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Conceptual design of intelligent platform for non-invasive thermal discomfort detection

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Abstract: Harsh climate conditions, events of over-heating and over-cooling created a gap between envisioned indoor environment and actual performance of the buildings. This paper suggests a potential development of the study which was held in Norwegian Institute of Science and Technology "The Study of Facial Muscle Movements for Non-Invasive Thermal Discomfort Detection via Bio-Sensing Technology". A new concept of intelligent platform is proposed for detection and prevention events of the thermal discomfort among silver age cluster of people. It suggests that involuntary facial muscle movements are an important part of the human thermal perception within indoor conditions since they are directly connected to the brainstem which is located within sub-cortical part of the brain that asses thermal state of the body. Such neighboring location might hint that unconscious facial muscle movements can also contain insights on thermal state of the body and not only show emotional state. It is proposed to collect bio-metrical data on activity level, heart rates profile and facial muscle movements itself in ZEB test cell which will be equipped in a way that mimics apartment environment. Collected data will be perfect ground for implementation of the Artificial Neural Network with aim to cluster data and be able to have prediction that would allow to adjust HVAC system in advance and create comfortable thermal profile.

Keywords: thermal comfort, artificial neural networks, intelligent platform, indoor environment.

1. INTRODUCTION

Last couple of years brought rapid development in computational power, sensors for bio-metrical data collection and artificial intelligence itself. The machine learning techniques become more sophisticated and less computationally costly. Such progress attracted a lot of researchers to adopt technology for indoor thermal comfort monitoring and investigate ways for discomfort prediction improvement by non-invasive means. It is not a mystery that thermal comfort is a complex therm that varies due to climate belt, season, willingness to adjust clothes and general health of a person (Bogataj et al. (2020); Temeljotov-Salaj and Bogataj (2021); Jowkar et al. (2020)). So far, main way to determine the thermal comfort of people is to use Predicted Mean Vote (PMV) and Predicted Percentage of Dissatisfied (PPD) models (indexes). Fanger et al. (1970) PMV model represents the mean thermal sensation vote on a standard 7-point scale: +3 "HOT"; +2 "WARM"; +1 "SLIGHTLY WARM"; 0 "NEUTRAL"; -1 "SLIGHTLY COLD"; -2 "COOL"; -3 "COLD". This scale often referred to as seven-point ASHRAE thermal sensation scale. While, the PPD is a quantitative measure of the thermal comfort for a group of people within specific thermal environment (Yang et al. (2014)). The ASHRAE-55 and ISO7730 together with other widely used indoor comfort standards adopted PPD and PMV (Standard (2010); ISO (2005)). One of the downside for both models is their constraint set which does not allow them to fully reflect on real-life cases (Yau and Chew (2014)). Such circumstance gave a push for adaptive thermal comfort model that was development in 1970 (Yao et al. (2009); Nicol et al. (1998)). Humphreys and Nicol suggested that individuals which feel thermal discomfort would react in a way that will restore comfort e.g. put a sweater in cold conditions or remove scarf in warm conditions (Nicol et al. (2012)). All possible variations in which a person might restore comfort can be put into the following groups of actions: physiological, psychological, social and behavioural.

As it was shown by Marchenko and Temeljotov-Salaj (2020), the majority of studies held during 2014-2019 in field of thermal discomfort detection via bi-sensing technology and machine learning algorithms implementation had almost equal number of male and female participants as opposite to 1997-2014 were main test groups would be presented by man. Even thought this is a good change for better data collection and attempt to represent different types of thermal human response, there is still a long road for making models flexible and inclusive. People of silver age group should be presented more within field and actively encouraged to provide a feedback. Especially since given group of people is more vulnerable to thermal pro-

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file fluctuations and can suffer bigger consequences from overheating / over-cooling.

This paper aim to present a platform for thermal discomfort detection among silver age people by suing bio sensing technology and artificial intelligence. If proven to be successful, it can provide time gap for adjustment of indoor conditions before event of discomfort. If done successfully, it will remove additional stress on physical well being of silver age group and possibly prevent associated ricks of increase in blood pressure, headaches or blood clots.

2. SYSTEM BACKGROUND AND GENERAL DESCRIPTION

The concept is the logical progression of the study which was held at The Norwegian University of Science and Technology (NTNU) Trondheim. The main focus of the study was on an adaptation of facial muscle movement theory that is used for emotion detection to allocate possible biomarkers which can hint at the thermal status of a person (Marchenko et al. (2020)). The emotions themselves are combinations of the facial expressions or in other words, facial muscle movements that are managed by the facial nerve which is directly connected to the brainstem and motor cortex (Meyer et al. (1994); Nordstrom et al. (1999); Fischer et al. (2005); Yildiz et al. (2005)). In general emotions are divided into two groups: voluntary and involuntary (Forgas et al. (2005); Coles et al. (2019); Bless et al. (1990)). The brainstem is responsible for involuntary facial expressions while the motor cortex is mainly active during intentional facial expressions. The brainstem itself is located within the subcortical part of the brain which is the same part of the brain that assesses the thermal state of the body. Such neighbouring location might suggest that unconscious facial muscle movements might also contain insights into the thermal state of the body and not only show an emotional state of mind. This statement is also a relevant outcome of facial feedback hypothesis proposed by Fritz Strack and his team in 1988 (Strack (2017); Strack et al. (1988); Coles et al. (2020)).

"The facial feedback hypothesis postulates that selective activation or inhibition of facial muscles has a strong impact on the emotional response to the stimuli"

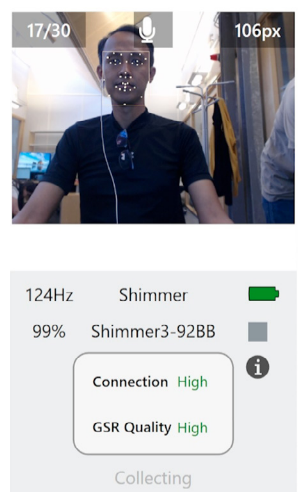
While there is an uncountable number of facial expressions (see Fig. 1), only the following categories may be detected and tracked at a particular stage of field development: joy, anger, surprise, fear, contempt, sadness and disgust (Wolf (2015)). These seven emotions do not depend on age, ethical background or any other parameters (Bartlett et al. (1999); Cohn and Ekman (2005)).

The experiment was developed to track those emotions using a bio-sensing platform which consists of:

- iMotions - software that allocates facial markers and tracks their movements while logging data into a database that is used for facial expression processing;
- Shimmer module - hardware which allows to track galvanic skin response and pulse of the person;
- HD camera - to capture the indoor environment and send data of image processing;
- Temperature sensors - to capture temperature profile.

Fig. 1. Example of the facial expressions variety

The iMotions software processes the continuous flow of the images from the HD camera placed in front of the test participant. The software is programmed in a way which allows to detect face and allocate it into a square box (see Fig. 2). The final step is an implementation of the feature extraction algorithm in order to mark facial landmarks and track their movement within the square box Degtyarev and Seredin (2010); Morency et al. (2007); Hakeem and Shah (2007). In total, iMotions software allows marking 34 tracking points.



1	Right Top Jaw	18	Inner Right Eye
2	Right Jaw Angle	19	Inner Left Eye
3	Gnathion	20	Outer Left Eye
4	Left Jaw Angle	21	Right Lip Corner
5	Left Top Jaw	22	Right Apex Upper Lip
6	Outer Right Brow Corner	23	Upper Lip Center
7	Right Brow Center	24	Left Apex Upper Lip
8	Inner Right Brow Corner	25	Left Lip Corner
9	Inner Left Brow Corner	26	Left Edge Lower Lip
10	Left Brow Center	27	Lower Lip Center
11	Outer Left Brow Corner	28	Right Edge Lower Lip
12	Nose Root	29	Bottom Upper Lip
13	Nose Tip	30	Top Lower Lip
14	Nose Lower Right Boundary	31	Upper Corner Right Eye
15	Nose Bottom Boundary	32	Lower Corner Right Eye
16	Nose Lower Left Boundary	33	Upper Corner Left Eye
17	Outer Right Eye	34	Lower Corner Left Eye

Fig. 2. Facial recognition and facial mapping

All data collection was held at NTNU's Zero Emission Building (ZEB) Test Cell Laboratory on the Gløshaugen campus in Trondheim (Cattarin et al. (2018)). This is a PASSYS instrumented test cell which was transformed to mimic an office-like environment. Test participants were asked to perform regular PC tasks which they would do during their workday. During each session temperature inside the test cell was altered to bring a feeling of thermal discomfort from time to time. Each participant was instructed to press a button when they would feel like changing something because the environment become not comfortable.

In total 8 temperature ramps were implemented: 4 ramps with an increase of slope and 4 with a decrease. The START and STOP temperature parameters for 1.4 heating and 1.4 cooling ramp run are presented on Fig. 3 - Fig. 4. "N" presents runs: for example in Fig. 4, "N" means that the 150-th run started with a temperature 22 (deg C) and ended with a temperature 23.8 (deg C). The coloured area shows the START and STOP temperature distribution.

One of the important experiment outcomes was that people would experience thermal discomfort at different temperature points, which means that the complexity of the thermal profile is bigger than a regular mathematical model can describe. Following means that implementation of the artificial intelligence and bio-metrical data is an important step to closing the gap between predicted and actual comfort for each individual.

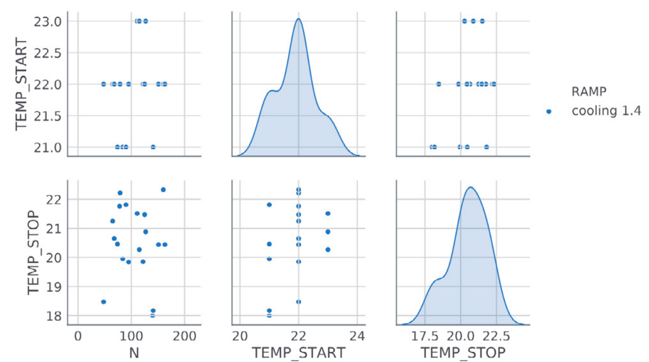


Fig. 3. Cooling temperature ramp with slope 1.4

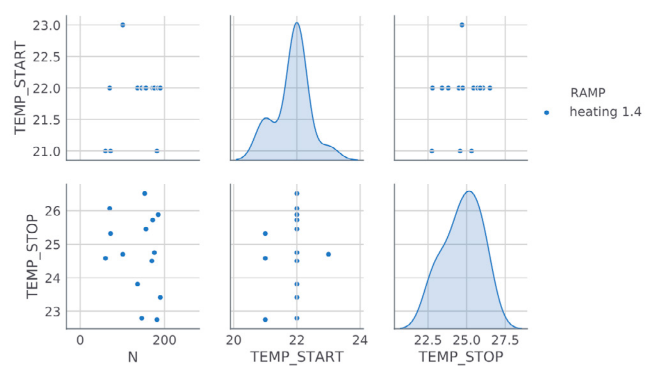


Fig. 4. Heating temperature ramp with slope 1.4

3. DIGITAL PLATFORM FOR THERMAL DISCOMFORT PREDICTION OF SILVER AGE PEOPLE

3.1 Artificial Neural Network and it's advantages

The ANN is an information processing unit built in a way which aims to mimic brain neural activity(Ketkar and Santana (2017); Beysolow II (2018); Manaswi et al. (2018)). It has the ability to learn complex non-linear relationships which is very important since our life rarely has linear dependence. The ability to generalize after a process of learning allows ANN to perform even in case of receiving unseen before data input. A general representation of the ANN with one hidden layer is shown in Fig. 5. It has 3 features [X1, X2, X3] in the feature vector and one target output [Y]. Information flow is going only one way which means it is feed-forward ANN. In cases when we need a faster process of learning it is common to use back-propagation to propagate the error rate obtained in the previous epoch to fine-tune weights of the neural network (Mitchell (1997); Alpaydin (2020); Goodfellow et al. (2016))

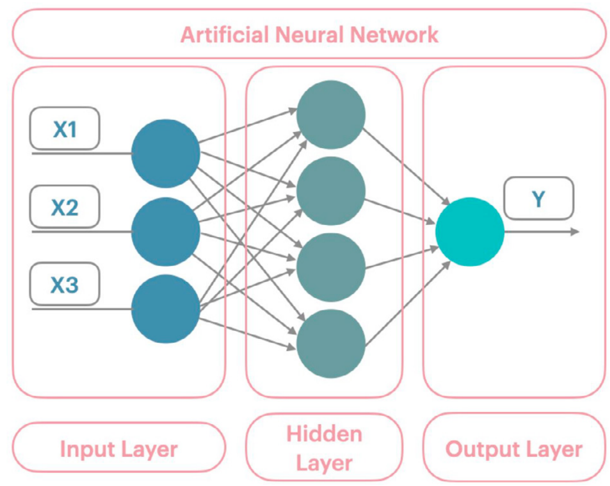


Fig. 5. General representation of the Artificial Neural Network with one Hidden Layer

Exists number of problems which are solved by ANN:

- Image processing and character recognition
- Forecasting
- Clustering
- Speech processing

The process of learning can be either supervised or unsupervised. During supervised learning data include the desirable outcome "label" which is defined to be correct by us. Unsupervised learning is the total opposite, the vector of input data doesn't have envisioned/suggested out or label. Such method expects ANN to find patterns and adjust weights by itself. It is beneficial for large amounts of data which we want to cluster. ANN will group unsorted data according to similarities, patterns or differences.

For the case of the above-discussed experiment and development of an intelligent platform, it is possible to say that accumulated data will be marked with "comfort", "discomfort due to cold conditions" and "discomfort due to warm conditions". As result - supervised learning will be used.

Over the last 10 years, the most common algorithms which were used in previous thermal comfort studies with labelled categorical data were Support Vector Machine (Cosma and Simha (2019); Laftchiev and Nikovski (2016); Chaudhuri et al. (2018b); Salamone et al. (2018); Lu et al. (2019); Katić et al. (2018)), random forest, K-nearest Neighbour(k-NN) (Lu et al. (2019); Cosma and Simha (2019); Li et al. (2018); Chaudhuri et al. (2018a)) and ANN (Chaudhuri et al. (2018b); Ueda et al. (1997); Zhai et al. (2017)).

All of them have the potential to be used for the thermal discomfort model but due to the complexity of the stated task, the need for a solution which is less invasive and more reliable evidently suggests the use of ANN.

3.2 Proposed platform

Base on the outcomes from previous data collection campaign and data pre-processing (Marchenko et al. (2020)) a new conceptual design can be feasible for creation of the intelligent platform which will cover silver age cluster of people and will allow to be more effective in prevention of the overheating and over-cooling events.

For data collection campaign, ZEB laboratory should be adjusted to resemble regular house space of a person. Each participant should be in silver age target group and live at least one month in the test environment. During this period person will be asked to fill in indoor environment surveys from time to time while remain option to press the discomfort button on their phone and provide a note on what was source of a discomfort.

Indoor and outdoor temperature should be collected continuously during all period of experiment. Also, it is envisioned to use Apple Watch for collection of day to day activity levels and how heart recovers from intensive load (such as fast walk or walk with groceries). Such kind of data will allow to train intelligent system to adjust indoor conditions in advance before person enters building which will create slow transition from one environment to another. In addition, Health app allows to see events of high heart rate during sitting or general low movement state - such alerts are important in order to give person chance to put attention on their breathing or call to doctor with health profile information within precise moment (see Fig. 6).

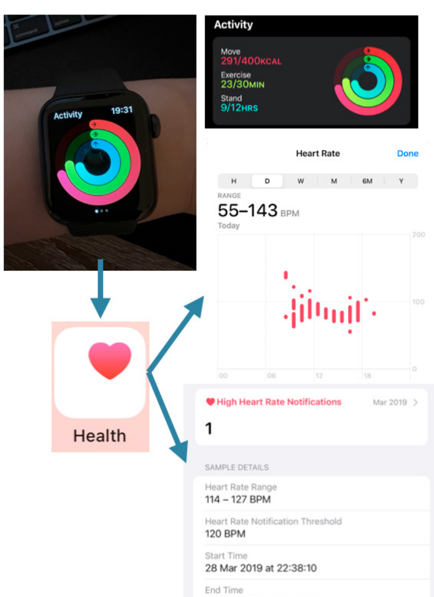


Fig. 6. Benefilts of Apple Watch Health app

While some data is collected directly from person's hand in order to help pre-adjust indoor environment, HD cameras or facial scanners should be installed in places where person spend most of their time (see Fig. 7). It will enable continuous flow of facial vector movements data which in combination with indoor temperature most likely is a key variable for non-invasive thermal discomfort detection.

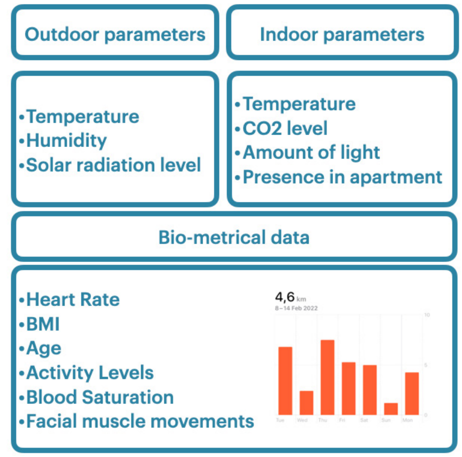


Fig. 7. Suggested data collection for ANN training

Collected facial vector data will be processed in groups (see Fig. 8) which will provide insides on the importance of particular facial regions for the predictions of the comfort level.

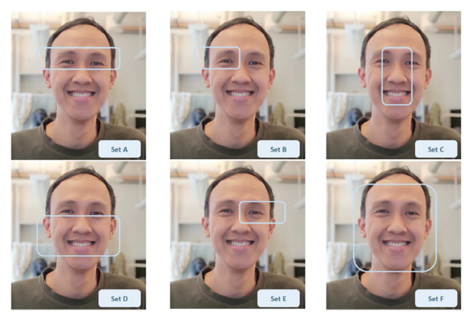


Fig. 8. Suggested facial regions for investigation

In the long run, such a system might not only be useful for the creation of a comfortable thermal profile within a house or apartment but also provide insights into a person's health and allow to build trends concerning heart performance within a bigger picture of everyday life.

Artificial Neural Network (ANN) is the heart of the platform which aims to evaluate the continuous flow of real-life data and adjust Heating, Ventilation and Air Conditioning (HVAC) respectively.

Previous data collection campaign was held only for people of age 20-40 years, it is most likely that future facial muscles movement data will be even more prominent since with age our muscles become more visible under skin layers due to loss of collagen and fat deposits.

4. POSSIBLE LIMITATIONS

It might be hard to find experiment participants who are willing to spend one month and more within the test facility even though it mimics the home environment. Also, each time a new experiment participant finishes the data collection campaign - the facility should be closed on quarantine to prevent any possibility of spreading COVID-19. The silver age group of people are less likely to learn new technology and are usually more sceptical about it. In addition, it is hard to predict if the collected data will be enough to get inside on the thermal comfort profile of the individual which might result in the need for a repeat of the data collection campaign with adjusted sensor placements.

5. CONCLUSIONS

This paper proposed a fresh look at technology which become available more with each year. It is evident from previous studies within the field of thermal comfort detection via use of bio-sensing technology that perception of the thermal environment greatly varies and it is not enough to use regular mathematical models to reduce the thermal comfort prediction gap.

Facial muscle movements were important bio-markers in a number of studies which are not in the field of thermal comfort (Nubani and Öztürk (2021); Franěk and Petružálek (2021); Hsu (2021); Agen et al. (2021); Masulli et al. (2022)) but there is a big potential of adoption and adaptation of the concepts for better insides on involuntary facial muscle behaviour and it's connection to the feeling of thermal discomfort.

Also, it is worth highlighting that all experimental data collection campaigns were involving an age group between 20 to 40 years old. That is why the new experimental design which was proposed is important to consider for future generations and current people who represent the silver age population.

The proposed bio-sensing platform has the potential to bring better insides into human perception of thermal comfort and the ways in which thermal discomfort affects our health and productivity.

Better prediction of people's condition and adaptive microenvironment in the room is a big step in an increase of life quality for an older generation. If deployed correctly, it can build a bridge between the individual and indoor temperature profile which is so important in day to day activities.

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