Ashdin Publishing
International Journal of Sensor Networks and Data Communications
Vol. 1 (2012), Article ID X110105, 9 pages
doi:10.4303/ijsndc/X110105

Research Article

Study on Sensor Fusion for Predicting Human's Thermal Comfort Accounting for Individual Differences by Using Neural Network

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Received 28 January 2011; Revised 19 August 2011; Accepted 21 August 2011

Abstract This paper presents a method for utilizing sensor networks to predict human's thermal comfort and sensation. A neural network is dynamically organized on the basis of correlations between the thermal sensation of office occupants and a number of values measured by the sensor network, and the structure of the neural network is cyclically updated. By way of an example, the air-conditioning system in an office is used. We place a number of temperature sensors and participants in this indoor environment, and conduct an experiment where the sensor readings and the thermal sensation of the participants are monitored concurrently. From the experimental results it can be seen that the various sensors are selected correctly and can be used to predict the desired system behavior.

Keywords sensor fusion; sensor network; thermal system; thermal comfort; measurement

1 Introduction

Recent advances in electronics and networking technologies has enabled the development of sensor networks [1,5,7,8,13,16,17]. Low-cost, high-performance sensors are now readily available and network infrastructures can be easily implemented. Even in harsh environments, such as mountains or isolated islands, a network can easily be built by using wireless technology. Additionally, we can use not only custom-built sensors but also the considerable amount of information available on the Internet. Hence, sensor network has been applicable to a wide range of applications such as an environmental monitoring [2,14], a structure health monitoring [3], medical applications [9,15], walfare applications, and a crime prevention [11]. Some applications use sensory data directly, others assemble values to assess the environment. Studies that treat such assembled data have been studied as a sensor fusion or a data fusion [4]. As for the fusion technologies, a number of data acquired from the sensors deployed in the environment are used for estimating the environmental phenomenon and predicting user's behavior in order to provide better services to each user.

This paper thus presents a method for associating measurements obtained from various sensors with a required prediction of the system behavior. Here, we employ a dynamically changing neural network to predict the system behavior. As an example case, the thermal sensation of occupants is predicted by using humidity sensors, and local and global temperature sensors. We place both a large number of sensors and the occupants in an indoor environment, and conduct an experiment where the sensor readings and the thermal sensation of the occupants are measured and correlated. From the experimental results, it can be seen that the sensors are not only selected correctly but also can be used to predict the desired system behavior.

2 Thermal sensation and thermal comfort

2.1 Thermoregulatory mechanism and thermal comfort

Hypothermia is a condition in which the core temperature of the human body is at least 2 °C below the average internal body temperature of 37 °C. The human body requires this constant internal temperature to maintain all normal metabolic and body functions, and this temperature is regulated continuously. The many physiological and behavioral processes involved in keeping the core temperature constant come under the collective title of thermoregulation.

The thermoregulatory system is controlled by the hypothalamus in the brain, which operates much like a thermostat. Whenever the temperature exceeds or falls below set points, physiological processes commence to return the temperature back to a normal level. The anatomical system that controls the body temperature comprises the temperature receptors in the skin, the afferent nerves, the thalamus and hypothalamus, vasodilatation, respiratory center, the sweat glands, the muscular system, and the hormonal and enzymatic systems involved in the calorigenic metabolism of stored fat and protein.

For the microclimate in residential and public buildings, standards to ensure thermal comfort are established in different ways to take into account the climatic zone, season, and

	Index	Proposer	Notes
(A)	Kata cooling power	L. Hill (1916)	A measure of the cooling effect of the ambient air as determined by the kata thermometer.
(B)	Globe temperature (GT)	H. M. Vermon (1930)	This index incorporates the effects of the air temperature and the mean radiant temperature, and approximates closely to the operative temperature.
(C)	—	Madsen (1972)	The amount of clothing, activity, and humidity are given as a constant of electrical circuit based on the comprehensive assessment of temperature, air velocity, and radiation.
(D)	Predicted 4-hour sweat rate (P4SR)	McAdle (1947)	The amount of sweat secreted by fit, acclimatized young men exposed to the environment for 4 hours while loading guns with ammunition during a naval engagement.
(E)	Effective temperature (ET)	Houghten, Yaglow (1923)	The different factors determining thermal comfort—air temperature, humidity and air movements are combined together into a single index.
(F)	Temperature-Humidity Index (THI)	The National Weather Service (1959)	An index to determine the effect of summer conditions on human comfort, combining temperature and humidity.
(G)	Wet Bulb Globe Temperature (WBGT)	Yaglow, Minard (1957)	A composite temperature used to estimate the effect of temperature, humidity, wind speed and solar radiation on humans.
(H)	Operative temperature (TO), Standard operative temperature (TSO)	Gagge (1937)	An imaginary environment of equal wall and air temperatures and air movement, in which the human body, with skin temperature, would lose the same amount of heat by radiation and convection as in the original environment.
(I)	Predicted mean vote (PMV)	Fanger (1970)	PMV establishes a thermal strain based on steady-state heat transfer between the body and the environment and assigns a comfort vote to that amount of strain. PPD is the predicted percent of dissatisfied people at each PMV.
(J)	New effective temperature (ET*), Standard effective temperature (SET*)	Gagge, Nishi (1971)	SET* numerically represents the thermal strain experienced by the cylinder relative to a "standard" person in a "standard" environment. SET* has the advantage of allowing thermal comparisons between environments at any combination of the physical input variables, but the disadvantage of also requiring "standard" people.

Table 1: Indices of note for evaluating thermal comfort.

occupants' age group. For most healthy adults living permanently in a temperate zone and wearing ordinary indoor clothing, thermal comfort is achieved at an ambient temperature of 18 to 22 °C in winter and 23 to 25 °C in summer. In addition, the following conditions must be met: the difference between the ambient temperature and the temperature of enclosed areas is not more than 3 °C; the relative humidity is 30% to 60%; and the rate of air movement is 0.05 to 0.15 m/s in winter and 0.2 to 0.4 m/s in summer [10].

The zone of thermal comfort changes somewhat under the influence of factors such as physical exertion, adaptation to heat or cold, and some pathological conditions.

2.2 Indices for thermal comfort

Thermal comfort is difficult to define because a range of environmental and personal factors must be considered when deciding what will make people feel comfortable. However, over the years, extensive research effort has been devoted to developing indices for predicting thermal comfort. Table 1 shows a summary of the indices of note that have been established for evaluating thermal comfort. These indices are all based on the measurement of particular physical quantities.

Thermal comfort and thermal sensation are not the same. Thermal comfort is defined as being "the state of mind that expresses satisfaction with the surrounding thermal environment" [6], whereas thermal comfort is merely represented by using the terms "comfortable" or "uncomfortable".

Thermal sensation is also defined in ISO 7730, which specifies methods for measurement and evaluation of moderate and extreme thermal environments to which human beings are exposed [12]. Thermal sensation is a human feeling that is mainly related to the thermal balance of his or her body as a whole. This balance is influenced by physical activity and clothing, as well as by environmental parameters: air temperature, mean radiant temperature, air velocity, and air humidity. When these factors have been estimated or measured, the thermal sensation for the body as a whole can be predicted by calculating what is conventionally known as the predicted mean vote (PMV) (see Table 1). A person's thermal sensation level can be expressed by using words such as "cool", "warm", "cold", or "hot". The level of sensation is often characterized by using the thermal sensation

Value	Sensation
+3	Hot
+2	Warm
+1	Slightly warm
0	Neutral
−1	Slightly cool
−2	Cool
−3	Cold

Table 2: ASHRAE thermal sensation scale.

Figure 1: Experimental indoor environment.

scale shown in Table 2, as defined by the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE).

Both thermal sensation and thermal comfort are not only related to the steady state but also to the transient nonuniform thermal environment.

2.3 Transient change of thermal comfort

We conducted experiments in which we investigated transient changes of thermal sensation and thermal comfort under two different psychological stress conditions—"neutral" and "stressed". Figure 1 shows an indoor environment in which we are able to adjust the inner air temperature, humidity, and air velocity. Participants move from one thermal environment—air temperature = 30 °C, relative humidity = 60%, physical activity level = 1 MET, and clothing insulation = 1.0 clo (with PMV = 1.97)—to a different thermal environment—air temperature = 25 °C, relative humidity = 30%, physical activity level = 1.0 MET, and clothing insulation = 1.0 clo (PMV = 0.07)—and state their thermal sensation and thermal comfort levels. Eighteen participants, aged 21 to 35 years old, took part in this experiment.

Each experiment starts after 30 min of exposure to the initial environment. For the first 15 min of the experiments the participants report their thermal sensation and thermal comfort in the initial environment once every 3 min.

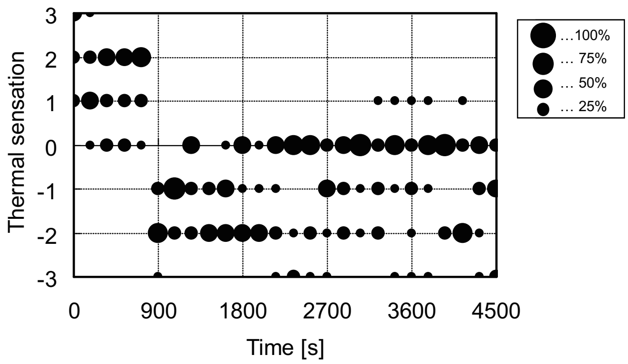

Figure 2: Thermal sensation response (psychologically neutral condition).

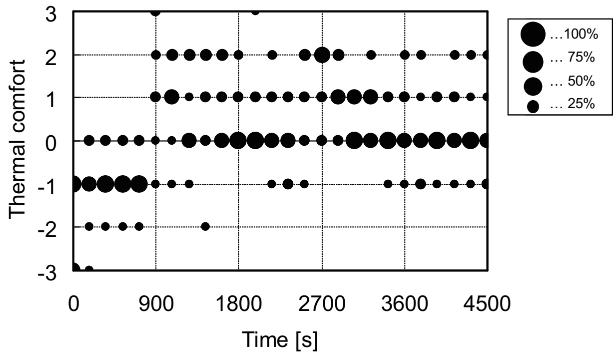

Figure 3: Thermal comfort response (psychologically neutral condition).

Then, the participants immediately move to the other environment and continue to report their sensation and comfort once every 3 min. After 60 min in this second environment, the experiment ends. The participants' levels of thermal sensation and thermal comfort are both expressed numerically in the form of seven-point scales. Thermal sensation is quantified as follows: "+3" is "Hot", "+2" is "Warm", "+1" is "Slightly warm", "0" is "Neutral", "−1" is "Slightly cool", "−2" is "Cool", and "−3" is "Cold". Thermal comfort is also expressed as follows: "+3" is "Very comfortable", "+2" is "Comfortable", "+1" is "Slightly comfortable", "0" is "Neutral", "−1" is "Slightly uncomfortable", "−2" is "Uncomfortable", and "−3" is "Very uncomfortable".

Figures 2 and 3 show the participants' thermal sensation and thermal comfort responses, respectively, under the psychologically neutral condition. Conversely, Figures 4 and 5 show their responses under the psychologically stressed condition. In these figures, the size of the black circle denotes the percentage of the participants expressing that response level. Even if the thermal environment remains unchanged and the PMV is constant, the responses of the participants change (Figures 2 and 3). However, when

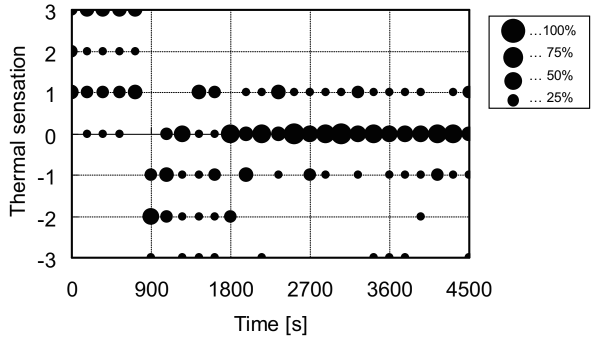

Figure 4: Thermal sensation response(stressed).

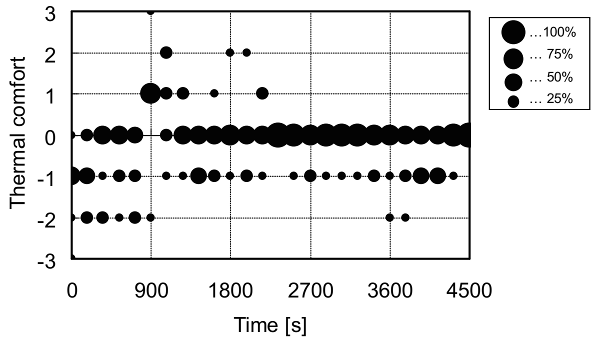

Figure 5: Thermal comfort response (stressed).

expressing thermal comfort under no psychological pressure, there are many declarations of "comfort" when there is no psychological pressure. In contrast, many participants stated "Neutral" for both thermal sensation and comfort when under psychological pressure (Figures 4 and 5). Hence, without psychological pressure, the results show the strong influence of each individual's subjective difference.

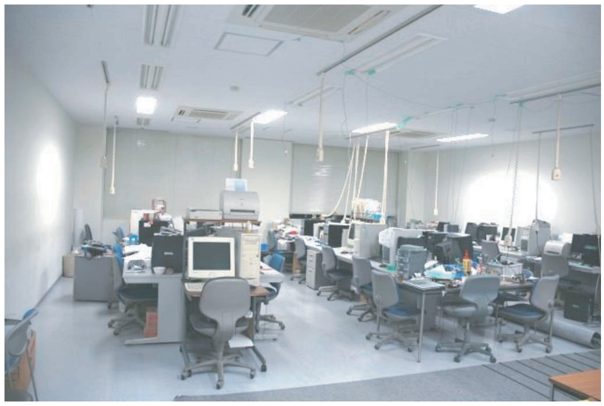

Figure 6: Indoor office environment.

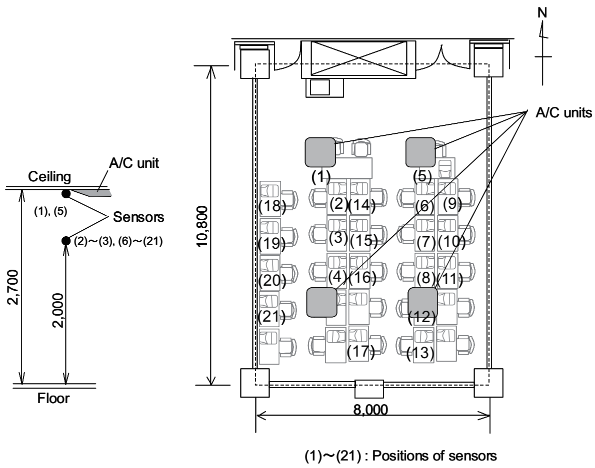

Figure 7: Schematic showing positions of sensors.

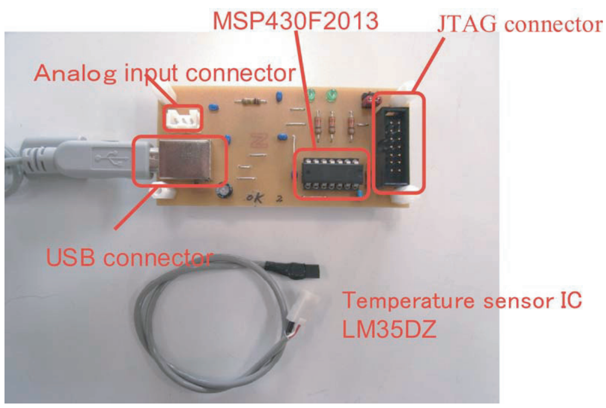

Figure 8: Example temperature sensor used in experiments.

3 Acquisition of human's thermal sensation

3.1 Experimental environment

As an example, the air-conditioning system in an office is used (Figures 6 and 7). For this system, 21 temperature sensors are located in the indoor environment, where 2 of the sensors are positioned at the outlets of two of the air-conditioners, and the remaining sensors are located above the desks of the office occupants. Figure 8 shows a photograph of a temperature sensor, and Figure 9 shows a diagram of the network topology. Each sensor is connected via a universal serial bus (USB) cable to a personal computer (PC) on the desk of the respective occupant. All of the PCs are connected to a Local Area Network (LAN). The sensors are self-organized in a dynamical manner through peer-to-peer (P2P) connections by running our customized software on the PCs. Owing to the network being self-organized, the connections are unstable, and the state of the network changes frequently.

3.2 Sensor networks

Sensor networks have various forms depending on the hardware, software, and topology used in their implementation. We utilize a sensor network that has the following features [1].

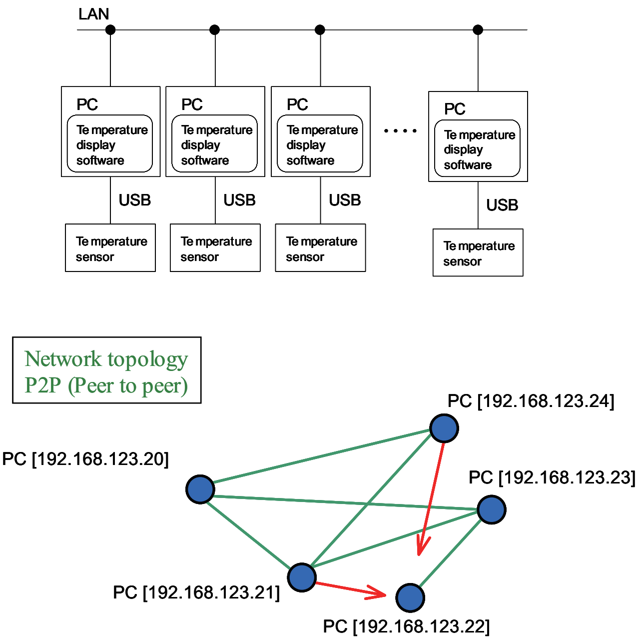

Figure 9: Network topology.

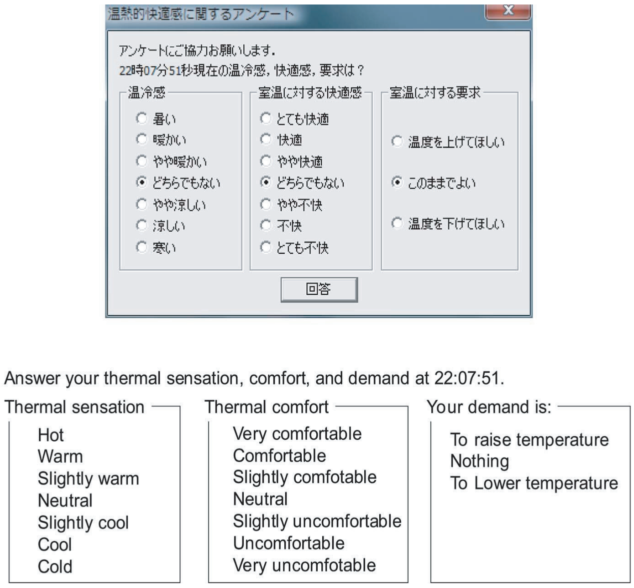

Figure 10: Inquiry dialog box (in Japanese).

– The number of sensor nodes in the network can be range over several orders of magnitude (e.g., ZigBee can consist of up to a maximum of 65535 nodes).
– Sensor nodes are densely deployed.
– Sensor nodes are prone to failure.
– The topology of the sensor network changes frequently.
– Sensor nodes can use both a broadcast communication paradigm and P2P communication.

Sensor networks with the above features have various applications. Such a network form is possible on the Internet, in a LAN, and in uniquely created networks. That is, our framework can be applied to almost all sensor networks that currently exist. Hence, the above-mentioned features do not correspond to strict specifications.

3.3 Acquisition of participants' thermal sensation

To capture the thermal sensation experienced by the participants over time, we implement custom software that the occupants of the office use to express their level of thermal sensation. The software simultaneously acquires measurements from the sensors and the response of the participants. At 15 min intervals, the software displays a dialog box, as shown in Figure 10, to inquire about the occupant's levels of thermal sensation and thermal comfort, as well as any request the occupant might have for a change in the temperature. As mentioned in the previous section, the levels of thermal sensation and thermal comfort are expressed numerically on a seven-point scale that quantifies the participant's feeling.

4 Predicting thermal sensation

4.1 Predicting thermal sensation by using neural network

To predict the behavior of the system, we used a self-organized neural network. Here, the behavior of the system corresponds to the thermal sensation of the participants. The neural network was dynamically organized on the basis of correlations between the thermal sensation responses of the office occupants and a number of values measured by the sensor network, and the structure of the neural network was cyclically updated. In addition, when it became computationally difficult to use a certain part of the information from the sensor network, the structure of the neural network was again updated. When updating the structure, we referred to the time and the positional correlations of the value requiring prediction and also the correlations of this value with each measurement in the sensor network.

4.2 Correlation coefficients between sensor measurements and thermal sensation responses

Figure 11 shows the indoor temperature measures and the thermal sensation responses of five occupants. The sections are taken from data measured over a two-week period, where each plot represents the changes over a span of about 3.5 days. For all cases, the plots showing the temperature changes have a similar profile. However, the respective thermal sensations obtained from the five occupants of the office show individual tendencies, and each is entirely different from the others. As these fluctuations originate from subjective differences, the values are not easily acquired by using a sensor.

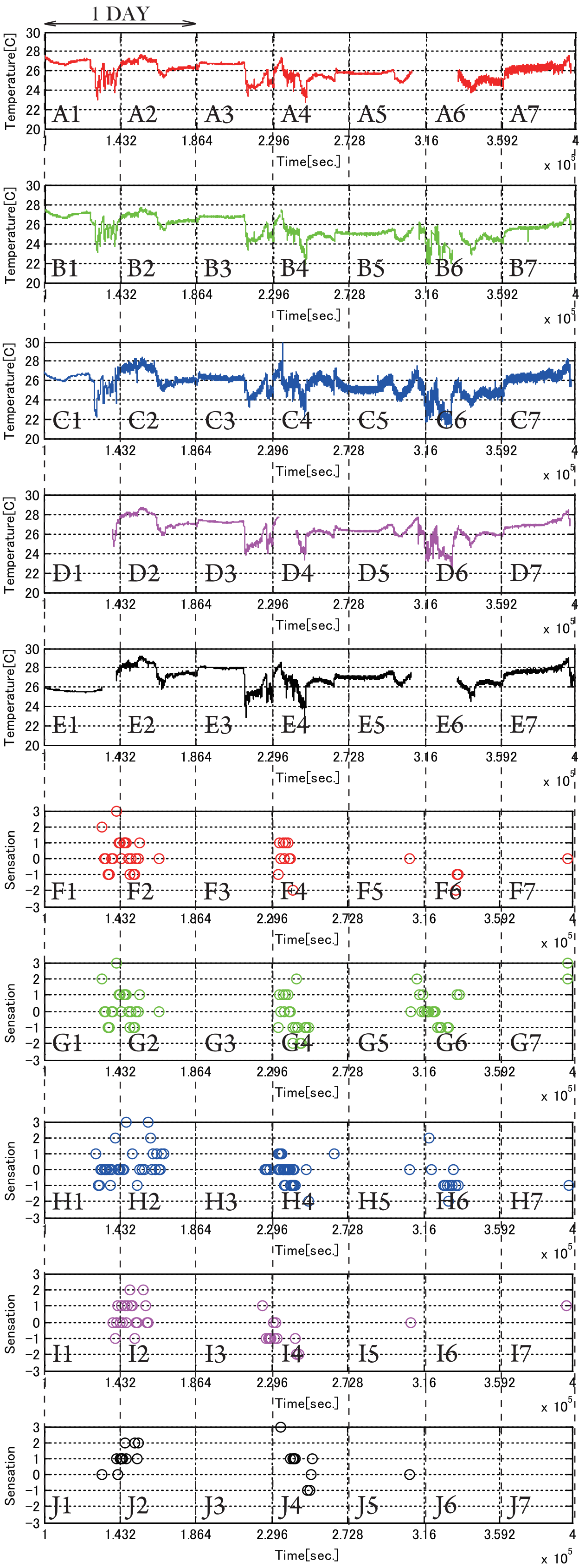

Figure 11: Indoor temperatures and levels of thermal sensation for five participants.

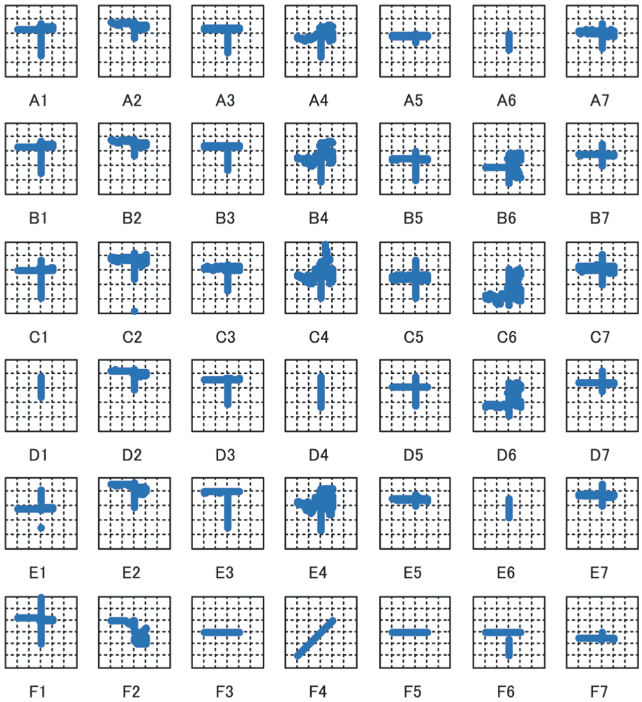

Figure 12: Scatter diagram of the relations between F4 and other sections.

Therefore, we assume that particular values correspond to particular situations. A value can be estimated by using sensor measurements that have a strong correlation with the target value. In general, the current value is estimated from both the current state and the previous state of the system. A simple method in this respect involves calculating the correlation coefficient per unit of time for each section. In Figure 11, the plots are divided into seven regular time intervals, each equivalent to a half-day unit, and each section is labeled with a letter and a number (A1, A2, etc.). With the variables in two arbitrary sections defined as x_n and y_n, the correlation coefficient, R, is given by

$$R = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^{n} (y_i - \bar{y})^2}}, \quad (1)$$

where $\bar{x}$ and $\bar{y}$ are the mean values for each section. For instance, Figure 12 shows scatter diagrams of the relations between the values in F4 and those of the other sections, Table 3 shows the correlation coefficients between F4 and the other sections, and Table 4 shows the correlation coefficients between F2 and the other sections. A correlation is sufficiently strong if the absolute value of the correlation coefficient approaches 1.

4.3 Self-organized neural network

Now, we consider prediction of the value for F4. Since the surrounding sensory data cannot be used immediately for

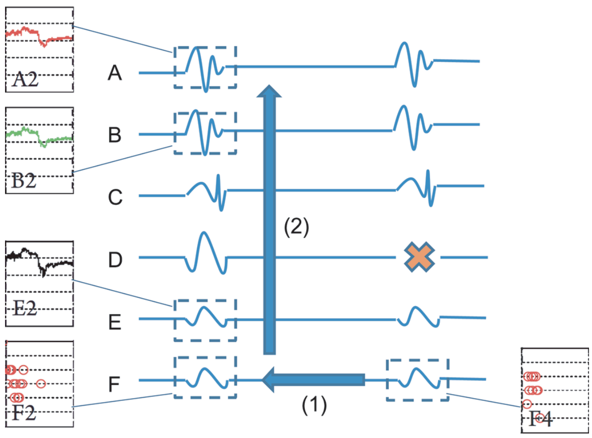

Figure 13: Reference to time and positional correlations.

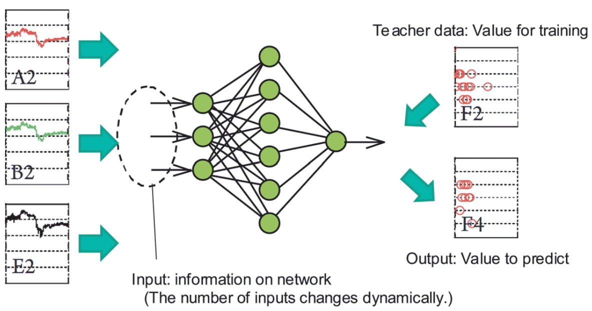

Figure 14: A dynamically changing neural network.

predicting the target F4 value, it is necessary to construct a model that considers the surrounding values as inputs and the F4 value as an output. For this model, we use a dynamically changing self-organized neural network.

The inputs to the neural network are selected in accordance with the following procedure. First, from the previous measurements, the time series displaying the strongest correlation is located (Figure 13(1)). From Table 3, we see that the correlation coefficient between F2 and F4 is the strongest, taking a value of −0.5508. Therefore, F2 is chosen in this instance. Next, the correlation coefficients between F2 and its related sensory data in other sections are examined (Figure 13(2)). According to Table 4, E2 has the strongest correlation with a coefficient of 0.42448, followed by D2, A2, and B2. Since D4 cannot be used for predicting F4, D2 cannot be chosen as an input. Therefore, E2, A2, and B2 are used as inputs for the neural network (Figure 14). For the case presented here, 720 sets of training data are used, and the number of nodes in the middle layer of the network is about twice the number of inputs. Although measurements from more input sensors can be used in an actual sensor network, an increase in the number of inputs for the neural network can increase the calculation cost substantially.

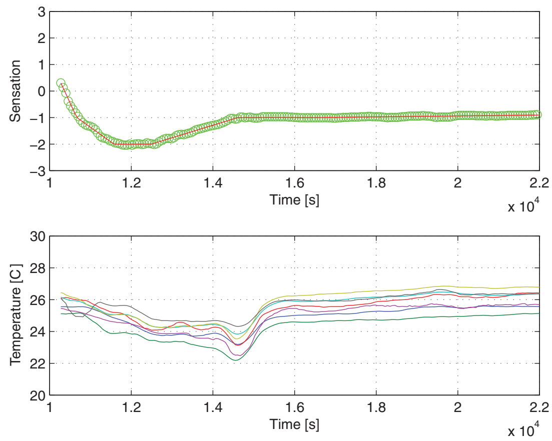

Figure 15: Experimental results (Thermal sensation).

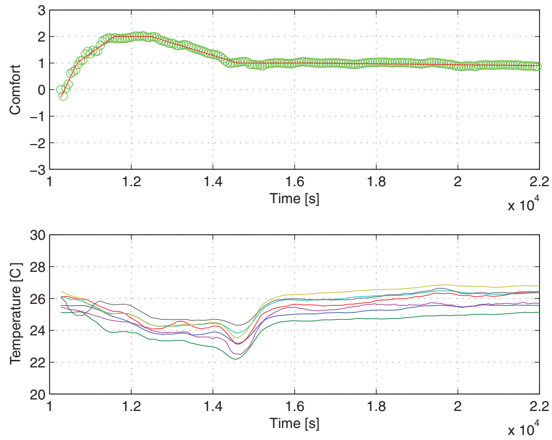

Figure 16: Experimental results (Thermal comfort).

5 Experiment

To examine the validity of this framework, an experiment in the indoor environment was conducted, as explained in Section 2.2. Via our custom software, 20 participants notified the network every 15 min of their level of thermal comfort, their level of thermal sensation, and any request to change the temperature. Participants could also notify the network of their levels and requests between these intervals if they so wished. The experiment was conducted continuously over a two-week period. With the experiment being completed, the software could calculate the correlation coefficients, construct the dynamical neural network, and train the neural network in the background. By using the constructed neural network, it is then possible to predict the thermal sensation that a person will experience in the example environment.

Figure 15 shows the transient change of thermal sensation, and Figure 16 shows the transient change of thermal comfort. From the upper graph in each figure, the solid line expresses the responses of a single occupant in the office, whereas the circles represent the predicted thermal sensation

	1	2	3	4	5	6	7
A	0.07721	0.03814	0.14579	0.09935	0.09108	−0.2219	0.05839
B	0.07721	0.03814	0.14579	0.08129	0.05564	0.0467	0.05775
C	0.04128	0.07359	0.13067	−0.0514	−0.0113	−0.014	0.05692
D	−0.0587	0.11275	0.14621	−0.3407	−0.0198	−0.0419	0.05786
E	0.08769	0.05953	0.1481	0.09806	0.08971	-0.2185	−0.0033
F	−0.0511	−0.5508	0	1	0	0.2108	−0.2424

Table 3: Correlation coefficients between F4 and other sections.

	1	2	3	4	5	6	7
A	0.18284	0.22556	0.2427	−0.1059	0.17186	−0.312	0.10885
B	0.18284	0.22556	0.2427	−0.2297	0.10687	−0.2727	0.10598
C	0.09531	0.1338	0.22456	−0.1757	0.00414	−0.2783	0.10482
D	−0.1104	0.39338	0.23569	0.14576	−0.0131	−0.383	0.10943
E	0.16187	0.42448	0.23634	−0.1454	0.17034	−0.3209	−0.0093
F	0.01443	1	0	−0.5508	0	0.2594	−0.2754

Table 4: Correlation coefficients between F2 and other sections.

or thermal comfort. The lower graph in each figure shows a plot of the indoor temperature changes as measured by several sensors. Note that the time scale in Figure 11 is much larger than the time scales for Figures 15 and 16. In the temperature plots, the temperature initially falls from about 26 °C to about 22 °C, it then rises again and becomes constant at around 25 °C. At the same time, the thermal sensation changes from "slightly warm" (+1) to "cool" (−2), then increases to "slightly cool" (−1). In addition, the thermal comfort increases from "neutral" (0) to "comfortable" (+2), before falling to "slightly comfortable" (+1). It can be seen from these figures that the sensation and the comfort levels reported by the participant and those predicted by the neural network are in good agreement.

6 Summary

This paper has explored a method for choosing the most relevant sensors out of a number of sensors, including information from sensors available on the Internet, and subsequently using the sensory data to derive system behavior for a given time and place. A method was described for predicting the thermal sensations of participants that had been previously measured by using a sensor network. We utilized a dynamically changing neural network to predict the system behavior in order to correlate the measurements from the sensors with the target value. As an example case, the thermal sensations of office workers were recorded for training the neural network by using temperature sensors in a sensor network. The thermal sensations reported by the participants and those predicted by the neural network were in good agreement.

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