 7, 9, 10, 12, 14, 15, 17, 20, 23, 25, 26, 28, and 45 (c.f. [33]).

4. Setup

A total of 7 people participated in the study, each being recorded for a period of 2 weeks. Participants were previously informed about the nature of the experiment and tasks involved. An Octopus was placed under their external monitor screen (a common setup in offices), which was found to be the optimum location.

Daily surveys were also emailed to participants at 4pm, where 4 questions provided information on temperature, air quality, lighting, and acoustics. Every Thursday, a much longer survey consisting of 50 questions gathered more detailed feedback around background, health, well-being, job satisfaction, and work-space satisfaction.

The system itself would preferentially be integrated into an existing BMS system. The Octopus has the ability to record on-the-fly and send data to a central time-series database (such as InfluxDB), where this data can then be analysed and viewed before recommendations or
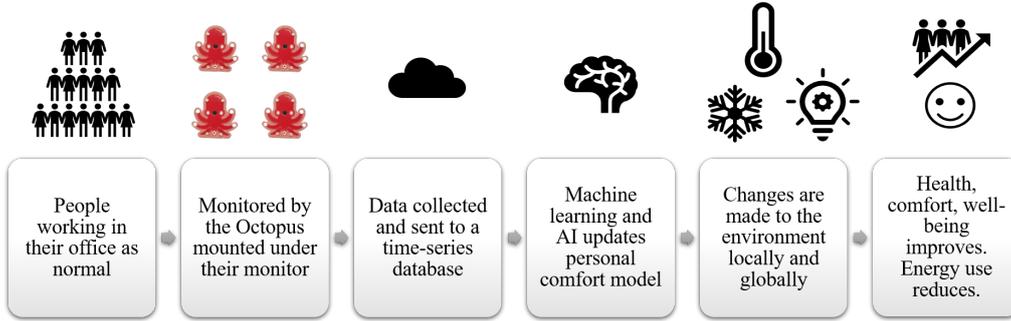
Figure 3. Schematic diagram of data process.

actions are taken. The Octopus also has the ability to recognise and locate individual occupants, thus allowing the use of personal comfort models to tailor the local environment in the vicinity of a particular occupant. This data process is schematically outlined in Figure 3.

5. Results

Videos were analysed on a powerful computer. In total over 2 weeks, 400GB of videos (800 hours) of video were produced and processed (!), hence the desire to process on-the-fly when implemented in the real world. The survey results were collected by Qualtrics and were used to split participants into two groups for analysis purposes. Results from the two longer surveys can be seen in Table 1. Results clearly show that the three occupants highlighted (1,5,7) expressed a particularly low overall satisfaction with indoor environmental quality.

- Warwick-Edinburgh Mental Well-being scale (WEMWBS): Used in monitoring of mental well-being in the general population and the evaluation of projects [34];
- Utrecht Work Engagement Scale (UWES): 17 statements about how one feels at work [35];
- Indoor Environmental Quality (IEQ): Based on the IEQ Survey from CBE Berkeley [36].

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Each frame of video results in 714 rows of data in .csv format, analysed in MATLAB. These include gaze, pose, facial landmarks, and the AUs. For each occupant, the 5-minute video .csv outputs were collated and the relevant columns retained leaving tables with *circa* 2 million rows and 37 columns of frame numbers, confidence scores, and FAUs. Data was then cleaned, removing rows with a confidence rating below 0.93 and Figure 4 shows the average AUs from both presence and intensity. Although more data and analysis needs to be gathered before any conclusive assertions can be made, there are already clear differences in average AU values between the two groups , particularly regarding action units in Table 2.

Occupant	WEMWBS [70]	UWES [119]	IEQ [178]
1	42	59	92
2	54	80	147
3	53	79	159
4	52	61	135
5	47	67	91
6	57	77	139
7	45	59	125

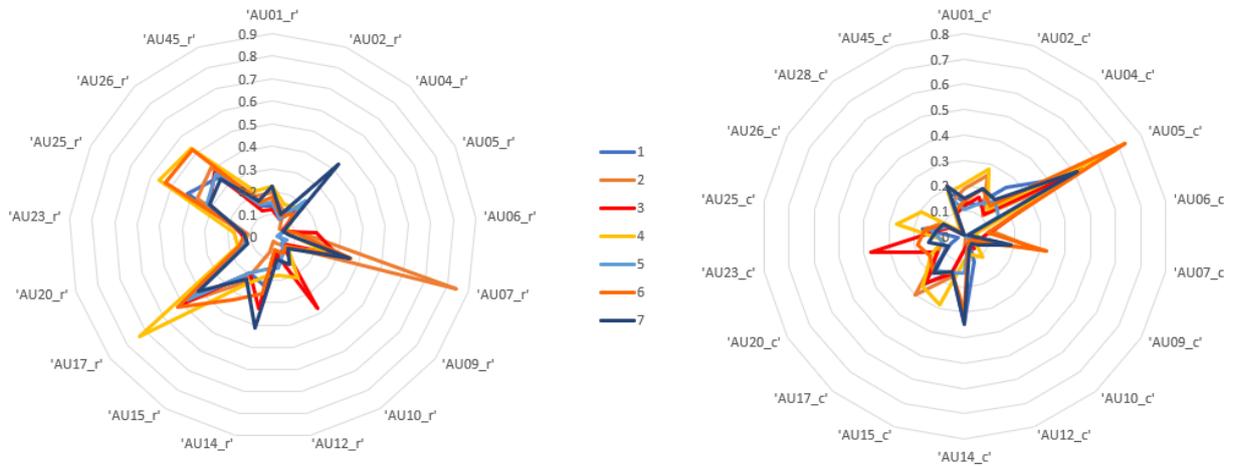**Table 1.** Table of long survey results, red highlights particularly low scores.

Figure 4. Spider-plot showing average action unit values for each participant 1 to 7 (blueish = not satisfied, reddish = satisfied) over the 2 week test period. Left - intensity, Right - presence.

6. Conclusion

This paper has set the framework and methodology necessary for effectively capturing occupants' FAUs. Findings show that their is potential for FAUs to assist in the control and design of buildings in a human-centric manner. Along with wearables and advanced AI driven data analysis, it is hence possible to create a unique digital twin of each individual, that takes into account and learns their preferences, ultimately leading to an optimisation of their comfort, health, and well-being in the built environment.

Action Unit	Average Not Satisfied	Average Satisfied	Difference (%)
AU04r (Brow Lowerer presence)	0.275746	0.13187	48%
AU06r (Cheek Raiser presence)	0.039057	0.131651	337%
AU07r (Lid Tightener presence)	0.154034	0.434213	282%
AU06c (Cheek Raiser intensity)	0.010538	0.085816	814%
AU14c (Dimpler intensity)	0.276914	0.12465	45%
AU20c (Lip stretcher intensity)	0.07331	0.13725	187%
AU23c (Lip Tightener intensity)	0.08897	0.182119	205%

Table 2. Table comparing the average of key action units between the two groups.

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