Occupant-aware thermal comfort control with elevated air speed

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OCCUPANT-AWARE THERMAL COMFORT CONTROL WITH ELEVATED AIR SPEED

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List of Abbreviations

ACMV Air Conditioning and Mechanical Ventilation

ARIMA Auto-Regressive-Integrated-Moving-Average

ASHRAE American Society of Heating, Refrigerating and Air Conditioning Engineers

BCA Building and Construction Authority

BEMS Building Energy Management Systems

CE Cooling Effect

CFD Computational Fluid Dynamics

DC Direct Current

EN European Standard

GPS Global Positioning System

GT Generalized t -Distribution

IMU Inertial Measurement Unit

ISO International Organization for Standardization

PMV Predictive Mean Vote

PMV_{adj} Adjusted Predictive Mean Vote

PPD Predicted Percentage Dissatisfied

RF Radio Frequency

RFID Radio Frequency Identification

RSS Received Signal Strength

RH Relative Humidity

SET Standard Effective Temperature

SMS Short Message Service

UPSS User Personal Space Setting

USB Universal Serial Bus

ZEB Zero Energy Building

List of Symbols

Symbol	Description	Unit
$(\cdot)^T$	transpose operation	-
D	distance between a reference node and a target	m
$E\{\cdot\}$	expectation operation	-
F_o	occupant feedback	-
f_{cl}	clothing surface area factor	-
g	empirical tuning parameter of the weighted centroid formula	-
h_c	convective heat transfer coefficient	W/(m ² K)
h_p	height of a seated person	m
h_f	height of a fan	m
H	observation matrix	-
I_{cl}	clothing insulation	m ² K/W
I_n	identity matrix with dimension of $n \times n$	-
K	calibrated gain matrix	-
k	time instant	-
M	metabolic rate	W/m ²
P	fan speed setting	-
$\bar{P}$	fan power consumption	W
P_{opt}	optimal fan speed setting	-
p_a	water vapor partial pressure	Pa

Q	effective mechanical power	W/m ²
t_a	air temperature	°C
t_{cl}	clothing surface temperature	°C
$\bar{t}_r$	mean radiant temperature	°C
V_d	desired air speed	m/s
V_{elev}	air speed within elevated-air-speed region (> 0.2 m/s)	m/s
V_{still}	air speed within still-air region (≤ 0.2 m/s)	m/s
$V(\cdot)$	air speed generated by electric fans	m/s
$\text{Var}\{\cdot\}$	variance operation	-
v	air speed	m/s
$x_i(k)$	the i th element of the state x at time instant k	-
$\varepsilon_i(k)$	the i th element of the noise ε at time instant k	-
α	standard deviation	-
η	path loss exponent	-
λ	forgetting factor	-
ν	shape parameter of the generalized t -distribution	-
σ	scale parameter of the generalized t -distribution	-

Abstract

Compressor-based cooling contributes a large part of energy consumption in buildings, especially in hot and humid climates. In Singapore, electricity comprises the largest percentage of building operating expense, of which about 50% is for air conditioning. Increasing cooling setpoint and utilizing elevated air speed generated by fans is a viable and promising approach of delivering thermal comfort with less energy use.

The work presents in this thesis leverages on recent advances in human thermal comfort research and indoor positioning techniques to develop cost-effective, energy-efficient and occupant-satisfied solutions for indoor location-based cooling. Specifically, the occupant-aware operations of both a single fan and a system of fans are introduced. In addition, an indoor tracking system with a more generalized noise model for obtaining more accurate occupancy information is developed. The effectiveness of the proposed solutions is demonstrated through simulations and experiments.

For personalized thermal comfort, a smart tracking fan system is developed using camera-based indoor localization. The position of the occupant is constantly tracked by a camera-based localization system and subsequently used for determining the occupant-fan distance and direction of airflow. Personal cooling is provided upon the detection of the occupant in the area bounded by virtual geofences. The state-of-art PMV-SET (Predicted Mean Vote-Standard Effective Temperature) thermal

comfort model is used to obtain the relationship between the air speed and thermal comfort. This relationship is used to determine the desired air speed under different environmental conditions. The fan is then controlled to give the desired air speed, taking into account the occupant-fan distance.

For multiple occupants, a patented technology for cooperatively controlling a system of fans to provide optimized air movement is developed. A cost-effective calibration method to obtain the relationship between air speed and fan speed setting is proposed to predict airflow in the actual environment. Fans operation is optimized by minimizing the maximum deviation between the actual air speed generated by fans and the desired air speed. This minimax-error problem is reformulated as a linear programming problem which can be solved readily using standard methods.

To obtain occupancy information, a received signal strength (RSS)-based indoor tracking system is implemented. A common problem with RSS-based indoor tracking is the disturbances encountered in dynamic and complex indoor environments. The proposed system uses the generalized t -distribution (GT) to model the disturbances. A recursive filtering algorithm based on the GT noise model is developed. Because of the more accurate noise model, the proposed filter can produce better position estimates than that of the Kalman filter which makes the usual assumption of Gaussian noise. An equation to compute the variance of the estimation error is also derived. The variance equation can be used as an analytic tool for designing and assessing the tracking system. Both theoretical and experimental results show that the variance of the estimation error from the proposed filter is less than that from the Kalman filter. The experiments also show that the filter with GT noise model can handle outlier better than the Kalman filter.

Chapter 1

Introduction

Nowadays, a large percentage of global energy consumption is attributed to buildings. Studies have found that the building sector accounts for about 37% of total energy consumption in the EU, about 39% in the UK [1], and about 41% in the US [2]. In Singapore, buildings consume approximately half of the country's electricity [3,4], of which about 50% is for air conditioning [5,6]. Figure 1.1 shows the breakdown. A study conducted by Building and Construction Authority of Singapore on 36 commercial buildings found that an efficient air conditioning system can reduce buildings' overall energy consumption by 16% per year which amounts to savings of \$22.7 million [7]. Therefore, it is crucial to improve energy efficiency in buildings while not sacrificing the thermal comfort of occupants.

Figure 1.1: Breakdown of energy consumption within a building [6]

Increasing indoor air temperature setpoint and utilizing elevated air speed generated by fans is a viable and promising approach of achieving satisfactory thermal comfort with less energy use. The attraction of utilizing air movement to save energy and maintain thermal comfort in warm environments is easy to understand, but challenges also come up against researchers and practitioners who intend to do this. Unlike air conditioning which provides a spatially uniform thermal environment, the cooling effect delivered by air movement is location dependent, and there is insufficient attention paid to intelligent operation of air movement devices. Factors like occupant location, personal thermal preference, heterogeneous and dynamic environmental conditions, and time-varying requirements of thermal comfort are rarely considered when generating air movement. Therefore, the work presents in this thesis aims to develop indoor location-based air movement devices and technologies that are intelligent, energy efficient, and comfortable to occupants.

Objectives

The main objective of the research is to make use of sensory technologies to obtain occupants' location information, air movement preferences and personal microclimate data for controlling fans to generate the desired air speed for thermal comfort. The following goals are pursued:

- To determine the desired air speed required for thermal comfort based on either thermal comfort model or occupants' feedback.
 - To obtain the location information of the occupants by using indoor localization technologies.
 - To identify the relationship between the generated air speed and fan speed setting by calibration.
 - To maximize occupants' satisfaction by taking into account their preferences of air movement and using optimization techniques.
-

1.1 Energy Savings from Increased Temperature Setpoints

Increasing indoor air temperature setpoint of the air conditioning system allows energy savings [8–12]. A simulation study conducted by Hoyt *et al.* [10] shows that increasing the temperature setpoint from 22.2 °C to 25 °C in office buildings can save on average 29% of cooling energy. For the tropical climate in Singapore, Rim *et al.* [11] reported that conditioning 10 L/s per person of ventilation air to a temperature of 26 °C and a relative humidity (RH) of 60% can be accomplished at an annual cost of only US \$40/year per person, but this amount increased to approximately US \$60/year for reducing the temperature setpoint (22 °C and 60%).

Saving energy should not deteriorate occupants comfort as it is directly related to their productivity and health [13–17]. When electric fans are used to maintain thermal comfort with increased temperature setpoints, the energy savings are still significant. A simulation study of a benchmark office building in Singapore [12] shows that a 3 °C increase in zone temperatures from baseline 23 °C would correspond to about 17% savings in the air conditioning mechanical ventilation (ACMV) system. In the meanwhile, the overall energy consumption increased only 0.7% when fans are used for maintaining thermal comfort. Another simulation study for fan-assisted buildings in [9] suggests that a cooling energy saving between 17% and 48% can be achieved if elevated air speed is used to offset the impact of increased temperature on occupants' comfort. Supportive evidence is also provided by the environmental chamber study in [18] where the average energy consumed by the fans for maintaining comfort under warm conditions (30 °C and 60% RH) was found to be lower than 10 W per person. Buildings employing such fan cooling promise substantial savings in their ACMV energy, more than 30% below that of conventionally conditioned buildings [19–21]. Therefore, it is believed that elevated air speed can

improve energy efficiency with minimal impact on thermal comfort [22].

1.2 Elevated Air Speed for Thermal Comfort

Elevated air speed is an effective method of cooling in moderately warm environments [23]. Electric fans can be used to supply desired airflow for occupants, thus can assist, or even replace, air conditioning systems to achieve thermal comfort. This is illustrated in Figure 1.2 where different combinations of temperature and air movement are applied to provide thermal comfort. Although elevated air speed may cause draft in cold environments, it can enhance thermal comfort in warm environments [24] and improve perceived air quality [18,25]. It has been reported that people living in tropical climates are more accustomed to slightly higher air movement [26], which suggests the utilization of elevated air speed for thermal comfort is very feasible in the tropics.

Figure 1.2: Increased air movement for thermal comfort [9]

However, the benefit provided by using elevated air speed for indoor cooling is often ignored due to the strict limits set by thermal comfort standards such as ASHRAE 55-1992, 2004 and Singapore Standard SS 553:2009 [27]. This has led to almost no innovation in designing interiors to use air movement and only modest

innovation in industrial products that move air [21].

In recent years, the demand for air movement indoors have been recognized by more and more researchers [28–30]. The ASHRAE database of comfort field studies [24,31–34] shows that more occupants prefer more air movement, while very few prefer less, when environments are in the range of slightly cool to slightly warm. Consistent evidence supporting the use of fans are also provided by environmental chamber experiments. It was found under warm conditions (28 °C and 50% RH) that 100% of the subjects (a total of 96 human subjects) perceived the thermal environment with fans comfortable, while this number decreased to 70% for the case without fans [21]. Another study in [18] shows that when personally controlled floor fan is provided, thermal comfort could be maintained up to 30 °C and 60% RH. This study was later extended to the case of ceiling fans [35] and more than 80% of the subjects rated the environments acceptable for up to 30 °C and 80% RH in the tests. Meanwhile, the preferred air speeds were in many cases higher than the limit specified in ASHRAE Standard, which is 0.8 m/s when local air speed control is not provided. Considering that the common temperature setpoint of air conditioning systems in Singapore is around 23 °C, the potential energy savings of utilizing elevated air speed is therefore enormous.

The three relevant standards regarding thermal comfort are the International Standard ISO 7730 [36], the European Standard EN 15251 [37] and the ASHRAE Standard 55 [38]. The current thermal comfort models used in these standards are of two types: adaptive and predictive models. Adaptive models are derived from empirical studies and assume that occupants in naturally ventilated buildings prefer a wider range of temperatures that reflect the swings of the outdoor climate [39,40]. The adaptation is due both to behavioral and physiological adjustments. Adaptive models as part of the ASHRAE 55 and the EN 15251 can be used in naturally ventilated buildings, with no mechanical cooling system installed and no heating system

in operation. The second type of thermal comfort model is based on physical and physiological properties. The most widely recognized models are Fanger's PMV model [41–43] and Standard Effective Temperature (SET) model [44,45]. These models specifies the combinations of indoor thermal environmental factors and personal factors that produce thermal environmental conditions acceptable to a majority of the occupants within a space. As described in ASHRAE 55, EN 15251, and ISO 7730, they can be applied to mechanically conditioned buildings, which aim to provide a uniform environment.

The work presents in this thesis follows the ASHRAE Standard 55-2013 which better accounts for the cooling effect of elevated air speed [24,46]. In ASHRAE Standard 55, thermal comfort is based on the PMV and SET comfort models. For elevated air speed levels ($v > 0.2$ m/s), the standard uses an integrated PMV-SET approach described in Section 2.1.2 and referred to as the elevated air speed model. According to ASHRAE Standard 55-2013 [38], air speed could have no limits or up to 0.8 m/s depending on whether or not the occupant control of air speed is available. Figure 1.3 shows the comfort range given by ASHRAE Standard 55-2013, which has included the effect of air movement on thermal comfort.

Studies show that people living in tropical climates have a tolerance to high air temperature and are accustomed to high air speed from electric fans [26,47]. Unlike air conditioning which provides a spatially uniform thermal environment, the cooling effect delivered by elevated air speed is location dependent. The methods for intelligent operation of fans to provide the desired air movement are rarely reported in the literature and yet to be explored. The challenge becomes how to implement indoor air movement devices and technologies that are highly energy efficient, comfortable to occupants, and easy to implement.

Figure 1.3: ASHRAE Standard 55-2013: Comfort range and air speed [38]

1.3 Indoor Positioning

Occupancy information has been shown to contribute to both occupant comfort and energy efficiency [48–50]. Occupancy detection is the essential foundation for many building energy and comfort management tasks, such as cooling load prediction [51,52], ventilation rates determination [53–55], ACMV system scheduling and control optimization [56–58]. While the traditional global positioning system (GPS) is ineffective in indoor environments because walls in buildings block GPS signals [59–62], various technologies based on video cameras, radio frequency (RF) signals or inertial measurement units (IMU) have been proposed to locate the occupants in an building.

The camera based approaches [63,64] can provide highly accurate location information. The effectiveness of this approach has been demonstrated by commercial projects such as Microsoft’s EasyLiving [65,66] and Sony’s CyberCode [67]. In camera based localization systems, targets are identified by analysing the images taken

from at least one camera in the monitored area. The observed images of the targets are then checked with a database of geo-referenced images to provide position estimates [68]. Unlike RF signal based methods which are easily affected by noise, camera based solutions are quite stable and accurate at the expense of heavy communication load and camera installation. This approach is convenient for the users since there is no need for them to carry extra devices, but is subject to loss of privacy in the case that occupants are not willing to be visually monitored [69].

Besides camera based methods, the following methods of measurements are also often used for indoor positioning applications [70,71]: time of arrival [72,73], time difference of arrival [74–76], angle of arrival [77–79], received signal strength (RSS) [80–82] and IMUs. Time of arrival and time difference of arrival obtain distance information via signal propagation time. These two methods rely on extensive hardware that is expensive and energy consuming. Angle of arrival can attain desired levels of accuracy with antenna arrays, but the size of nodes may become prohibitive. These methods are, therefore, less suitable for energy-efficient and cost-effective applications. The IMU data, including accelerations, gyroscope readings and magnetic signals, are usually used in a fusion framework as dead reckoning is subject to cumulative errors requiring additional aids [83,84]. Compared with methods above, RSS can be easily obtained by common commercial RF chips, including infrared, WiFi, radio frequency identification, ultra-wide band, ZigBee, Bluetooth, etc., without exaggerating energy consumption and the size of node. Besides, it can be either solely used to achieve positioning tasks or combined with other technologies such as optical (e.g. infrared), inertial, magnetic and ultrasonic by sensor fusion [85,86].

1.4 Summary of Current Fan Technologies

Several fan speed control approaches and apparatus have been disclosed in the patent literature. U.S. Pat. No. 4,734,012 to Dob et al. [87] describes a control circuit for reliable and cost-effective fan speed control in proportion to ambient temperature. U.S. Pat. No. 5,197,858 to Cheng [88] describes a thermal control variable speed DC brushless fan that can change its speed almost linearly with respect to the temperature sensed. U.S. Pat. No. 5,449,275 to Gluszek et al. [89] describes a fan speed controller that is able to maintain a constant level of thermal comfort by varying fan speed in response to dry bulb air temperature, relative air humidity, thermal radiation and distance between the human body and the fan. U.S. Pat. No. 5,627,527 to Menta [90] describes an apparatus and a method for thermostatically controlling the operation of a multiple speed fan and light assembly by inputting a desired temperature range and airflow direction for each fan speed and by inputting a single number for controlling the on time and duration of the light assembly. U.S. Pat. No. 6,415,984 to Parker et al. [91] describes a ceiling fan operation control approach for automatically turning the fan on and off based on a passive infrared sensor, combined with a temperature sensor to regulate the speed of the fan. Even though the above mentioned technologies provide means for automatic operation of fans, there are still rooms for improvement. First, recent emerged localization techniques are not utilized for these air movement devices and technologies. The direction of airflow and occupant-fan distance are not accurately determined due to the capabilities of infrared sensors. This is critical because the distance has great influence on the thermal sensation of comfort as the air speed attenuates during its propagation. Second, the linear speed regulation rules, commonly adopted in response to temperature variation, are far from satisfactory because the desired air speed required for thermal comfort depends also on other environmental parameters

and personal variables such as metabolic rate and clothing insulation. Third, all of these technologies mainly concern about one single fan design and are not capable of cooperatively scheduling a plurality of fans to generate the most desirable air speed that maximizes the occupants' satisfaction. As for multiple-fan operation, the following summarizes the disadvantages of the conventional technologies. 1. Fans work individually. 2. The relations of the speed setting to the air speed at different positions are unknown. The assumption of a homogeneous air speed field is far from reality. 3. Mainly rely on sensor measurements. The occupants' attitude towards the air movement is unknown. 4. Adjust fan speed only according to a predetermined speed regulation rule. Personal thermal comfort needs are ignored. 5. Follow the predetermined regulation rule, regardless of occupancy variation.

1.5 Contributions

The work presents in this thesis leverages on recent advances in human thermal comfort research and indoor positioning techniques to develop cost-effective, energy-efficient and occupant-satisfied solutions for indoor location-based cooling. Specifically, the occupant-aware operations of both a single fan and a system of fans based on either thermal comfort model or human feedback are introduced. In addition, an indoor tracking system with a more generalized noise model for obtaining more accurate occupancy information is developed. These technologies can be used either independently or cooperatively to help reduce energy consumption and improve thermal comfort in buildings leading to a “greener” world. The main contributions of this thesis are summarized as follows.

1.5.1 Smart Tracking Fan System

Most of the cooling fans on the market are not “smart”, i.e., they cannot sense either environmental conditions or user location, and the fan speed setting and orientation have to be manually adjusted by users. As a result, such fans cannot adapt to time-varying thermal comfort requirements of occupants, leading to inconvenience, wasted energy and sub-optimal thermal comfort. To address this problem, a smart tracking fan system using geofence and camera-based indoor localization is proposed. Personal cooling is provided upon the detection of the occupant in the area bounded by virtual geofences.

Specifically, a camera-based indoor localization system is developed to constantly track the position of the occupant, determine the direction of airflow, and calculate the occupant-fan distance. Since the traditional PMV (Predicted Mean Vote) index [41] underestimates the influence of air movement on thermal comfort, the state-of-art PMV-SET (Predicted Mean Vote-Standard Effective Temperature) thermal comfort model [24] is used to quantify the effect of elevated air speed on thermal comfort and determine the desired air speed under different environmental conditions. The fan input power is then obtained based on the desired air speed and occupant-fan distance according to a calibrated mapping scheme. Experimental results show that the proposed tracking fan system is able to provide thermal comfort for occupants at low power consumption rate. This work has been published in [92].

1.5.2 Optimized Air Movement for Thermal Comfort With Cooperative Control of a System of Fans

Conventionally, the fans operate independently and there is no coordination among them. The airflow generated by the fans is non-uniform and the occupants may experience extremely strong or weak airflow, leading to uncomfortable situations.

To mitigate this problem, a novel cooperative control approach for a system of fans is proposed to optimize fans operation, improve thermal comfort condition and save energy. To the best of the author’s knowledge, this is the first time that a system of fans is controlled cooperatively in the research of built environment.

A cost-effective calibration method is proposed to predict the airflow under different fan speed settings in the actual environment, instead of using the conventional Computational Fluid Dynamics (CFD) software which is limited by the models employed and has an unfavorable price. This is a significant advantage since the airflow field generated by fans depends on many parameters (e.g. furniture layout) and now can be predicted during the design phase in a cost-effective manner. Optimized air movement is then generated for thermal comfort control by minimizing the worst-case deviation between the actual air speed generated by fans and the desired air speed inferred from human feedback. Experimental results show that the proposed approach is able to effectively control a system of electric fans and maintain good thermal comfort under higher temperature setpoints.

A US provisional patent (No. 62/307,223) has been granted for this work on 11 March 2016.

1.5.3 Indoor Tracking With the Generalized t -Distribution Noise Model

A common problem with indoor positioning and tracking is the disturbances encountered in dynamic and complex indoor environments and this thesis attempts to use the generalized t -distribution (GT) [93] to model them. By being a superset encompassing Gaussian, uniform, t , Cauchy, and double exponential distributions, GT has the flexibility to characterize noise with Gaussian or non-Gaussian statistical properties.

A RSS-based tracking system is implemented, which consists of first using the

weighted centroid localization algorithm to give a coarse estimate of the position and then a filter with GT noise model and forgetting factor to improve on the estimate. Because of the more accurate noise model, the filter with GT noise model can produce a better estimate than that of the Kalman filter which makes the usual assumption of Gaussian noise.

An equation to compute the variance of the estimation error is also derived. The variance of the experimental data is calculated and it matches the variance calculated theoretically from the equation. This is useful as the variance equation can be used for the design and assessment of the system before implementation. The variance of the estimation error from the proposed filter is less than that from the Kalman filter. The experiments also show that the filter with GT noise model can handle outlier better than the Kalman filter. This work has been published in [94].

1.6 Organization of the Thesis

The thesis consists of five chapters. Chapter 2 describes a smart tracking fan system using geofence and camera-based indoor localization. In Chapter 3, a novel cooperative control approach for a system of fans is proposed. In Chapter 4, an indoor tracking system with GT noise model is introduced. Finally, Chapter 5 summarizes the work presents in this thesis and discusses the future work arising from these studies.

Chapter 2

Smart Tracking Fan Using Geofence and Camera-based Indoor Localization Technology¹

Compressor-based cooling systems have a large impact on energy consumption in modern buildings, particularly in the tropics. Air movement at elevated air speed generated by electric fans is a cost-effective cooling method for both energy savings and thermal comfort improvement. In this chapter, a tracking cooling fan using geofence and camera-based indoor localization technology is proposed. Personal cooling service is provided based on the detection of the occupant in the area bounded by virtual geofences. The proposed camera-based indoor positioning system is able to accurately locate the position of the occupant, control the direction of airflow, and calculate the occupant-fan distance. The tracking fan is able to provide the desired air speed determined by PMV-SET thermal comfort model using a calibrated mapping scheme. The effectiveness of the proposed system is verified through experiments showing that the system is able to provide thermal comfort at

¹The content of this chapter has been published in [92].

low power consumption rate.

2.1 Preliminaries

Research studies have shown that air movement has a significant cooling effect and increases the acceptable range of indoor temperatures [18,47,95,96]. Unlike compressor-based cooling systems which provide a uniform thermal environment, the cooling effect delivered by electric fans is location dependent. However, most of the cooling fans on the market are not “smart”. First, fans do not know the position of the occupant including the direction and occupant-fan distance. When an occupant moved from one position to another position as demonstrated in Figure 2.1, the fan speed setting and direction are not changed accordingly. Second, the desired air speed required by an occupant to maintain thermal comfort is unknown to the fans. Even if the fans knew the position of the occupant, they would not be able to determine the desired air speed for certain environmental conditions. Third, fans do not know the relationship between the generated air speed and the fan speed setting. Even if the fans knew the desired air speed at a given position, they would not be able to determine a suitable speed setting. For example, some previously developed fan systems [97–99] are able to direct airflow towards people based on occupant detection, but automatic adjustment of fan speed is not available. Other fan systems [100,101] can determine the fan speed setting by sensing temperature or humidity but neglects an important factor, i.e., the occupant-fan distance. Since air speed attenuates during propagation, the occupant-fan distance has a great influence on the thermal sensation of an occupant. To address these problems, this chapter develops a smart tracking cooling fan that is able to sense both environmental conditions and user location and provide desired air speed whenever occupant appears in the area bounded by virtual geofence.

Figure 2.1: An example of how occupant position may change in time

2.1.1 Occupancy Information for Location-Based Cooling Control

Occupancy information plays an important role in location-based cooling control. For the heating, ventilation and air condition (HVAC) system, Daikin employs “intelligent eye” infrared sensor [102] to detect human movement but it is no more than ascertaining whether or not there are people in the room. Mitsubishi utilizes eight “move-eye” infrared sensors [103] in their residential air conditioners for human detection and environment sensing. However, infrared sensors are known to be inaccurate for measuring skin temperature especially when the distance between the sensor and the target is long. Moreover, they cannot distinguish human heat sources from non-human heat sources such as computers and printers. Therefore, infrared sensors are usually used to obtain binary information indicating the presence or absence of a human subject only [58,104,105].

RFID (radio-frequency identification) based occupancy detection [58,106,107] is

another famous approach. This approach utilizes the received signal strength to measure the range between a reference node and a target. By processing range information collected from multiple reference nodes, the position of the occupant can be estimated. The number of reference nodes is a crucial factor that influences the localization precision; however, there is no common standard to determine it [57]. The variation in the received signal strength due to multipath and obstacles also has a significant influence on the accuracy and stability of this method, which is still a big challenge that needs to be addressed.

Compared to infrared, CO₂ and RFID sensors, cameras [63,64,69] are able to provide more accurate and robust position estimates at the expense of higher price and installation cost [108]. Because the determination of occupant-fan distance and airflow direction requires an accurate position estimate of the occupant, the proposed tracking fan system leverages a camera. The camera-based tracking system identifies the targets from the images taken by the camera fixed in the monitored area. The captured images are then checked with a database of geo-referenced images to give position estimates. In this way, the system estimates the position of the occupant, determines the direction of airflow, and calculates the occupant-fan distance. The input power of the tracking fan is then automatically adjusted by a calibrated mapping scheme to generate the desired air speed.

2.1.2 Thermal Comfort Assessment: PMV-SET Model

Thermal comfort is defined as the condition of mind that expresses satisfaction with the thermal environment [36]. Intelligent control of fans requires a thermal comfort model to measure a resident's satisfaction with the thermal environment.

Fanger's PMV Model

The PMV model developed by Fanger [41] allows one to express the score that a person gives to an environment as a function of four environmental variables (i.e., air temperature, mean radiant temperature, relative humidity and air speed) and two individual variables (i.e., metabolic rate and clothing index). The equations for calculating the PMV index is given as

$$\text{PMV} = [0.303 \cdot \exp(-0.035 \cdot M) + 0.028] \cdot L \quad (2.1)$$

$$\begin{aligned} L = & (M - Q) - 0.0014 \cdot M \cdot (34 - t_a) \\ & - 3.05 \cdot 10^{-3} \cdot [5733 - 6.99 \cdot (M - Q) - p_a] \\ & - 0.42 \cdot (M - Q - 58.15) - 1.72 \cdot 10^{-5} \cdot M \cdot (5867 - p_a) \\ & - 39.6 \cdot 10^{-9} \cdot f_{cl} \cdot [(t_{cl} + 273)^4 - (\bar{t}_r + 273)^4] - f_{cl} \cdot h_c \cdot (t_{cl} - t_a) \\ t_{cl} = & 35.7 - 0.028 \cdot (M - Q) \\ & - 0.155 \cdot I_{cl} \cdot \{39.6 \cdot 10^{-9} \cdot f_{cl} \cdot [(t_{cl} + 273)^4 - (\bar{t}_r + 273)^4] \\ & + f_{cl} \cdot h_c \cdot (t_{cl} - t_a)\} \end{aligned} \quad (2.2)$$

$$\begin{aligned} h_c = & \begin{cases} 2.38 \cdot (t_{cl} - t_a)^{0.25}, & A > 12.1 \cdot \sqrt{v} \\ 12.1 \cdot \sqrt{v}, & A \leq 12.1 \cdot \sqrt{v} \end{cases} \\ A = & 2.38 \cdot (t_{cl} - t_a)^{0.25} \\ f_{cl} = & \begin{cases} 1.0 + 0.2 \cdot I_{cl}, & I_{cl} \leq 0.5 \cdot clo \\ 1.05 + 0.1 \cdot I_{cl}, & I_{cl} > 0.5 \cdot clo \end{cases} \end{aligned} \quad (2.3)$$

The percentage of occupants that will be dissatisfied with the thermal conditions can be predicted using the Predicted Percentage of Dissatisfied (PPD) index [41]. It is a function of PMV, given that as PMV moves further from 0, PPD increases.

Fanger related the PPD to the PMV as follows:

$$\text{PPD} = 100 - 95e^{-(0.03353 \cdot \text{PMV}^4 + 0.2179 \cdot \text{PMV}^2)} \quad (2.4)$$

The variables involved in the calculation are summarized in Table 2.1, where the ranges of these variables are also given. It is expected that the closer to zero the PMV value, the better the occupants' thermal comfort sensation. ASHRAE recommends a PMV-based comfort zone that comprises PMV values being from -0.5 to $+0.5$. Within this comfort zone, 90% of the occupants are expected to express satisfaction with the indicated thermal environment.

Table 2.1: Variables that relate to thermal comfort

Symbol	Parameter	Range	Units
M	Metabolic rate	46-232	W/m ²
Q	Effective mechanical power	≥ 0	W/m ²
I_{cl}	Clothing insulation	0-0.31	m ² K/W
f_{cl}	Clothing surface area factor	0-1	-
t_a	Air temperature	10-30	°C
$\bar{t}_r$	Mean radiant temperature	10-40	°C
v	Relative air velocity	0-1	m/s
p_a	Water vapor partial pressure	0-2700	Pa
t_{cl}	Clothing surface temperature	10-30	°C
h_c	Convective heat transfer coefficient	0-12.1	W/(m ² K)

The SET Model and Integrated PMV-SET Approach

The Standard Effective Temperature (SET) is defined as the equivalent air temperature of an isothermal environment at 50% relative humidity in which a subject, wearing clothing standardized for the activity concerned, has the same heat stress (skin temperature) and thermoregulatory strain (skin wettedness) as in the actual environment [109,110]. The SET model reduces any combination of real environmental and personal variables into the temperature of the imaginary standard environment [38]. The role of SET here is to help evaluate all cases of comfort under

elevated air speed above 0.2 m/s.

As the PMV model underestimates the influence of air movement, the PMV-SET approach is developed to set a comfort zone for temperature, radiation, humidity and air movement at elevated air speed level [46]. The two-step procedure consists of first using the original PMV model to determine the comfort zone at the still-air region ($v \leq 0.2$ m/s) and then utilizing the SET model to extend the comfort zone to the elevated air speed region ($v > 0.2$ m/s). The idea was first described in [24] and ASHRAE Standard 55-2013 adopted this change. The core structure of the PMV-SET model is described below.

Consider the two functions, PMV and SET. Let t_a be the air temperature, $\bar{t}_r$ be the mean radiant temperature, V_{elev} be the elevated air speed and V_{still} be the air speed in still air. The cooling effect, CE, due to the elevated air speed could be obtained by iteratively solving the following equation [46]:

$$\text{SET}(t_a, \bar{t}_r, V_{elev}, *) = \text{SET}(t_a - \text{CE}, \bar{t}_r - \text{CE}, V_{still}, *) \quad (2.5)$$

where $*$ denotes the invariant parameters which should be the same for both cases. Equation (2.5) means that the adjusted air temperature, $(t_a - \text{CE})$, and the adjusted mean radiant temperature, $(\bar{t}_r - \text{CE})$, at still air yields the same SET value as the actual air temperature and actual mean radiant temperature do at elevated air speed. Equation (2.5) can be solved by using the secant and bisection iterative algorithm. The CE of elevated air speed has the same unit as the dry-bulb air temperature t_a and mean radiant temperature $\bar{t}_r$, i.e., degree Celsius ($^{\circ}\text{C}$). Once the CE is obtained by using the SET model, the adjusted PMV value denoted as PMV_{adj} is given by

$$\text{PMV}_{adj} = \text{PMV}(t_a - \text{CE}, \bar{t}_r - \text{CE}, V_{still}, *) \quad (2.6)$$

This is different from the original PMV value, which is directly calculated as

$$\text{PMV}(t_a, \bar{t}_r, V_{elev}, *) \quad (2.7)$$

Since the PMV model underestimates the influence of air movement on thermal comfort [24,46], V_{elev} is replaced with CE and V_{still} in the calculation of the adjusted PMV value (PMV-SET output). In rest of the thesis, all the PMV values are adjusted PMV values calculated by the PMV-SET approach.

2.2 The Smart Tracking Fan System

2.2.1 System Overview

The system was implemented and tested in a large open-space office and a typical cubicle-desk workstation shown in Figure 2.1 was chosen as the cooling area. Since there are no significant radiant sources in the office and the cubicle is far from windows, it can be assumed that the mean radiant temperature equals to the dry-bulb air temperature. Although this assumption is made to simplify the hardware implementation process for the experiment, the proposed system can incorporate more sensors such as black-globe thermometer to obtain a more accurate estimate of the mean radiant temperature. The system employs a three-phase brushless direct current (DC) fan (Model FSAW98RI-A, Airmate, China) which provides 32-level speed settings. The noise generated by the fan varies from 29 dB to 59 dB depending on the selected speed level. This is in accordance with the Singapore noise regulation rule for ACMV systems in non-industrial buildings [111], in which the maximum limits for noise sensitive premises and residential premises during the daytime are 60 dB and 65 dB, respectively. The fan power ranges from 3.8 W to 19.3 W corresponding to the speed setting from level 1 to level 20 (Table A.1 in Appendix

A). The fan power was measured using a power meter (Energy monitoring socket, Efergy, UK) with an accuracy of $\pm 2\%$ of readings. The images used for vision analysis were taken by a normal cell phone camera (Model Exmor RS, Sony) of which the highest frame rate is 30 frames per second and the maximum resolution is 4224×3176 pixels. A standard laptop (HP G4-2318TX) was programed as the system engine for vision-based localization and fan control.

The block diagram of the proposed system is shown in Figure 2.2. The system engine first estimates the position of the occupant and the fan will automatically switch on/off depending on whether or not the occupant enters the cooling area bounded by predefined geofences. Based on the estimated position $(\hat{x}, \hat{y})$, the system engine then calculates the slope of the straight line crossing $(\hat{x}, \hat{y})$ and the position of the fan located at the original point $(0, 0)$ to direct airflow. In the meantime, the occupant-fan distance is calculated for fan power determination through a calibrated mapping scheme. At a given occupant-fan distance, the calibrated mapping scheme actually provides a mapping from the desired air speed to a specific fan power. There are two inputs to the calibrated mapping scheme, i.e., the occupant-fan distance and the desired air speed determined by the PMV-SET model, and one output, i.e., the input power to the tracking fan. The details for determining the occupant-fan distance and the desired air speed are introduced in Subsections 2.2.2 and 2.2.3, respectively, followed by the calibration process in Subsection 2.2.4.

2.2.2 Localization and Geofencing

The proposed tracking fan system utilizes vision analysis to estimate the position of the occupant. An example of locating a target is given in Figure 2.3, where a reference marker denoting the target to be tracked was placed behind the chair. By extracting the pixels that represent the reference marker, the position of the target can be estimated based on a pre-calibrated database which contains the mapping

Figure 2.2: Block diagram of the smart tracking fan system

information from the pixels in the image to the geometric locations in the office.

Once the estimated position, $(\hat{x}, \hat{y})$, is obtained, the system will first check whether or not the occupant is inside the defined geofence. The criterion of entering the geofence is defined as $\{0 < \hat{x} < 3.7 \text{ m}, 0 < \hat{y} < 2.0 \text{ m}\}$, which is the size of the cubicle desk shown in Figure 2.3. If no occupant is detected in a preset time interval, the fan will automatically switch off. Notice that the size of the geofence is customizable for different furniture layouts, but should be no larger than the fan coverage. The concept of geofencing has been employed in many applications including logistics management, commercial promotion and tourism guidance [112–114].

In Figure 2.4(A), the fan is placed at the original point $\mathcal{O}$ (0,0) and can oscillate from 0° to 90° . Starting from x-axis, three sub-areas I, II, III are separated by

Figure 2.3: Example of locating a target: (A) identification of a reference marker; (B) position estimation

Figure 2.4: Localization: (A) airflow direction; (B) occupant-fan distance

two straight lines whose slopes are 0.58 and 1.73 respectively. This is to ensure that each sub-area has an equal central angle of 30° . These sub-areas are used for

determination of airflow direction. For instance, if an occupant is found in sub-area I, then the fan will automatically turn to sub-area I for delivering air movement.

The occupant-fan distance can be obtained in the following ways. In warm environments, the head region is one of the dominant body parts affecting overall comfort [115–118] and the head height of a seated person, h_p , is assumed to be 1.1 m according to thermal comfort standards. The fan is placed at a height of $h_f = 2.3$ m. The occupant-fan distance is therefore calculated as

$$d = \sqrt{\hat{x}^2 + \hat{y}^2 + (h_f - h_p)^2} \quad (2.8)$$

$$\text{subject to } \{0 < \hat{x} < 3.7; 0 < \hat{y} < 2.0\}$$

which will be used for fan power determination. This procedure is illustrated in Figure 2.4(B). It should be mentioned that the height parameters can be changed and adapted to different scenarios.

2.2.3 Desired Air Speed Determination

The desired air speed is determined by utilizing the PMV-SET model. The PMV value is generally a function of four environmental parameters (i.e., dry-bulb air temperature, mean radiant temperature, relative humidity and air speed) and two individual parameters (i.e., metabolic rate, and clothing index). The proposed tracking fan system senses the dry-bulb air temperature, which is the most influential parameter affecting thermal comfort, and assumes the mean radiant temperature is the same as the dry-bulb air temperature as described in Subsection 2.2.1. By fixing the rest parameters at reasonable values, the desired air speed is determined as the air speed that achieves a preset target PMV value. It should be mentioned that if cost-effective sensors for measuring the rest parameters become available in the future, then they can be easily incorporated into the existing framework.

The target PMV values and the parameters used for desired air speed determination are summarized in Table 2.2. Since the temperature setpoint of an air conditioning system is usually set around 23 °C in tropical climates [8,119], it is proposed to increase the setpoint to save energy. Moreover, based on the work in [47], it is expected that 29 °C is the upper acceptable limit for office work conditions in tropical climates. Therefore, three air temperature levels: 26 °C, 27.5 °C and 29 °C were considered in the experiment. The relative humidity, RH , and metabolic rate, M , were assumed to be 50% and 1.2 met, respectively, for common office work. The typical value of business clothing in the tropics is 0.7 clo (short sleeve button or polo shirt, long trousers, socks, business shoes and office chair). For higher temperature setpoints, the clothing insulation was reduced down to 0.5 clo (recommended value for summer conditions), expecting people to dress according to the indoor climate. This assumption can be changed freely according to the actual situations. Given the air temperature and other environmental parameters, the SET model is utilized to calculate the cooling effect of elevated air speed. By taking into account this cooling effect, the adjusted PMV value can be calculated. This procedure is described in detail in Section 2.1.2.

Table 2.2: PMV-SET model parameters ($RH = 50\%$, $M = 1.2$ met)

Temperature (°C)	Clothing	Target PMV	Desired air speed V_d (m/s)
26	0.7	0.00	0.55
27.5	0.6	0.15	0.64
29	0.5	0.30	0.78

For the purpose of keeping occupants comfortable in a warm environment, the target values of PMV are limited to the range from 0 to 0.5. For lower temperatures, the PMV value at each position can be set as zero, representing thermal neutrality. However, for higher temperatures, slightly higher PMV values should be used to minimize the airflow intrusion to other desks and to comply with the current limit on air speed being 0.8 m/s.

2.2.4 Calibration

Before the experiment, calibration was performed in the open-space office shown in Figure 2.3 to obtain the air speed-fan power relationship. It was reported in [23] that the air speed generated by a DC fan can be regarded as a natural logarithm function of the fan power. Let $V(\bar{P})$ be the generated air speed due to fan power $\bar{P}$, the relationship between $V(\bar{P})$ and $\bar{P}$ can be represented by Eq. (2.9).

$$V(\bar{P}) = a \ln(\bar{P}) - b \quad (2.9)$$

where a and b are the parameters for the natural logarithm function, which can be identified by calibration. The air distribution measuring system (AirDistSys 5000, Sensor-Electronic, Porland) with omnidirectional air speed sensor (SensoAnemo 5100SF), as shown in Figure 2.5, was used to measure the air speed at an accuracy of 0.02 m/s and the temperature at an accuracy of 0.2 °C. The air speed sensors were placed at nine different positions being away from the fan from 0.5 m to 4.5 m in a step of 0.5 m. The sampling interval is 2 seconds and the height of the measuring point is 1.1 m, which is around the head region of a seated person. At each position, 20 groups of measurements were taken for 20 specific fan input powers, respectively, and each group of measurements consists of 90 samples, resulting in a total of $90 \times 20 \times 9 = 16200$ samples. The average value of 90 samples for each group was calculated and the results are summarized in Appendix A (Table A.1). For each position, the 20 average values were then used to fit the model of Eq. (2.9) using least-squares estimation.

The achieved result is shown in Figure 2.6, where the scatter plots represent the average air speeds and the curves refer to the fitted natural logarithm models at different distances. It can be seen that the natural logarithm model fits the data very well. The obtained parameters for the models at different distances are given

Figure 2.5: Air distribution measuring system [120]

in Table 2.3. The mean absolute error, e_{ma} , and the root mean square error, e_{rms} , between the measured air speeds and the fitted curves are summarized in Table 2.4. The former metric shows the absolute deviation of measured data from fitted curves while the latter amplifies the effect of large errors.

Figure 2.6: Natural logarithm model is obtained by least-squares fitting

As shown in Table 2.4, both e_{ma} and e_{rms} at all distances are less than 0.07 m/s indicating a good fit for the proposed fan system.

Table 2.3: Parameters of the natural logarithm model

Distance (m)	Natural logarithm models	
	a	b
0.5	1.28	0.63
1.0	0.80	0.16
1.5	0.74	0.21
2.0	0.62	0.19
2.5	0.52	0.16
3.0	0.47	0.15
3.5	0.42	0.20
4.0	0.34	0.08
4.5	0.31	0.12

Table 2.4: Errors between measured air speeds and fitted curves

Distance (m)	Natural logarithm models	
	e_{ma} (m/s)	e_{rms} (m/s)
0.5	0.07	0.07
1.0	0.06	0.07
1.5	0.04	0.04
2.0	0.02	0.03
2.5	0.03	0.04
3.0	0.03	0.04
3.5	0.02	0.03
4.0	0.03	0.03
4.5	0.02	0.03

2.3 Experimental Results

2.3.1 Localization Results

The localization results are summarized in Table 2.5. The estimated coordinates of the five test positions are given in the 2nd column. Once this information is obtained, the slope of the straight line crossing the original point and the estimated position can be calculated. The slope is then used to determine the direction of airflow according to the criterion given in Subsection 2.2.2. The airflow directions are depicted in Figure 2.4 for easy reference. The occupant-fan distance is calculated using Eq. (2.8) and the results are used to select the most suitable calibrated

mapping curve for fan power determination.

Table 2.5: Localization results of the five test positions

Test positions	Estimated position $(\hat{x}, \hat{y})$	Slope $k = \hat{x}/\hat{y}$	Airflow direction	Occupant-fan distance d	Calibrated mapping curve
1	(0.8,0.9)	1.13	II	1.7 m	1.5 m
2	(1.7,0.8)	0.47	I	2.2 m	2.0 m
3	(0.8,1.9)	2.38	III	2.4 m	2.5 m
4	(2.8,0.9)	0.32	I	3.2 m	3.0 m
5	(2.8,1.9)	0.68	II	3.6 m	3.5 m

2.3.2 Fan Power Determination

Based on the PMV-SET model, the desired air speeds for 26 °C, 27.5 °C and 29 °C cases are determined as 0.55 m/s, 0.64 m/s and 0.78 m/s, respectively, as described in Subsection 2.2.3. The calibrated mapping curves for calculating the fan power at the five test positions under three temperature levels are shown in Figure 2.7. Note that the desired air speeds at different positions under the same temperature are the same due to the fair assumption that the room temperature is uniform around the cubicle desk. However, the required fan power for the same air speed at different distances could be different, due to the attenuation of air speed during propagation.

The obtained fan power is explicitly summarized in Table 2.6. It can be seen that the fan power in all test conditions is less than 11 W.

Table 2.6: Obtained fan power at target positions

Test positions	Fan input power (W)		
	26 °C	27.5 °C	29 °C
	target air speed	target air speed	target air speed
	0.55 m/s	0.64 m/s	0.78 m/s
1	2.8	3.2	3.8
2	3.3	3.8	4.8
3	4.0	4.7	6.2
4	4.5	5.4	7.3
5	6.0	7.4	10.3

Figure 2.7: Fan power determination by using calibrated mapping curves

2.3.3 Air Speed Measurement

Figure 2.4 shows the layout of the office, and the test positions are marked as red numbered circles. To verify the effectiveness of the proposed method, the fan power obtained at Position 1 was employed as baseline configuration for all test positions. This is to illustrate the case where the proposed method is not available. The air speeds at all 5 positions were then measured for the cases with and without the proposed method. The results for both cases are presented as box-and-whisker plots in Figure 2.8(A) and Figure 2.8(B), respectively. In Figure 2.8, each plot contains 90 samples measured at one position using a 2-second sampling interval, and the target air speeds are shown as dashed lines.

It can be easily understood that if an occupant moves from Position 1 to Position 5, the occupant-fan distance will increase accordingly. This is reflected in Figure 2.8(A) where the air speeds deviate away from the target values when the distance increases. Without the proposed method, it is difficult to find a suitable fan power to meet the requirement of thermal comfort. Although a specific fan power is applicable

Figure 2.8: Air speed measurements: (A) without proposed method; (B) with proposed method

at one position, it may no longer satisfy the occupant when he or she moves to other positions. In contrast, as shown in Figure 2.8(B), the proposed method is able to maintain the air speeds around the target values for all temperature levels since the fan power is customized for different environmental conditions and occupant positions.

In Figure 2.8, the variance of the air speed measurements increases with distance due to the typical behavior of isothermal jets. Nevertheless, the standard deviation is less than 0.1 m/s. The details of the air speed measurements shown in Figure 2.8 are summarized in Appendix A (Table A.2).

2.3.4 Thermal Comfort Assessment

The effect of elevated air speed on thermal comfort is assessed by using the PMV-SET model. The PMV values corresponding to the air speed measurements in Figure 2.8 are plotted in Figure 2.9 together with the target values, and the statistical analysis is given in Appendix A (Table A.3). For the case without the proposed method, the PMV values deviate from the target values and even go outside the thermal comfort zone. With the proposed method, the PMV values at all test positions are kept below 0.5 around the target values.

Figure 2.9: PMV values: (A) without proposed method; (B) with proposed method

2.4 Discussion

2.4.1 Automatic Mode and Occupant-Control Mode

The proposed system can operate in two different modes: the automatic mode and the occupant-control mode. The first mode refers to the methodology described in this chapter. To comply with the ASHRAE 55-2013 standard, only the first 12 fan speed settings (Table A.1 in Appendix A) are enabled, so that the generated air speed at a given position will not likely exceed the 0.8 m/s limit. However, this is not applicable for the case when the occupants want to take control over the thermal conditions. For example, for those who are doing high-metabolic activities, the provided air movement can be higher than 0.8 m/s. In this case, the occupant-control mode can be applied and the fan is able to provide as high as 3.0 m/s air speed. By doing this, the potential of the fan can be fully exploited.

2.4.2 Multiple-Occupant Case

The experiments are designed for single-occupant case but the system can be extended to the case where multiple occupants are detected. If more than one occupant is detected in the same sub-area, the system will operate as normal since the fan is able to direct airflow to the occupants in the same geofenced sub-area simultaneously. If the occupants are detected in different sub-areas, the system will operate in swing mode and dynamically adjust fan power based on the respective occupant-fan distances. A more sophisticated approach based on minimax-error optimization will be introduced in Chapter 3.

2.4.3 Potential Energy Savings

The proposed fan system can reduce energy consumption in two ways. First, the system is able to detect the presence and absence of the occupants. When there is no occupant in the geofenced area, the fan will automatically switch off, leading to energy savings. Second, by increasing temperature setpoints of the ACMV systems, energy consumption can be reduced. Studies show that increasing the temperature setpoint in hot and humid climates brings substantial energy savings [8,12,121], and elevated air movement provided by fans compensates the negative impact of increased temperature on occupants' thermal comfort, perceived air quality and cognitive performance [18,47,122]. With a fan running, room temperature can be raised by 3 °C with no reduction in comfort [18,35], which corresponds to about 17% savings in the ACMV system according to the whole building energy simulation study for Singapore's tropical climate in [12].

2.4.4 Personal Thermal Comfort Models

One major contribution of this work is the development of a general framework, which takes into account the occupant-fan distance, airflow direction, fan power-air speed relationship and the desired air speed, for the design of a smart tracking cooling fan. Although the PMV-SET model that reflects the statistical average thermal preference with fixed personal factors is used in this chapter to determine the desired air speed, improved performance can be achieved by upgrading the fan with personal thermal comfort models and machine learning techniques [123–125]. For example, in [125] a personal comfort model is proposed to predict individual's thermal comfort responses, instead of the average response of a large population. By recording occupants' control behavior as well as environmental conditions and employing machine learning algorithms, the model achieves an improved prediction

accuracy compared to conventional models such as PMV. In the future, we can upgrade the developed tracking fan system with personal thermal comfort models to better suit individual thermal preference.

2.4.5 Limitations

The fan used in the proposed system may have the risk of disturbing the lighting system in the environment and the noise generated in high-air-speed condition may cause discomfort. The camera used in the system is currently separated from the fan and this could be improved by integrating the camera into the fan in the future. The use of camera may have the risk of privacy leakage. It is suggested to improve the system in a way that the information is encrypted and processed independently in the camera avoiding privacy and security concerns. A RSS-based indoor tracking system is also proposed in Chapter 4 to provide an alternative to the camera-based approach.

In the experiment, a thermally homogeneous environment is assumed. When the served space is not thermally homogeneous, the air temperature and humidity at different positions can be measured by wireless sensor nodes, and the temperature and humidity for positions in between the nodes can be estimated by interpolation. In practice, the calibration results obtained in factories may become less satisfactory in the actual environment where the fan system is installed due to different room layouts and furniture. In this case, the fan system should allow the user to make revisions to the default settings. This can be done by gradually changing the air speed and recording the most satisfied speed setting for the user at a certain position.

2.5 Summary

In this chapter, a tracking cooling fan using geofence and camera-based indoor localization technology is proposed for maintaining thermal comfort and saving energy. The proposed camera-based positioning system is able to accurately locate the position of the occupant, determine the direction of airflow, and calculate the occupant-fan distance. A calibrated mapping scheme is proposed to automatically adjust the fan input power to generate the desired air speed determined by the PMV-SET model. The effectiveness of the proposed system is demonstrated through experiments. The system can be used in an air-conditioned environment with a higher temperature setpoint to save energy or in a naturally ventilated environment to improve thermal comfort.

Chapter 3

Optimized Air Movement for Thermal Comfort With Cooperative Control of a System of Fans²

Personally controlled air movement can maintain or enhance thermal comfort in warm environments and reduce energy consumption. In the previous chapter, the smart operation of a single fan is introduced and the operation of multiple fans remains an issue to be resolved. Unlike controlling a personal fan, applying a system of fans for multiple occupants is not easy as it is difficult to find an appropriate fan speed setting that maximizes satisfaction. Here the system of fans is defined as a group of fans that are cooperatively controlled by a central controller to serve an area. In this chapter, a novel cooperative control approach for a system of fans is proposed to provide optimized air movement for multiple occupants. The core idea of the proposed control approach is to maximize occupants' satisfaction, and to the

²A US provisional patent (No. 62/307,223) has been granted for this work on 11 March 2016.

best knowledge of the author, this is the first time that a method is developed to cooperatively control a system of fans to achieve this goal. Although simple control algorithms such as stepped control and PI control can be applied to control a single fan, they are unable to maximize occupants' satisfaction by taking into account all the users' preferences. When some one adjusts the fans to suit him/herself, other people may experience too weak or too strong airflow leading to unsatisfactory thermal sensation.

The proposed approach predicts airflow in a cost-effective manner by calibrating fans in real environments. The operation of fans is optimized by minimizing the worst-case deviation of the generated air speed from the desired air speed inferred from occupants' feedback regarding their thermal preferences. This minimax-error problem is formulated as a linear programming problem which can be solved using standard methods such as the simplex method [126,127] and the interior-point method [128,129]. Experiment involving human subjects is conducted to demonstrate the effectiveness of the proposed approach.

3.1 Preliminaries

Unlike controlling a personal fan [92,130,131], applying a system of fans for multiple occupants is difficult as it is usually hard to find an appropriate fan speed setting that maximizes satisfaction. There are several reasons for this. First, fans commonly generate a strongly non-uniform air speed field. The assumption of a homogeneous air speed field generated by fans is incorrect. Second, thermal environment is spatially and temporally non-uniform [132]. People sitting at different positions may be exposed to different environmental conditions. Third, people have different thermal preferences. This diversity among occupants should be considered in the operation of fans. Fourth, the configuration of the fans (e.g., number of fans and their place-

ments) and their operation are not optimized. Occupants may experience too weak or too strong airflow. Fifth, occupancy distribution changes from time to time. If the fan speed setting is not updated according to occupancy changes, wasted energy and suboptimal thermal comfort may happen. As a consequence, there will always be different opinions among the users regarding the fan speed setting. When someone adjusts the fans to suit him/herself, it is highly possible that other people may feel uncomfortable. This problem can be solved if fans are cooperatively controlled by taking into account the preferences of the occupants.

In this chapter, a cooperative control approach is proposed for a system of fans to improve thermal comfort and save energy. Conventionally, predicting airflow is usually based on the simulation results obtained by using Computational Fluid Dynamics (CFD) software. However, the performance of CFD is sometimes limited by the models employed [133–135]. The proposed approach predicts airflow in a cost-effective manner by calibrating fans in real environments to establish the relationship between air speed and fan speed setting. The operation of fans is optimized based on a minimax-error solution that minimizes the worst-case deviation of the generated air speed from the desired air speed by using linear programming algorithm.

Two methods can be adopted to determine the desired air speed. The first method is to measure environmental conditions and calculate the desired air speed based on the PMV-SET model [24,46]. This is a passive-design approach which has been introduced in Chapter 2. In this case, personalization and customization can be provided by setting different target PMV values for different individuals upon their request. Alternatively, the desired value of air speed can also be determined according to the real-time feedback (e.g., short message service, smartphone app or Internet graphical user interface) of the occupants regarding their preferences of air movement. In this chapter, the second method will be put into use.

3.2 Optimization of Fans Operation

3.2.1 Problem Formulation

In practice, there may be more people than fan and so not everyone can have his desired air speed. Due to diversity of thermal demand, controlling the fans according to a single person's preference may result in extremely uncomfortable cases. Therefore, it is proposed to determine a fan speed setting that achieves a best compromise between the occupants with respect to some criterion. As thermal dissatisfaction grows exponentially when a deviation from the comfort condition increases [41], the minimax-error criterion that aims at limiting the maximum error within an acceptable range is adopted. For example, if the initial deviations from the desired air speed for three occupants are 0.1 m/s, 0.2 m/s and 0.3 m/s, then the worst case is 0.3 m/s and the goal is to reduce the worst case as much as possible. The problem of optimizing fans operation is therefore formulated as to find the optimal fan speed setting P_{opt} that minimizes the maximum absolute error between the generated air speed $V(P)$ and the desired air speed V_d , i.e.,

$$\text{Minimize } \|V(P) - V_d\|_{\infty} \quad (3.1)$$

where P is the speed setting applied to the fans. In general, the generated air speed increases as the fan speed setting increases, and a linear model would be capable of describing this trend. Therefore, it is assumed that the generated air speed $V(P)$ is a linear function of the fan speed setting P . This assumption was verified experimentally for the tested fans and the results are given in Appendix B (Figure B.1 and Table B.2) for easy reference. For the nonlinear case, numerical optimization can be performed via linearization which will be introduced in Subsection 3.2.3.

3.2.2 Minimax-Error Solution and Linear Programming

Simple Example

Before discussing the general case, we first give the mathematics for a simple example of one fan with speed setting p and two people with desired air speeds v_{d1} and v_{d2} . Let the generated air speeds at the two positions be linear functions of the fan speed setting given by

$$v_1(p) = k_1 p \quad (3.2)$$

$$v_2(p) = k_2 p \quad (3.3)$$

where k_1 and k_2 are dimensionless scaling factors. Let the absolute errors between the generated air speed and the desired air speed be less than or equal to the maximum error, ε , which we want to minimize, the following inequalities can be obtained

$$|v_{d1} - v_1(p)| \leq \varepsilon \quad (3.4)$$

$$|v_{d2} - v_2(p)| \leq \varepsilon \quad (3.5)$$

Removing the modulus sign in inequalities (3.4) and (3.5) gives

$$v_1(p) - v_{d1} \leq \varepsilon \quad (3.6)$$

$$v_2(p) - v_{d2} \leq \varepsilon \quad (3.7)$$

$$v_{d1} - v_1(p) \leq \varepsilon \quad (3.8)$$

$$v_{d2} - v_2(p) \leq \varepsilon \quad (3.9)$$

Substituting Eqs. (3.2) and (3.3) into inequalities (3.6) to (3.9) and rearranging give

$$\begin{bmatrix} k_1 & -1 \\ k_2 & -1 \\ -k_1 & -1 \\ -k_2 & -1 \end{bmatrix} \begin{bmatrix} p \\ \varepsilon \end{bmatrix} \leq \begin{bmatrix} v_{d1} \\ v_{d2} \\ -v_{d1} \\ -v_{d2} \end{bmatrix} \quad (3.10)$$

The optimal speed setting p_{opt} that minimizes the maximum error ε can then be obtained by solving the following linear programming problem [136]:

$$\text{Minimize } \begin{bmatrix} 0 & 1 \end{bmatrix} \begin{bmatrix} p \\ \varepsilon \end{bmatrix} \quad (3.11)$$

subject to constraint (3.10)

General Case

For the general case where n fans and m positions are considered, the generated air speed $V(P)$ due to the fans with speed setting P are given by

$$K \cdot P = V(P) \quad (3.12)$$

where K is an $m \times n$ matrix, P is an $n \times 1$ vector and V is an $m \times 1$ vector. The system represented in Eq. (3.12) is overdetermined if $m > n$ (more occupants than fans) and no value of P will exactly satisfy it. Therefore, it is proposed to find an approximate solution to the system, i.e., the minimax-error solution.

Substituting Eq. (3.12) into Eq. (3.1) and adding operational constraints, the

minimax-error problem can be written as

$$\begin{aligned} & \text{Minimize } \|K \cdot P - V_d\|_\infty \\ & \text{subject to } P_{\min} \leq P \leq P_{\max} \end{aligned} \quad (3.13)$$

where V_d is the desired air speed, $P_{\min}$ and $P_{\max}$ are the minimum and maximum speed settings that can be applied to the fans. The minimax-error solution P_{opt} to the problem given in Eq. (3.13) can be obtained by solving an equivalent linear programming problem given as

$$\begin{aligned} & \text{Minimize } \begin{bmatrix} 0 & \dots & 0 & 1 \end{bmatrix} \begin{bmatrix} P \\ \varepsilon \end{bmatrix} \\ & \text{subject to } \begin{bmatrix} I_n & 0_n \\ -I_n & 0_n \\ K & -1_m \\ -K & -1_m \end{bmatrix} \begin{bmatrix} P \\ \varepsilon \end{bmatrix} \leq \begin{bmatrix} P_{\max} \\ -P_{\min} \\ V_d \\ -V_d \end{bmatrix} \end{aligned} \quad (3.14)$$

where I_n is an $n \times n$ identity matrix, 0_n is an $n \times 1$ vector with all entries equal to zero, 1_m is an $m \times 1$ vector with all entries equal to one, ε is a scalar, and where for vectors a and b , $a \leq b$ indicates every entry of a is no more than the corresponding entry of b . This linear programming problem can be expressed as to find a minimum ε^* that satisfies $\|K \cdot P - V_d\|_\infty = \varepsilon^*$, which is equivalent to the minimax-error problem stated in Eq. (3.13).

3.2.3 Numerical Optimization

In the case that $V(P)$ is a nonlinear function of P , a numerical optimization scheme can be used. Let $\hat{P}$ be the initial fan speed setting, the first-order approxi-

mation for $V(P)$ around $\hat{P}$ is given by

$$V(P) \approx V(\hat{P}) + K \cdot \Delta P \quad (3.15)$$

where $\Delta P = P - \hat{P}$. The matrix K can be determined by calibration.

Before proceeding further, consider a simple example of two fans (fan one and fan two) serving three positions. For this case, P is a 2×1 vector, $V(P)$ is a 3×1 vector, and K is a 3×2 matrix. Given an initial speed setting $\hat{P}$ (which means that the two fans have been switched on), $V(\hat{P})$ can be obtained by measuring the generated air speeds at the three positions. Then, by increasing the speed setting of fan one by Δp_1 , one obtains the adjusted fan speed setting represented as

$$\hat{P}^{(1)} = \hat{P} + \begin{bmatrix} \Delta p_1 \\ 0 \end{bmatrix} \quad (3.16)$$

Subsequently, $V(\hat{P}^{(1)})$ can be obtained by measuring the generated air speeds at the three positions again. Finally, k_1 can be calculated as $k_1 = \frac{V(\hat{P}^{(1)}) - V(\hat{P})}{\Delta p_1}$, which reflects the contribution of fan one to the three positions. By resetting the fan speed setting to $\hat{P}$ and repeating the procedure for fan two, k_2 can likewise be calculated.

For the general case where n fans serving m positions, the matrix K can be determined by measuring $V(\hat{P}^{(1)})$ through $V(\hat{P}^{(j)})$, where each $\hat{P}^{(j)}$ is $\hat{P}$ slightly perturbed by Δp_j as follows

$$\hat{P}^{(1)} = \hat{P} + \begin{bmatrix} \Delta p_1 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \quad \hat{P}^{(2)} = \hat{P} + \begin{bmatrix} 0 \\ \Delta p_2 \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \quad \dots, \quad \hat{P}^{(n)} = \hat{P} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ \vdots \\ \Delta p_n \end{bmatrix} \quad (3.17)$$

and K can be obtained by

$$K = \begin{bmatrix} k_1 & k_2 & \cdots & k_n \end{bmatrix} \quad (3.18)$$

where $k_j = \frac{V(\hat{P}^{(j)}) - V(\hat{P})}{\Delta p_j}$ is the j th column of K reflecting the contribution of the j th fan to all m positions, and $j = 1, 2, \dots, n$.

Substituting Eq. (3.15) into Eq. (3.1), the optimization problem can then be formulated as

$$\begin{aligned} &\text{Minimize } \|K \cdot \Delta P - \Delta V_d\|_\infty \\ &\text{subject to } -\hat{P} \leq \Delta P \leq P_{\max} - \hat{P} \end{aligned} \quad (3.19)$$

where $\Delta V_d = V_d - V(\hat{P})$ is the desired air speed change. The optimal fan speed setting adjustment ΔP_{opt} can be obtained by solving the following equivalent linear programming problem

$$\begin{aligned} &\text{Minimize } \begin{bmatrix} 0 & \cdots & 0 & 1 \end{bmatrix} \begin{bmatrix} \Delta P \\ \varepsilon \end{bmatrix} \\ &\text{subject to } \begin{bmatrix} I_n & 0_n \\ -I_n & 0_n \\ K & -1_m \\ -K & -1_m \end{bmatrix} \begin{bmatrix} \Delta P \\ \varepsilon \end{bmatrix} \leq \begin{bmatrix} P_{\max} - \hat{P} \\ \hat{P} \\ \Delta V_d \\ -\Delta V_d \end{bmatrix} \end{aligned} \quad (3.20)$$

and the optimal fan speed setting can be obtained as $P_{opt} = \hat{P} + \Delta P_{opt}$. It should be mentioned that if the relationship between $V(P)$ and P is linear, then the optimal fan speed setting obtained from the problem in the incremental form of Eq. (3.20) is equivalent to the solution of the problem in the standard form of Eq. (3.14). The most important notations used for problem formulation are summarized in Table

3.1.

Table 3.1: Important notations used for problem formulation

K	Pre-calibrated matrix, calculated by using Eq. (3.18) during the calibration process
ΔV_d	Desired air speed change, determined based on occupants' feedback regarding their preferences of air movement
ΔP_{opt}	Optimal fan speed setting adjustment, obtained by solving the optimization problem in Eq. (3.20)

Equation (3.15) can be viewed as a linearized model around a certain operating point of a nonlinear relationship. In theory, there are many possible combinations of fan speed settings leading to many possible K matrices. However, in practice one usually has some prior knowledge about the nominal settings of the fans and hence we can obtain a few linearized models around typical operating points.

3.2.4 Solution Overview

To build a connection between theory and practice, a brief sketch of the proposed approach is presented before proceeding to the experiment. The whole process for optimization of fans operation is shown in Figure 3.1. The input to the system is the collected occupants feedback, F_o , which is used to infer the desired air speed, V_d (or, alternatively, ΔV_d). The output is the optimized air speeds, V_{opt} , generated by the electric fans due to the optimal fan speed setting, P_{opt} . The four steps shown in Figure 3.1 are explained as follows:

Step 1: Calibration. The calibration process is to determine the gain of the air speed to the fan speed setting, K , at target positions or zones. This can be done by applying Eq. (3.18) and following the instructions therein.

Step 2: Determination of desired air speed. The desired air speed, V_d , can be determined based on the feedback from the occupants. The details of this process

will be introduced in Subsection 3.3.1 of this chapter.

Step 3: Optimization. The optimization process aims to find the optimal fan speed setting P_{opt} that minimizes the maximum deviation of the generated air speed from the desired air speed. This minimax-error solution is obtained by solving the equivalent linear programming problem in Eq. (3.14) or Eq. (3.20).

Step 4: Output. The optimal fan speed setting P_{opt} from Step 3 are then applied to the electric fans to generate the optimized air speed V_{opt} at the target positions or zones.

These steps can be repeated every few minutes to adapt to changes in environmental conditions and users' preferences.

Figure 3.1: Steps to generate the optimized air speed

3.3 Experiment

3.3.1 Methods

The proposed optimization approach was tested using human subjects surveys in a university classroom. The experiment was conducted in April (the typical hot season in Singapore) in an 80-seat classroom (10.5 m × 9.5 m × 2.5 m) at the

National University of Singapore as shown in Figures 3.2(A) and 3.2(B). Ten three-phase brushless direct current (DC) fans (Model FSAW98RI-A, Airmate, China) were placed on both sides of the room to provide air movement. The fan has a maximum power of 27 W and its 32 speed settings can be adjusted wirelessly. The technical details of the fan are summarized in Appendix B (Table B.1).

Figure 3.2: Classroom: (A) room layout; (B) photograph of the room and (C) experiment procedure

Before the experiment, the fans were calibrated in the classroom by following the procedure described in Subsection 3.2.3 with $\hat{P} = 2$ and $\Delta p_j = 20$. An air distribution measuring system (AirDistSys 5000, Sensor-Electronic, Poland) with omnidirectional air speed sensors (SensoAnemo 5100SF) was used to measure the air speed at an accuracy of 0.02 m/s. At a sampling interval of 2 seconds, 90 samples were taken for each position at the height of 1.1 m, which is around the head region of a seated person. The average values of the 90 samples for each position were then used to calculate the matrix K using Eq. (3.18), which is given in Appendix B (Table B.3) for easy reference.

During the experiment, the air temperature and relative humidity were recorded at one-minute sampling rate by HOBO data loggers (Model U12-013, Onset, USA) with ± 0.35 °C uncertainty for air temperature, and $\pm 2.5\%$ uncertainty for relative

humidity. The data loggers were attached to the back of the chairs with a styrofoam cushion placed in the middle and their locations are shown as blue circles in Figure 3.2(A).

The occupants' feedback was used to determine the desired air speed. A control system that can collect users' feedback through short message service (SMS) was implemented based on NUS PeerQuestions service. An illustrative framework for the whole system is shown in Figure 3.3. It should be mentioned that the feedback collection can also be implemented in other ways such as a smartphone app or a website.

Figure 3.3: SMS-based remote fan control

A valid feedback message should contain the seat number and a '+'/'-' symbol to indicate the preference of increasing/decreasing air speed. The optimization algorithm running in the system then quantifies the occupants' desire to have more or less air movement by counting how many '+'/'-' symbols that each individual sends in one optimization cycle (2 minutes). The numbers from the count are then multiplied by a coefficient, α , to determine the desired air speed change ΔV_d in Table 3.1. To prevent sudden changes, α is set to 0.05 and a limit of three is imposed on each of these numbers so that the change of at most $0.05 \times 3 = 0.15$ m/s in air speed can be experienced by an occupant within one optimization cycle.

This optimization process is repeated every 2 minutes and the fan speed setting is adjusted accordingly. The pseudocode of the optimization algorithm is given in Algorithm 3.1.

Algorithm 3.1 Pseudocode of optimization algorithm based on occupant feedback

Parameters: $\alpha = 0.05$, K in Eq. (3.18)
Input: Feedback.symbol, Feedback.position
Output: ΔP_{opt}
Function Optimization(Run every 2 minutes)
 n = Number of occupants
 for $i = 1 : n$
 $\Delta v_i = 0$
 end
 m = Number of feedback items in one optimization cycle
 for $j = 1 : m$
 k = Feedback(j).position
 if Feedback(j).symbol = '+'
 $\Delta v_k = \Delta v_k + 1$
 elseif Feedback(j).symbol = '-'
 $\Delta v_k = \Delta v_k - 1$
 end
 if $|\Delta v_k| > 3$
 $\Delta v_k = 3 * \text{sign}(\Delta v_k)$
 end
 end
 $\Delta V_d = \alpha * [\Delta v_1, \Delta v_2, \dots, \Delta v_n]^T$
 $\Delta P_{opt} = \text{LinearProgramming}(K, \Delta V_d)$ in Eq. (3.20)
return ΔP_{opt}

Forty undergraduate students (27 males, 13 females) participated in the experiment and randomly seated in the room as shown in Figure 3.2(B). The occupancy distribution is shown in Figure 3.2(A). No restrictions were imposed on their clothing but most of them came with typical summer dresses (about 0.5 clo). Before the experiment, all the students have already attended a training session to become familiar with the experimental room, the experimental procedure, SMS-based fan control and survey questionnaires. To avoid bias in the results, all the measurements of environmental variables were not made known to the students.

The experimental procedure is shown in Figure 3.2(C). The lecture started at 14:00

in the afternoon. For the first 40-minute session, no optimization was performed and the speed setting of each fan was initially set as 2 to avoid any discomfort. From 14:40 to 14:50, there was a break. During the second 40-minute session from 14:50 to 15:30, the students could send their feedback towards preferred air movement whenever they wanted. The operation of the fan system was then optimized based on the feedback using Algorithm 3.1 and the obtained optimal fan speed setting is recorded in Appendix B (Figure B.2).

Prediction of thermal comfort based on physical measurements is not considered for this multi-occupant case, because it is impractical to keep measuring all the thermal conditions such as air speed and metabolic rate for every participant during the experiment. Instead, subject responses which can be regarded as gold standard for evaluating thermal comfort are considered. The students were required to complete a survey questionnaire (Figures B.3 to B.5 in Appendix B) at the end of each session, i.e., at 14:40 and 15:30, respectively. In the questionnaire, they recorded their conditions in a continuous scale (from -3 to $+3$) regarding (1) thermal acceptability, (2) thermal sensation, and (3) acceptance of air movement; and the results are reported in Subsection 3.3.2. The air temperature and relative humidity were continuously measured at an one-minute sampling interval during the experiment as shown in Figure 3.4. The details of the measurements are summarized in Appendix B (Table B.4). The purpose of using HOBO data loggers is not to reflect the thermal state of all the occupants' location but to record the overall environmental conditions of the room. It can be seen from Figure 3.4 that the measured air temperature and humidity at all four positions remains nearly stable during the two instances when the surveys were conducted. hence, the main factor affecting thermal comfort in the experiment is air movement.

Figure 3.4: Measurements of environmental variables: (A) air temperature and (B) relative humidity

3.3.2 Results and Analysis

Thirty-four valid questionnaire responses regarding thermal sensation, thermal acceptability and acceptance of air movement were collected in the experiment. For statistical analysis of the survey results, Shapiro-Wilk test was used to test the normality of the data distribution. Paired-sample t -test was used for normally distributed data. Wilcoxon signed rank test was used for non-normally distributed data. Statistical significance was obtained when $p < 0.05$. Cohen's d [137] was also employed as effect size index.

The data distributions are reported using box-and-whisker plots. The band inside the box, the bottom and top of the box are the median, 25th and 75th percentiles, respectively. The end of the whisker is the lowest/highest datum within 1.5 times the interquartile range from the lower/upper quartile. Any measurements not included between the whiskers are plotted as an outlier with a dot. Notice that Survey 1 refers to the case without the optimization of fans operation while Survey 2 refers to the case with the optimization as illustrated in Figure 3.2(C).

Thermal sensation using the ASHRAE 7-point scale votes (from $-3 = \text{cold}$ to $+3 = \text{hot}$) for the two tested conditions are shown in Figure 3.5. Thermal sensation is barely normally distributed ($W = 0.96$, $p = 0.05$). In Survey 1, the median value

without optimization of fans operation is 0.73 (1st quartile = 0, 3rd quartile = 1.63) and most occupants recorded their thermal sensation in the range from neutral to warm. After fans operation was kept being optimized for 40 minutes, the median value in Survey 2 decreased to -0.04 (1st quartile = -0.62 , 3rd quartile = 0.13) and most occupants reported that their thermal sensation was in the range from neutral to slightly cool, which is the preferred sensation in hot and humid climates like Singapore [138]. The difference is significant ($p < 0.001$) since the operation of the fans was optimized and the occupants could request higher air speed in Session 2. Compared to the descriptors for values of Cohen's d , recommended by Ferguson [137] (where $d = 0.41$ refers to minimum effect size representing a practically significant effect, $d = 1.15$ refers to moderate effect and $d = 2.70$ refers to strong effect), the two groups for thermal sensation (Survey 1 and Survey 2) have a small and statistically significant difference ($d = 0.96$).

Figure 3.5: Overall thermal sensation for the two tested conditions

Thermal acceptability votes (from -3 = clearly unacceptable to $+3$ = clearly acceptable) for the two tested conditions are shown in Figure 3.6(A). Thermal acceptability is non-normally distributed ($W = 0.95$, $p = 0.01$). The median value before optimization is 0.3 (1st quartile = -0.68 , 3rd quartile = 1.45) while the me-

dian value after optimization is 1.14 (1st quartile = 0.41, 3rd quartile = 2.00). The improvement in thermal acceptability is statistically significant ($p < 0.001$), and the effect size shows a moderate difference between the two groups ($d = 1.24$). If we look at the data in a dichotomous way (acceptable and unacceptable) as shown in Figure 3.6(B), the percentage of students who express satisfaction with the thermal environment are 62% and 94% in Survey 1 and 2, respectively. In accordance with standards ASHRAE 55 and ISO 7730, 80% or more of the occupants should express satisfaction with the environment. It is clear that the thermal environment does not meet the requirements when fans operation is not optimized according to occupants feedback (Survey 1).

Figure 3.6: Overall thermal acceptability for the two tested conditions: (A) boxplots and (B) bar charts (dichotomous)

Acceptance of air movement votes (from -3 = clearly unacceptable to $+3$ = clearly acceptable) for the two tested conditions are shown in Figure 3.7(A). Acceptance of air movement is normally distributed ($W = 0.97$, $p = 0.18$). The median acceptance of air movement is 0.27 (1st quartile = -0.55 , 3rd quartile = 0.64) before optimization and 1.09 (1st quartile = 0.45, 3rd quartile = 2.00) after optimization ($p < 0.001$, $d = 1.15$). The percentage of students who express satisfaction with the air movement are 68% and 94% in Survey 1 and 2, respectively, as shown in Figure

3.7(B). For each occupant, the score of Survey 1 is subtracted from Survey 2 and 80% of the occupants increased their vote regarding acceptance of air movement as well as thermal acceptability.

Figure 3.7: Overall acceptance of air movement for the two tested conditions: (A) boxplots and (B) bar charts (dichotomous)

In the experiment, high occupant satisfaction level (94%) is achieved while the room temperature is about 26 °C, which is about 3 °C higher than the common temperature setpoint in Singapore. This would correspond to about 17% savings in the ACMV system according to the whole building energy simulation study for Singapore’s tropical climate [12].

3.4 Discussion

3.4.1 Pre-Calibration Process

The proposed approach predicts airflow through a pre-calibration process by establishing a linear (or approximately linear) relationship between air speed and fan speed setting in real environments. This is a significant advantage since the airflow field generated by fans depends on many parameters (e.g. furniture layout) and

now can be predicted in a cost-effective manner by using the proposed method. The pre-calibration process is also useful for determining the number of fans and their placements in the design phase. During the calibration process, the air speeds at a plurality of target positions are measured. If the measured air speeds at certain positions are too small or too large and violate the requirement of thermal comfort, the number of fans and their relative positions will be adjusted accordingly to eliminate unsatisfactory results.

3.4.2 Benefits of Utilizing Occupancy Information

The operation of a system of fans is optimized to generate the most desirable airflow for the thermal comfort of occupants. This is achieved by minimizing the worst-case deviation of the generated air speed from the desired air speed at target positions. The optimization can be performed with or without the occupancy information. If occupancy information is available, only the occupied positions will be considered and the proposed method will adapt to occupancy variation by re-optimizing the fans operation. If occupancy information is unavailable, all the calibrated target positions will be considered. A detailed discussion of indoor positioning techniques is given in Chapter 4.

3.4.3 Limitations

The fan used in the experiments is a standing DC fan, other types of fans such as ceiling fans were not tested. The experiment involving human subjects is limited by the sample size and the specific test scenario. For further verification, the ceiling fans can be used just like the work in [139]. The proposed approach can also be tested in different scenarios including semi-outdoor environments where fans are commonly used in the tropics. The real-time feedback data is a valuable resource for self-learning. In future, machine learning techniques can be integrated to improve

the performance of the fan control system. In addition, it would be interesting to coordinate the system of fans with the air conditioning and mechanical ventilation (ACMV) system for energy conservation and thermal comfort.

To avoid lowering the efficiency of ACMV systems, the placement of fans should be carefully determined such that the air flow pass of fans will not or only minimally conflict with the air flow pass of air-conditioning terminal. When the terminal units are in the form of displacement ventilation and the conditioned cold air is moving upward, wall-mounted fans that blow horizontally to supply air into the occupants' breathing zones can be employed instead of ceiling fans which force the air moving downward. In this case, the operation of fans is adjusted not only to provide cooling effect but also to improve air circulation and perceived air quality.

3.5 Summary

In this chapter, a novel cooperative control approach for a system of fans is proposed to improve thermal comfort and save energy. The airflow is predicted in a cost-effective manner by using a linear relationship between air speed and fan speed setting obtained from a pre-calibration process. The fans operation is then optimized to minimize the worst-case deviation from the desired air speed, which is determined based on occupants' feedback regarding their preferences of air movement. The minimax-error solution is obtained by solving an equivalent linear programming problem. When multiple people stay in the same zone, the request sent by a single person does not necessarily result in an adjustment of fan speed. The system will take into account all occupants' requests instead of the request raised by a single occupant (no requests received from an occupant means no changes are required for that occupant). This ensures that each occupant can only partially contribute to the actual adjustments and hence minimizes the negative impact of a

person with excessive demand and satisfies the majorities. Even though there is a compromise between the served occupants due to the diversity of thermal demand, the proposed control strategy aims to find the best compromise by minimizing the worst-case scenario, thereby preventing extremely uncomfortable cases. To the best of the authors' knowledge, this is the first time that a control strategy is developed to achieve this goal. In the experiment, occupant thermal satisfaction and air movement acceptability increased from 62% to 94% and from 68% to 92%, respectively, after optimization. This confirms that the proposed method is able to control a system of electric fans effectively to improve thermal comfort with higher temperature setpoints for energy savings. It can be applied in air-conditioned spaces such as offices, theatres or classrooms to assist air conditioning system with a higher temperature setpoint or non-air-conditioned spaces such as hawker centres (open-air food centres) where the fans conventionally operate at a predetermined speed setting.

Chapter 4

Indoor Tracking System With the Generalized t -Distribution Noise Model³

Position information plays an important role in energy conservation and demand-driven operation in smart buildings [58,92]. Although the camera-based localization system developed in Chapter 2 is able to provide accurate position estimates, the communication and computation load can increase dramatically with increased size of monitored area. Moreover, multi-camera surveillance is subject to substantial installation costs and loss of privacy. Therefore, a cost-effective and easy-to-deploy solution that is able to provide coarse-grained localization information is proposed in this chapter.

4.1 Preliminaries

For indoor localization applications, Received Signal Strength (RSS) is commonly used due to its ubiquitous availability, low cost and convenient deployment. RSS-

³The content of this chapter has been published in [94].

based fingerprinting is a popular indoor localization technique [140,141], which compares the measured RSS to a database of fingerprints and returns the closest match as the estimated position. Fingerprint here refers to the unique characteristic of the received signal at a specific position. Although fingerprint-based systems have shown encouraging results, the training process for generating the fingerprint database is known to be time-consuming and labor-intensive. Instead of forming fingerprint databases, the target position can also be estimated using simple geometry. For example, path loss models [142] were used to establish a relationship between the RSS and the target-receiver distance, and using simple geometrical process of lateration [143] or weighted centroid [144] the position of the target can be estimated.

A common problem with indoor tracking is the disturbances encountered in dynamic and complex indoor environments. Factors like signal scattering or blockage due to obstacles, multi-path interference caused by walls and furniture, and even human movements can significantly affect the RSS and impair the performance of localization techniques. Therefore, the estimate from a localization algorithm, such as weighted centroid, is usually highly corrupted by noise and outliers [71,145]. Conventionally, the zero-mean Gaussian distribution is used to model the unknown noise. However, the occurrence of outliers, transient data in steady-state measurements, instrument failure, human error, model nonlinearity, etc. can all induce non-Gaussian noise [93,146]. Moreover, even high-quality data may not fit the Gaussian distribution and the presence of a single outlier can spoil the statistical analysis completely for the case of least squares estimation and the Kalman filter [146,147].

The Generalized t -distribution (GT) has been employed in many applications, from industrial manufacturing to statistical finance [148,149]. GT was also explored in [150] to help understand the nature of genetic association signal. By being a superset encompassing Gaussian, uniform, t , Cauchy, and double exponential distributions, GT has the flexibility of characterizing noise with Gaussian or non-Gaussian

statistical properties [151]. In practice, noise modelling in the GT setting can proceed by likelihood methods analogous to those for the Gaussian distribution. For instance, Figure 4.1 shows the histogram for the error (estimated position – true position) distribution of 3000 x-position estimates of a target obtained from the weighted centroid localization algorithm. The maximum likelihood criterion is used to fit a GT and a Gaussian distribution. It can be seen that the GT (solid line) fits the histogram better than the Gaussian distribution (dashed line). Hence, we can expect a more precise estimation result if the GT is used.

A two-dimensional tracking system based on RSS and weighted centroid is implemented. The RSS technique is chosen for its ubiquitous availability, large user base and hence representativeness [82,152,153]. The weighted centroid method is chosen for its simplicity and robustness to changes in wireless propagation properties compared to other RSS-based methods such as lateration [144]. The variance of the experimental data is also calculated and it matches the variance calculated theoretically from equation (4.51). This is useful as the variance equation can be used for the design and assessment of the indoor tracking system before implementation. The variance of the estimation error from the filter with GT noise model is less than that from the Kalman filter. The experiments also show that the filter with GT noise model can handle outlier better than the Kalman filter. This is the first time that GT is used to model the noise in a realistic two-dimensional indoor tracking problem.

4.2 Weighted Centroid Method

Weighted centroid localization requires only simple calculations. Receivers are placed at known positions. The target broadcasts a unique identifier and the RSS values at the receivers are transformed into respective target-receiver distances

Figure 4.1: Histogram of the error distribution of 3000 x-position estimates

through a path loss model. The distances are then employed as weights to estimate the target position as the weighted centroid [144,154].

Consider m RSS values. The x-position and y-position of the target denoted by z_1 and z_2 , respectively, are estimated as the weighted centroid:

$$z_1 = \frac{\sum_{i=1}^m w(i)x_r(i)}{\sum_{i=1}^m w(i)} \quad (4.1)$$

$$z_2 = \frac{\sum_{i=1}^m w(i)y_r(i)}{\sum_{i=1}^m w(i)} \quad (4.2)$$

$$w(i) = D(i)^{-g} \quad (4.3)$$

where $w(i)$, $x_r(i)$ and $y_r(i)$ are the weight, x-position and y-position coordinates of the receiver with the i th RSS and $g > 0$ is an empirical tuning parameter that controls the relative weight of the receivers.

The target-receiver distance $D(i)$ can be obtained from the path loss model. One commonly used path loss model for indoor localization is the International Telecommunication Union (ITU) indoor propagation model [59,60,62]. For 2.4 GHz single

floor applications, it is given as

$$\text{RSS} = \text{RSS}_0 + 10\eta \log_{10}(D) \quad (4.4)$$

where RSS is in dBm and D in meters. The reference coefficient, RSS_0 , and the path loss exponent, η , can be determined through calibration.

Note that the procedure of calibration is different from the concept of site survey in fingerprinting. What we need to know is the relationship between distance and signal strength as shown in Figure 4.2, instead of the signal characteristic over all the places of interest. Additionally, all the receivers can be calibrated simultaneously, saving labor cost and time.

Figure 4.2: Path loss model is obtained by fitting the RSS in the least-squares sense

4.3 Filtering with GT Noise Model

The positions z_1 and z_2 estimated from the weighted centroid formulas of Eqs. (4.1) and (4.2) are highly corrupted by noise and it is necessary to pass them through a filter.

4.3.1 Constant-Velocity Model

In an indoor environment, the constant-velocity model is usually used to describe the motion of a target [155–157]. It achieves a good balance between complexity and accuracy, and can successfully model motion uncertainties over short to moderate intervals of time [157].

Consider the following constant-velocity state-space model used for the tracking system

$$x(k+1) = \Phi_A x(k) + \Omega \varepsilon(k) \quad (4.5)$$

$$z(k) = Hx(k) + \varepsilon(k) \quad (4.6)$$

where

$$\begin{aligned} x(k) &= \begin{bmatrix} x_1(k) & x_2(k) & x_3(k) & x_4(k) \end{bmatrix}^T \\ \varepsilon(k) &= \begin{bmatrix} \varepsilon_1(k) & \varepsilon_2(k) \end{bmatrix}^T, \quad z(k) = \begin{bmatrix} z_1(k) & z_2(k) \end{bmatrix}^T \\ \Phi_A &= \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \\ \Omega &= \begin{bmatrix} C_1(1,1) + 2 & C_1(1,2) \\ C_1(2,1) & C_1(2,2) + 2 \\ \frac{C_1(1,1) + C_2(1,1) + 1}{T} & \frac{C_1(1,2) + C_2(1,2)}{T} \\ \frac{C_1(2,1) + C_2(2,1)}{T} & \frac{C_1(2,2) + C_2(2,2) + 1}{T} \end{bmatrix} \end{aligned} \quad (4.7)$$

and T is the sampling interval. The states $x_1(k)$ and $x_2(k)$ are the positions in x and y directions; $x_3(k)$ and $x_4(k)$ are the speeds in x and y directions. The noise input,

$\varepsilon(k)$, in the constant-velocity model of Eq. (4.5) allows for motion uncertainty and hence speed variation [157]. The measurements $z_1(k)$ and $z_2(k)$ are the estimated positions from the weighted centroid formulas of Eqs. (4.1) and (4.2).

Note that this constant-velocity state-space model is equivalent to the following second-order multivariate Auto-Regressive-Integrated-Moving-Average (ARIMA) model given as

$$A(q^{-1})z(k) = C(q^{-1})\varepsilon(k) \quad (4.8)$$

where $k = 1, 2, \dots, N$ is the sampling instance, q^{-1} is the backward shift operator and

$$\begin{aligned} A(q^{-1}) &= A_0 + A_1q^{-1} + A_2q^{-2} \\ C(q^{-1}) &= C_0 + C_1q^{-1} + C_2q^{-2} \\ A_0 &= A_2 = C_0 = I \\ A_1 &= -2I \end{aligned}$$

The notation I refers to an identity matrix of appropriate dimension. The matrix polynomial C related to Ω in Eq. (4.7) is a tuning parameter that determines the order of the uncertainties in the position and velocity over a sampling interval T .

Let the two independent noises $\varepsilon_1(k)$ and $\varepsilon_2(k)$ be modeled by the zero-mean GT probability density functions.

$$f_i(\varepsilon_i) = \frac{p_i}{2\sigma_i\nu_i^{1/p_i}\beta(1/p_i, \nu_i)\left(1 + \frac{|\varepsilon_i|^{p_i}}{\nu_i\sigma_i^{p_i}}\right)^{\nu_i+1/p_i}} \quad (4.9)$$

where σ_i is the scale parameter, p_i and ν_i are the shape parameters, $i = 1, 2$. The beta function is given by $\beta(a, b) = \int_0^1 \theta^{a-1}(1-\theta)^{b-1}d\theta$. By different choices of p and

ν , the GT can represent a wide range of distributions that one commonly meets in practice as shown in Figure 4.3. For example, the Gaussian distribution is obtained if the shape parameters are set as $p = 2$ and $\nu = \infty$, and the scale parameter σ is set as $\sqrt{2}\alpha$, where α is the measurement standard deviation.

Figure 4.3: Different well-known distributions obtained by different choices of the GT shape parameters p and ν [93]

Substituting Eq. (4.6) into Eq. (4.5) gives

$$x(k+1) = \Phi x(k) + \Omega z(k) \quad (4.10)$$

where

$$\begin{aligned} \Phi &= \Phi_A - \Omega H \\ &= \begin{bmatrix} -(C_1(1,1) + 1) & -C_1(1,2) & T & 0 \\ -C_1(2,1) & -(C_1(2,2) + 1) & 0 & T \\ -\frac{C_1(1,1) + C_2(1,1) + 1}{T} & -\frac{C_1(1,2) + C_2(1,2)}{T} & 1 & 0 \\ -\frac{C_1(2,1) + C_2(2,1)}{T} & -\frac{C_1(2,2) + C_2(2,2) + 1}{T} & 0 & 1 \end{bmatrix} \end{aligned} \quad (4.11)$$

Iterating from the initial value $x(1)$, Eqs. (4.6) and (4.10) give

$$\begin{aligned} x(2) &= \Phi x(1) + \Omega z(1) \\ x(3) &= \Phi^2 x(1) + \Phi \Omega z(1) + \Omega z(2) \\ &\vdots \\ x(N) &= \Phi^{N-1} x(1) + \bar{x}(N) \end{aligned} \tag{4.12}$$

$$z(N) = H\Phi^{N-1}x(1) + H\bar{x}(N) + \varepsilon(N) \tag{4.13}$$

where

$$\bar{x}(N) = \sum_{k=1}^{N-1} \Phi^{k-1} \Omega z(N-k) \tag{4.14}$$

4.3.2 Maximum Likelihood Estimation

Given N measurements $z(k)$, $k = 1, \dots, N$, and using Eq. (4.13), the noise vectors $\varepsilon(k)$ can be expressed as

$$\varepsilon(k) = z(k) - H\Phi^{k-1}x(1) - H\bar{x}(k) \tag{4.15}$$

The initial condition, $x(1)$, can be estimated by minimizing the following maximum likelihood objective function

$$J = - \sum_{i=1}^2 \sum_{k=1}^N \ln f_i(\varepsilon_i(k)) \tag{4.16}$$

where $f_i(\cdot)$ is the GT probability density function given by Eq. (4.9) and $\varepsilon_i(k)$ is the i th element of $\varepsilon(k)$ given by Eq. (4.15). Let $\psi(\varepsilon)$ be the partial derivative of J

with respect to $x(1)$. It follows from Eq. (4.16) that

$$\begin{aligned}\psi(\varepsilon) &= \frac{\partial J}{\partial x(1)} \\ &= - \sum_{i=1}^2 \sum_{k=1}^N \frac{\partial \varepsilon(k)}{\partial x(1)} \frac{\partial f_i(\varepsilon_i(k))}{\partial \varepsilon(k)} \frac{\partial \ln f_i(\varepsilon_i(k))}{\partial f_i(\varepsilon_i(k))}\end{aligned}\quad (4.17)$$

$$= - \sum_{k=1}^N (H\Phi^{k-1})^T \begin{bmatrix} \frac{(p_1\nu_1+1)\varepsilon_1(k)|\varepsilon_1(k)|^{p_1-2}}{\nu_1\sigma_1^{p_1}+|\varepsilon_1(k)|^{p_1}} \\ \frac{(p_2\nu_2+1)\varepsilon_2(k)|\varepsilon_2(k)|^{p_2-2}}{\nu_2\sigma_2^{p_2}+|\varepsilon_2(k)|^{p_2}} \end{bmatrix}\quad (4.18)$$

and the maximum likelihood estimate of $x(1)$ is obtained as the solution of the equation

$$\psi(\varepsilon) = 0 \quad (4.19)$$

Denoting the estimate of $x(1)$ given N samples as $\hat{x}(1|N)$, Eq. (4.19) can be solved for $\hat{x}(1|N)$ numerically for example using the Newton-Raphson algorithm. Once $\hat{x}(1|N)$ is solved, $\hat{x}(N|N)$ the estimate of $x(N)$ given N samples can be obtained from Eq. (4.12). However, unlike recursive algorithms such as the recursive least-squares estimator, solving Eq. (4.19) numerically using iterative methods is not suitable for real-time applications such as indoor tracking.

4.3.3 Influence Function Approximation

The influence function $\text{IF}(\varepsilon)$ [146,158] can be used to solve Eq. (4.19) approximately. The solution is given in [159] as

$$\begin{aligned}\hat{x}(1|N) &= \text{IF}(\varepsilon) \\ &= - \left(\int_{-\infty}^{+\infty} \frac{\partial \psi(\varepsilon)}{\partial x(1)} dF(\varepsilon) \right)^{-1} \psi(\varepsilon)\end{aligned}\quad (4.20)$$

where $dF(\varepsilon) = f_1(\varepsilon_1)f_2(\varepsilon_2)d\varepsilon_1d\varepsilon_2$.

Equation (4.20) can be interpreted intuitively. Consider the first-order Taylor series approximation of the nonlinear function $\psi(\varepsilon)$. If the approximation is taken about an operating point that is defined as zero then it is given by $\psi(\varepsilon) = \frac{\partial\psi(\varepsilon)}{\partial x(1)}x(1)$. If we do not consider the sign then taking expectation of $\frac{\partial\psi(\varepsilon)}{\partial x(1)}$ gives Eq. (4.20). A formal derivation is given in [146,158,159].

Differentiating $\psi(\varepsilon)$ in Eq. (4.18) with respect to $x(1)$ gives

$$\frac{\partial\psi(\varepsilon)}{\partial x(1)} = \sum_{k=1}^N (H\Phi^{k-1})^T L \cdot H\Phi^{k-1} \quad (4.21)$$

where

$$L = \begin{bmatrix} l_1 & 0 \\ 0 & l_2 \end{bmatrix}$$

and for $i = 1, 2$

$$l_i = \frac{(p_i\nu_i + 1)[(p_i - 1)\nu_i\sigma_i^{p_i} - |\varepsilon_i|^{p_i}][|\varepsilon_i|^{p_i-2}]}{(\nu_i\sigma_i^{p_i} + |\varepsilon_i|^{p_i})^2}$$

Substituting Eq. (4.21) into Eq. (4.20) gives

$$\begin{aligned} \hat{x}(1|N) &= \left(\sum_{k=1}^N (H\Phi^{k-1})^T S \cdot H\Phi^{k-1} \right)^{-1} \\ &\quad \times \left(\sum_{k=1}^N (H\Phi^{k-1})^T S \cdot W(k) \right) \end{aligned} \quad (4.22)$$

where

$$W(k) = \begin{bmatrix} w_1(k) \\ w_2(k) \end{bmatrix}$$

$$S = \begin{bmatrix} s_1 & 0 \\ 0 & s_2 \end{bmatrix}$$

and for $i = 1, 2$

$$w_i(k) = \frac{(p_i \nu_i + 1) \varepsilon_i(k) |\varepsilon_i(k)|^{p_i-2}}{\nu_i \sigma_i^{p_i} + |\varepsilon_i(k)|^{p_i}} \times \frac{1}{s_i}$$

$$s_i = \int_{-\infty}^{+\infty} \frac{(p_i \nu_i + 1) [(p_i - 1) \nu_i \sigma_i^{p_i} - |\varepsilon_i|^{p_i}] |\varepsilon_i|^{p_i-2}}{(\nu_i \sigma_i^{p_i} + |\varepsilon_i|^{p_i})^2} f_i(\varepsilon_i) d\varepsilon_i$$

Once $\hat{x}(1|N)$ is found, $\hat{x}(N|N)$ can be obtained from Eq. (4.12) as

$$\hat{x}(N|N) = \Phi^{N-1} \hat{x}(1|N) + \bar{x}(N) \quad (4.23)$$

4.3.4 Recursive Algorithm with Forgetting Factor

Notice that Eq. (4.22) is the least-squares solution $\hat{x}(1|N)$ from the minimization of the following least-squares loss function

$$\begin{aligned} V &= \frac{1}{2} \sum_{k=1}^N (W(k) - H\Phi^{k-1} \hat{x}(1|N))^T \\ &\quad \times S (W(k) - H\Phi^{k-1} \hat{x}(1|N)) \end{aligned} \quad (4.24)$$

In other words, through influence function approximation, the maximum likelihood objective function in Eq. (4.16) can be approximated by the least-squares objective function in Eq. (4.24).

In the loss function of Eq. (4.24), it is common to reduce the influence of old data

by introducing a forgetting factor as follows

$$V = \frac{1}{2} \sum_{k=1}^N \lambda^{N-k} (W(k) - H\Phi^{k-1}\hat{x}(1|N))^T \times S (W(k) - H\Phi^{k-1}\hat{x}(1|N)) \quad (4.25)$$

The forgetting factor, $\lambda \leq 1$, is a measure of how fast old data are forgotten. When the loss function of Eq. (4.25) is used to obtain the least squares estimate, Eq. (4.22) is changed to

$$\hat{x}(1|N) = P(1|N) \left(\sum_{k=1}^N (H\Phi^{k-1})^T \lambda^{N-k} S \cdot W(k) \right) \quad (4.26)$$

where

$$P(1|N) = \left(\sum_{k=1}^N (H\Phi^{k-1})^T \lambda^{N-k} S \cdot H\Phi^{k-1} \right)^{-1} \quad (4.27)$$

and the recursive solution in Table 4.1 is given in many textbooks that discuss least-squares [160].

Table 4.1: Filter with GT Noise Model. The output is $\hat{x}(1|N)$

$$P(1|N) = [P(1|N-1) - K(N)H\Phi^{N-1}P(1|N-1)] \frac{1}{\lambda} \quad (4.28)$$

$$K(N) = P(1|N-1)(H\Phi^{N-1})^T \times [\lambda S^{-1} + H\Phi^{N-1}P(1|N-1)(H\Phi^{N-1})^T]^{-1} \quad (4.29)$$

$$\hat{x}(1|N) = \hat{x}(1|N-1) + K(N)[W(N) - H\Phi^{N-1}\hat{x}(1|N-1)] \quad (4.30)$$

Table 4.1 gives $\hat{x}(1|N)$, the estimate of $x(1)$ at sample N . The filtering problem is to produce $\hat{x}(N|N)$, the estimate of $x(N)$ at sample N . This can be easily done by iterating from $\hat{x}(1|N)$ to $\hat{x}(N|N)$ using Eq. (4.12). The results are given in Table 4.2. For easy reference, the derivation is given in Appendix A. For initialization,

$P(1|0)$ can be set as an identity matrix multiplied by some large number.

4.3.5 Kalman Filter Connection

Figure 4.3 shows that the GT reduces to the Gaussian distribution when $p = 2$, $v = \infty$. Furthermore, it is well-known that Gaussian noise is assumed in the Kalman filter. The connection between the proposed filter with GT noise model and the Kalman filter will be shown below.

If the Gaussian instead of GT noise is assumed in the algorithm of Table 4.2 then it will be reduced to the Kalman filter in [160] which is given in Table 4.3 for easy reference. Let $p_i = 2$, $\nu_i = \infty$ and $\lambda = 1$. First, notice that Eq. (4.39) gives $s_i = \frac{2}{\sigma_i^2}$, hence Eqs. (4.37) and (4.46) give $S^{-1} = \sigma^2$ and Eq. (4.34) is reduced to Eq. (4.45). Second, substituting Eqs. (4.11) and (4.34) into Eq. (4.33) gives Eq. (4.44). Third, Eq. (4.38) gives $w_i(N) = \varepsilon_i(N)$ and Eqs. (4.35), (4.36) and (4.40) gives $\xi(N) = z(N)$. Substituting $\xi(N) = z(N)$ into Eq. (4.31) gives Eq. (4.42). Finally, substituting Eqs. (4.11) and (4.31) into Eq. (4.32) gives Eq. (4.43). Hence the algorithm in Table 4.2 is reduced to the Kalman filter in Table 4.3.

4.4 Statistical Analysis

The variance is an indication of precision and in this section the equations for the expectation and variance of the estimation error are derived.

4.4.1 Expectation

Consider the estimation error

$$\tilde{x}(N) = x(N) - \hat{x}(N|N) \quad (4.47)$$

Table 4.2: Filter with GT Noise Model. The output is $\hat{x}(N|N)$

Filtered Estimate:

$$\hat{x}(N|N) = \hat{x}(N|N-1) + K_f(N)[\xi(N) - H\hat{x}(N|N-1)] \quad (4.31)$$

Predicted Estimate:

$$\hat{x}(N+1|N) = \Phi\hat{x}(N|N) + \Omega z(N) \quad (4.32)$$

Covariance Update:

$$P(N+1|N) = \Phi[I - K_f(N)H]P(N|N-1)\Phi^T \frac{1}{\lambda} \quad (4.33)$$

Kalman Gain:

$$K_f(N) = P(N|N-1)H^T[\lambda S^{-1} + HP(N|N-1)H^T]^{-1} \quad (4.34)$$

Transformed Output:

$$\xi(N) = W(N) + H\bar{x}(N) \quad (4.35)$$

where

$$W(N) = [w_1(N) \ w_2(N)]^T \quad (4.36)$$

$$S = \text{diag}(s_1, s_2) \quad (4.37)$$

$$w_i(N) = \frac{(p_i\nu_i + 1)\varepsilon_i(N)|\varepsilon_i(N)|^{p_i-2}}{\nu_i\sigma_i^{p_i} + |\varepsilon_i(N)|^{p_i}} \times \frac{1}{s_i} \quad (i = 1, 2) \quad (4.38)$$

$$s_i = \int_{-\infty}^{+\infty} \frac{(p_i\nu_i + 1)[(p_i - 1)\nu_i\sigma_i^{p_i} - |\varepsilon_i|^{p_i}]\varepsilon_i^{p_i-2}}{(\nu_i\sigma_i^{p_i} + |\varepsilon_i|^{p_i})^2} f_i(\varepsilon_i) d\varepsilon_i \quad (4.39)$$

$$\varepsilon(N) = z(N) - H\bar{x}(N) \quad (4.40)$$

$$\bar{x}(N+1) = \Phi\bar{x}(N) + \Omega z(N) \quad (4.41)$$

Table 4.3: Kalman Filter

Filtered Estimate:

$$\hat{x}(N|N) = \hat{x}(N|N-1) + K_f(N)[z(N) - H\hat{x}(N|N-1)] \quad (4.42)$$

Predicted Estimate:

$$\hat{x}(N+1|N) = \Phi_A \hat{x}(N|N-1) + K(N)[z(N) - H\hat{x}(N|N-1)] \quad (4.43)$$

Covariance Update:

$$P(N+1|N) = \Phi_A P(N|N-1) \Phi_A^T + R_1 - K(N)[HP(N|N-1)H^T + R_2]K^T(N) \quad (4.44)$$

Kalman Gain:

$$K_f(N) = P(N|N-1)H^T[R_2 + HP(N|N-1)H^T]^{-1} \quad (4.45)$$

where

$$\begin{aligned} R_1 &= \Omega \sigma^2 \Omega^T, \quad R_{12} = \Omega \sigma^2, \quad R_2 = \sigma^2, \\ \sigma &= \text{diag}\left(\frac{\sigma_1}{\sqrt{2}}, \frac{\sigma_2}{\sqrt{2}}\right) \\ K(N) &= [\Phi_A P(N|N-1)H^T + R_{12}] \times [HP(N|N-1)H^T + R_2]^{-1} \end{aligned} \quad (4.46)$$

Substituting Eqs. (4.12) and (4.23) into Eq. (4.47) gives

$$\tilde{x}(N) = \Phi^{N-1}x(1) - \Phi^{N-1}\hat{x}(1|N) \quad (4.48)$$

Let $E\{\cdot\}$ denote the expectation operator. Substituting Eqs. (4.26) and (4.27) into Eq. (4.48) and then taking expectation yields

$$\begin{aligned} E\{\tilde{x}(N)\} &= E\{(\Phi^{N-1}x(1) - \Phi^{N-1}\hat{x}(1|N))\} \\ &= \Phi^{N-1}E\{x(1)\} - \Phi^{N-1}E\{\hat{x}(1|N)\} \\ &= \Phi^{N-1}E\{x(1)\} \\ &\quad - \Phi^{N-1} \left(\sum_{k=1}^N (H\Phi^{k-1})^T \lambda^{N-k} S \cdot H\Phi^{k-1} \right)^{-1} \\ &\quad \times \left(\sum_{k=1}^N (H\Phi^{k-1})^T \lambda^{N-k} S \cdot E\{W(k)\} \right) \\ &= 0 \end{aligned} \quad (4.49)$$

given the assumption that $x(1) = 0$ and according to Eq. (4.38) $W(k)$ depends on $\varepsilon_1(k)$ and $\varepsilon_2(k)$ which are zero-mean independent random variables.

4.4.2 Variance

Using Eqs. (4.48) and (4.49), the variance of the estimation error can be obtained as follows

$$\begin{aligned} \text{Var } \{\tilde{x}(N)\} &= \text{E } \{\tilde{x}(N)\tilde{x}^T(N)\} \\ &= \text{E } \{(\Phi^{N-1}\hat{x}(1|N))(\Phi^{N-1}\hat{x}(1|N))^T\} \end{aligned} \quad (4.50)$$

Substituting Eq. (4.26) into Eq. (4.50) gives

$$\text{Var } \{\tilde{x}(N)\} = \sum_{k=1}^N \lambda^{2(N-k)} M_N (H\Phi^{k-1})^T \Gamma (H\Phi^{k-1}) M_N^T \quad (4.51)$$

where

$$M_N = \Phi^{N-1} \left(\sum_{k=1}^N (H\Phi^{k-1})^T \lambda^{N-k} S \cdot H\Phi^{k-1} \right)^{-1} \quad (4.52)$$

$$\Gamma = \begin{bmatrix} \gamma_1 & 0 \\ 0 & \gamma_2 \end{bmatrix} \quad (4.53)$$

and for $i = 1, 2$

$$\gamma_i = \int_{-\infty}^{+\infty} \left(\frac{(p_i \nu_i + 1) \varepsilon_i |\varepsilon_i|^{p_i-2}}{\nu_i \sigma_i^{p_i} + |\varepsilon_i|^{p_i}} \right)^2 f_i(\varepsilon_i) d\varepsilon_i \quad (4.54)$$

The experimental verification of Eq. (4.51) is described in the next Section.

4.5 Experiment

4.5.1 Hardware Implementation

The tracking system was implemented in a typical office environment. The photograph and the floor plan are shown in Figures 4.4 and 4.5, respectively. The Texas Instrument CC2530 ZigBee Development Kit with 2.4 GHz omni-directional antenna was programmed to work as transducers. Nine receivers were placed in the office to form a rectangular grid covering the monitored area as shown in Figures 4.4 and 4.5. The target broadcasts packages with a unique identifier to the receivers. The receivers then send the measured RSS together with their coordinates to a computer equipped with a CC2531 USB Dongle which then calculates the position of the target at $T = 0.3$ second interval. The block diagram of the proposed tracking system is shown in Figure 4.6. The inputs to the system are the RSS. They are first converted into target-receiver distances, D , through the log-distance path loss model of Eq. (4.4). The distances are used as weights in the weighted centroid formulas of Eqs. (4.1) and (4.2) to give $z(N)$ and subsequently through the proposed filter with GT noise model (Table 4.2), the estimated state $\hat{x}(N|N)$.

4.5.2 Parameter Selection

Before the experiment, all the receivers were calibrated simultaneously with 1000 RSS measured at seven different distances. The parameters in the path loss model of Eq. (4.4) were obtained from the experimental data using least-squares estimation giving $\text{RSS}_0 = -49.87$ dBm and $\eta = -2.11$. The achieved result is shown in Figure 4.2, where the squares represent RSS measurements and the solid line refers to the path loss model obtained by least-squares fitting.

To obtain the GT parameters, 3000 initial x-position estimates, z_1 , of a target ob-

Figure 4.4: Receivers are numbered in the photograph

Figure 4.5: Layout of hardware implementation

Figure 4.6: Block diagram of the tracking system

tained from the weighted centroid formula of Eq. (4.1) were collected and compared with true positions. The error (estimated position – true position) distribution is represented by the histograms in Figure 4.1. The GT of Eq. (4.9) was fitted to the noise. For simplicity, the shape parameters were fixed as $p_1 = 2$, $\nu_1 = 1.5$ and the scale parameter was then obtained as $\sigma_1 = 0.42$ by using maximum likelihood estimation. For the Gaussian distribution, a standard deviation of 0.44 was also obtained.

The quantile-quantile plot was used as an assessment of goodness of fit [161] and the results for both GT and Gaussian distribution are shown in Figure 4.7. It is clear that the plot for the GT follows the 45-degree reference line more closely, especially at the tails. This indicates that the GT provides a more accurate representation of the actual noise distribution and better describes the heavy-tailed samples and outliers.

The fitted curves for both GT (solid line) and Gaussian (dashed line) distribution are also shown in Figure 4.1. It can be seen that the GT (solid line) fits the histograms better than the Gaussian distribution (dashed line). Hence we can expect a more precise estimation result if the GT is used. For y-position, the same values were obtained for the GT and Gaussian distribution parameters.

The polynomial C was chosen as to give

$$\Omega = \begin{bmatrix} 0.3 & 0 \\ 0 & 0.3 \\ 0.08 & 0 \\ 0 & 0.08 \end{bmatrix}$$

in Eq. (4.7) to model the process noise. A detail discussion on the choice of the process noise model for tracking with the constant velocity model is given in [157]. The value of the empirical tuning parameter g in Eq. (4.3) was empirically deter-

Figure 4.7: Quantile-quantile plots for the Gaussian distribution and GT

mined as $g = 2.5$. The forgetting factor λ is problem dependent. For this tracking application, different values of λ in the range of 0.4 to 1 were tested and 0.5 gave the smallest average distance error as defined in [62]. The filter with GT noise model was implemented according to Table 4.2 with $p_1 = p_2 = 2$, $\nu_1 = \nu_2 = 1.5$, and $\sigma_1 = \sigma_2 = 0.42$. The Kalman filter was implemented according to Table 4.2 with $p_1 = p_2 = 2$, $\nu_1 = \nu_2 = \infty$, and $\sigma_1 = \sigma_2 = 0.44\sqrt{2}$. Note that if $\lambda = 1$ was chosen then Tables 4.2 and 4.3 give the same estimation results for the Kalman filter.

4.5.3 Statistical Results

The variance equation (4.51) can be verified experimentally. Thirteen samples of x-position and y-position estimates were determined in an experiment as a target moved from point “a” to point “b” as shown in Figure 4.5 and to obtain statistical results, the experiment was repeated 200 times. The computational time needed by MATLAB 2016a on a standard laptop (Intel i5-3230M, 8-GB RAM, 3.2 GHz) for both the filter with GT noise model and Kalman filter to process the data are 0.1402 and 0.1264 s, respectively.

The variance of the estimation error (estimated position – true position) in the experimental results is shown in Figure 4.8. Notice that in Figure 4.8, the variances of the estimation errors are given by $\square$ and $\triangle$ for the filter with GT noise model and Kalman filter, respectively. The variances calculated from Eq. (4.51) for the filter with GT noise model and Kalman filter are given by $\times$ and $*$, respectively. It can be seen that the variance calculated from Eq. (4.51) matches the variance from the experiment. A sample calculation for the variances at $N = 2$ using Eq. (4.51) is given in Appendix D.

As shown in Figure 4.1, the GT can model the noise more accurately than the Gaussian distribution used in the Kalman filter. Hence the variance of the estimation error of the filter with GT noise model is less than that of the Kalman filter. For large N , Figure 4.8 shows that the variance of the estimation error from the filter with GT noise model is about half of the Kalman filter.

4.5.4 Outliers

A snapshot of the estimation errors for the 200 experiments at $N = 7$ is shown in Figure 4.9. Notice that the quantile-quantile plot of Figure 4.7 shows the GT can model the outliers more accurately than the Gaussian distribution used in the

Figure 4.8: Variances of the estimation errors in the 200 experiments

Kalman filter. Hence in Figure 4.9, for Experiments 2, 18, 86, 150, 160 and 162, the estimates (triangles) from the Kalman filter are affected by the outliers (crosses) but the estimates (squares) from the filter with the GT noise model are not.

The target now moved along the path “*abcd*” as shown in Figure 4.5. The estimates from the weighted centroid formulas of Eqs. (4.1) and (4.2), the Kalman filter and the filter with GT noise model are shown in Figures 4.5 and 4.10 by the crosses, triangles and squares, respectively.

In Figure 4.5, large deviations of the weighted centroid estimates (crosses) from the true path (dotted line) are observed. This is probably due to the wireless-unfriendly office environment where magnetic whiteboards are installed at every cubicles. Signal blockage, attenuation, and multipath effect easily spoil the RSS measurements and hence proper filtering is needed.

Consider the x-position estimates in Figure 4.10 (top). For the outliers (crosses) at $N = 10, 19, 22, 26, 33$ and 62 , the estimates (squares) from the filter with GT noise model are close to the true positions (circles) while the estimates (triangles) from the Kalman filter are faraway. Note that for $30 \leq N \leq 46$ the true x-position

is constantly at 8 m because the target was traveling along the path “bc” during that time.

Figure 4.9: Snapshot of the estimation error for the 200 experiments at $N = 7$

4.5.5 Lift Lobby Experiment

Another experiment was conducted at the lift lobby and the floor plan is shown in Figure 4.11. In Figure 4.12, the parameters obtained by fitting the distribution to the noise using the maximum likelihood objective function are for the GT probability density function $p_1 = 2$, $\nu_1 = 1.5$, $\sigma_1 = 0.22$ and for the Gaussian probability density function, standard deviation of 0.28. The results of the estimates when the target moved along the path “ab” and path “bc” in Figure 4.11 are shown in Figure 4.13. It can be seen that the deviations of the weighted centroid estimates (crosses) from the true positions (circles) are larger along the path “bc” where there are six lifts with metal doors as shown in Figure 4.14 which exacerbated the effect of multipath. Compared to the Kalman filter which assumed Gaussian noise, the filter with the GT noise model fitted to the actual noise distribution in Figure 4.12 is less affected by the outliers at $N = 9$ and 32 in Figure 4.13 (right).

Figure 4.10: Estimates for x-position and y-position as the target moved along the path “abcd” are given by the top and bottom graphs, respectively

Figure 4.11: Floor plan for the lift lobby experiment

Figure 4.12: Histogram of the error distribution of the weighted centroid estimates collected in the lift lobby experiment

4.6 Summary

In this chapter, an indoor tracking system based on GT noise model is implemented. Because of better noise modeling, more precise position estimate is obtained. An equation to compute the variance of the estimation error from the filter with GT noise model and the Kalman filter is also derived. The variance of the es-

Figure 4.13: Estimates for x-position as the target moved along the path “*ab*” and y-position as the target moved along the path “*bc*” are given by the left and right graphs, respectively

Figure 4.14: Photograph showing the path “*bc*” where six metal lift doors exacerbate the effect of multipath.

timation error from the tracking experiments matches the variance calculated from the equation. This is useful as the equation can be used for the design and assessment of the indoor tracking system before implementation. The variance equation and experimental results also show that the variance of the estimation error from the proposed filter with GT noise model is smaller than that of the Kalman filter. Hence the proposed filter with GT noise model produces a more precise estimate.

Another way to deal with non-Gaussian noise is to use the particle filter. However, this may come at the expense of heavy computational load. One approach that has been proposed for improving particle filtering is to combine it with another filter such as the extended Kalman filter or the unscented Kalman filter [162,163]. For future work, we can combine the filter with GT noise model with particle filter just like the combination of Kalman filter and particle filter [164].

Chapter 5

Summary and Future work

5.1 Summary

This thesis develops energy-efficient and occupant-satisfied cooling solutions by utilizing occupancy information for fans operation in buildings. The methods for occupant-aware operations of both a single fan and a system of fans based on either thermal comfort model or human feedback are introduced. An indoor tracking system with the GT noise model for obtaining more accurate occupancy information is developed. The proposed smart tracking fan system, cooperative control approach for a system of fans and indoor tracking system can be integrated together to act as a coordinated whole or used separately to cope with a particular problem of interest.

In Chapter 2, a smart tracking fan system using geofence and camera-based indoor localization is proposed for thermal comfort improvement and energy conservation. Personal cooling service is provided upon the detection of the occupant in the area bounded by geofences. The proposed camera-based indoor localization system is able to locate the position of the occupant, determine the direction of airflow, and calculate the occupant-fan distance. The tracking fan is able to consistently provide the desired air speed determined by PMV-SET thermal comfort model using a

calibrated mapping scheme. The effectiveness of the proposed system is verified through experiments.

In Chapter 3, a cooperative control approach for a system of fans is proposed to optimize fans operation, improve thermal comfort and save energy. A cost-effective calibration method to obtain the relationship between air speed and fan speed setting is proposed to predict airflow in the actual environment. Optimized air movement is generated by minimizing the maximum deviation of the actual air speed generated by fans from the desired air speed inferred from occupant feedback. The minimax-error problem is reformulated as a linear programming problem which can be solved readily by using standard methods. Experimental results show that the proposed approach is able to control a system of electric fans effectively and maintain thermal comfort at higher indoor air temperatures.

The tracking fan system in Chapter 2 aims to provide an automatic, intelligent and convenient approach of providing thermal comfort. The fan speed setting and orientation will be automatically adjusted whenever the user's position or the environmental conditions are changed. While in Chapter 3, the goal is to maximize occupants' satisfaction. Therefore, real-time feedback from all occupants are adopted to determine the desired air speed, instead of using the PMV-SET model. However, it should be mentioned that the PMV-SET model can also be applied in Chapter 3 for automatic operation of multiple fans. This provides more flexibility to the building operators. The proposed approaches for occupant-aware fans operation can automatically determine the optimal fan speed setting under different environmental conditions and adapt to occupancy variation. They can be applied in air-conditioned spaces such as offices, theaters and classrooms to assist air conditioning system for energy conservation or naturally ventilated spaces such as hawkers centers for thermal comfort enhancement. They are independent of existing building management systems and can be easily incorporated into them for improved thermal comfort and

energy efficiency.

In Chapter 4, an indoor tracking system with the GT noise model is developed. It consists of first using the weighted centroid localization algorithm to give a coarse estimate of the position and then a filter with GT noise model to improve on the estimate. Because of the more accurate noise model, the filter with GT noise model can produce more precise position estimates compared to the Kalman filter which makes the usual assumption of Gaussian noise. An equation to compute the variance of the estimation error is also derived. The variances from the experimental results match the theoretical variance thus verifying the equation. This is useful as the variance equation can be used as an analytic tool for design and assessment of the system before implementation. Both theoretical and experimental results show that the variance of the estimation error from the proposed filter is less than that from the Kalman filter. Hence the proposed filter produces a more precise estimate. Experimental results also show that the proposed filter with GT noise model can handle outlier better than the Kalman filter.

5.2 Future work

- Thermal infrared imaging offers a tremendous advantage in differentiating human subjects from background by virtue of temperature differences [165–167]. Although the cost involved with thermal cameras are higher than ordinary cameras, thermal cameras can provide temperature information and work properly under weak lighting scenarios. As technology progresses, it may one day be possible to have very high quality thermal cameras with affordable prices. In future, a thermal camera can be used to capture the thermal image of an occupant and improve the performance of the system. In the meantime, the skin temperature can be sensed, which can be viewed as an indirect
-

measure of human thermal sensation and used for desired air speed determination. In addition, the clothing insulation can be estimated by analysing its correlation with the skin and clothing temperatures [168].

- The cooperative approach for thermal comfort control in Chapter 3 can also be applied to a system of ceiling fans which are more common in practice [139]. The challenge of using ceiling fans is the interaction between airflow generated by different fans. Unlike pedestal fans, ceiling fans cannot turn and change the direction of airflow. Therefore, the placement of ceiling fans (e.g., fan-to-fan distance) is a critical factor that affects the performance of the proposed approach. Investigation of this issue is ongoing.
- The indoor tracking system in Chapter 4 can be implemented in a more realistic WiFi network. Therefore, instead of carrying a RFID tag, the occupants can be tracked via their mobile phones. Besides, more accurate position information can be obtained by fusion smart phone inertial sensors with RSS, which has become a trend in recent researches [169,170].
- The proposed technologies can be integrated with air conditioning and mechanical ventilation (ACMV) system as shown in Figure 5.1. The indoor tracking system described in Chapter 4 provides the occupancy information to the coordinator which is responsible for determining the suitable operating points for both the ceiling fans and the ACMV system. In the meanwhile, personal cooling service can be delivered to the occupants by the smart fan system proposed in Chapter 2. The graphic user interface of a user personal space settings (UPSS) application developed for our ongoing work is shown in Figure 5.2. The UPSS application is a web-based application which enables the user to access up to date energy usage information of the allocated personal space and to provide feedback for controlling the personal space according to

Figure 5.1: Integration of the proposed technologies with ACMV system

his/her personal preference. It will collect the feedbacks from the occupants and communicate with the coordinator for energy efficient operations. One good candidate for applying these technologies is the Zero-Energy Building (ZEB) located at Building & Construction Authority (BCA) Academy, Singapore. The ZEB of BCA is the first retrofitted zero-energy building in Southeast Asia. It serves as a test bed for integration of green building technologies and is regarded as a paradigm for future green-building deployment. The plan of installing both ceiling fans and power meters in the large office space at ZEB has been approved and the construction work is underway. Upon completion of the construction, the real time energy consumption of the ACMV and fan systems will be monitored and compared with baseline configuration (ACMV system only) to quantify the energy savings resulted from increased temperature setpoints and elevated air movement.

My Preferences

Would you like to feel warmer or cooler?

No Change

Cooler Slightly Cooler No Change Slightly Warmer Warmer

Would you like more or less air movement?

Slightly More

Less Slightly Less No Change Slightly More More

Would you like the lights to be dimmer or brighter?

No Change

Dimmer Slightly Dimmer No Change Slightly Brighter Brighter

Submit

Figure 5.2: The user interface of the UPSS application for the proposed technologies

Author's Publication

1. L. Yin, S. Liu, W. K. Ho, K. V. Ling, "Indoor tracking with the generalized t -distribution noise model", IEEE Transactions on Control Systems Technology, Volume 26, Issue 3, 2018, Pages 915-926.
2. S. Liu, L. Yin, W. K. Ho, K. V. Ling, S. Schiavon, "A tracking cooling fan using geofence and camera-based indoor localization", Building and Environment, Volume 114, 2017, Pages 36-44.
3. S. Liu, L. Yin, S. Schiavon, W. K. Ho, K. V. Ling, "Coordinate control of air movement for optimal thermal comfort", Science and Technology for the Built Environment, DOI:10.1080/23744731.2018.1452508, *Accepted for publication*.
4. S. Liu, L. Yin, W. K. Ho, K. V. Ling, "Improved indoor tracking based on generalized t -distribution noise model", in Control Automation Robotics & Vision (ICARCV), 2014 13th International Conference on, pp. 687-692, 10-12 Dec 2014.
5. S. Schiavon, W. K. Ho, K. V. Ling, S. Liu, L. Yin, "Method of controlling a plurality of fans disposed in an area to provide thermal comfort control, and device thereof", WO patent, WO2017155472 A1, 2017.

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Appendices

Appendix A

Supplementary Information for Chapter 2

The fan power and the corresponding air speed at tested distances are summarized in Table A.1. The fan power was measured using a commercial power meter (Energy monitoring socket, Efergy, UK) with the accuracy of 2% of readings.

The medians (1st quartiles, 3rd quartiles) of air speed measurements in Figure 2.8 and their corresponding PMV values in Figure 2.9 are summarized in Table A.2 and A.3 respectively. In Table A.2, without the calibrated mapping scheme, the deviation of air speed from the target value for each temperature level becomes larger when the occupant-fan distance grows and the objective of achieving the desired air speed cannot be fulfilled. Therefore, the PMV values deviate farther from the targets with increased distance and even go outside the thermal comfort range at farther positions as shown in Table A.3.

Table A.1: Fan power and the corresponding air speed at tested distances.

Fan power (W)	Average air speed (m/s)								
	0.5 m	1.0 m	1.5 m	2.0 m	2.5 m	3.0 m	3.5 m	4.0 m	4.5 m
3.8	0.96	0.77	0.67	0.58	0.46	0.39	0.32	0.31	0.28
4.4	1.13	0.93	0.81	0.69	0.54	0.46	0.38	0.37	0.28
4.7	1.30	1.07	0.94	0.79	0.65	0.57	0.46	0.44	0.35
5.2	1.51	1.20	1.03	0.85	0.72	0.66	0.54	0.51	0.40
5.7	1.67	1.29	1.12	0.92	0.79	0.72	0.57	0.55	0.42
6.4	1.79	1.38	1.18	0.96	0.84	0.76	0.59	0.58	0.44
6.8	1.87	1.44	1.24	1.01	0.85	0.76	0.60	0.59	0.47
7.9	2.06	1.53	1.32	1.06	0.94	0.84	0.68	0.64	0.54
8.6	2.21	1.64	1.42	1.17	0.98	0.90	0.73	0.69	0.57
9.1	2.21	1.66	1.45	1.21	1.00	0.91	0.75	0.71	0.62
9.6	2.33	1.73	1.50	1.24	1.02	0.92	0.75	0.69	0.58
10.9	2.44	1.81	1.59	1.31	1.04	0.95	0.80	0.73	0.67
11.8	2.56	1.87	1.63	1.35	1.13	1.03	0.84	0.78	0.68
13.0	2.57	1.85	1.63	1.38	1.14	1.02	0.83	0.77	0.69
14.2	2.82	2.00	1.76	1.45	1.16	1.04	0.89	0.80	0.73
15.4	2.90	2.05	1.80	1.48	1.28	1.13	0.95	0.85	0.71
16.4	3.02	2.11	1.88	1.59	1.33	1.19	1.02	0.92	0.74
17.6	2.98	2.11	1.89	1.58	1.30	1.16	1.00	0.90	0.71
18.4	2.98	2.05	1.85	1.58	1.32	1.17	0.99	0.85	0.72
19.3	3.04	2.15	1.93	1.63	1.37	1.22	1.06	0.93	0.77

Table A.2: Medians (1st quartiles, 3rd quartiles) of air speed measurements in Figure 2.8

Test positions	Mapping scheme	26 °C: desired		27.5 °C: desired		29 °C: desired	
		Fan power (W)	Measured air speed (m/s)	Fan power (W)	Measured air speed (m/s)	Fan power (W)	Measured air speed (m/s)
1	Used (baseline data)	2.8	0.55(0.53,0.56)	3.2	0.64(0.63,0.66)	3.8	0.78(0.75,0.80)
2	Used	3.3	0.58(0.57,0.60)	3.8	0.69(0.68,0.71)	4.8	0.79(0.77,0.80)
	Not used	2.8	0.45(0.43,0.47)	3.2	0.50(0.48,0.52)	3.8	0.67(0.63,0.70)
3	Used	4.0	0.55(0.50,0.58)	4.7	0.65(0.63,0.68)	6.2	0.73(0.69,0.76)
	Not used	2.8	0.39(0.36,0.40)	3.2	0.46(0.44,0.48)	3.8	0.55(0.51,0.58)
4	Used	4.5	0.56(0.53,0.60)	5.4	0.67(0.63,0.70)	7.3	0.76(0.73,0.80)
	Not used	2.8	0.32(0.29,0.35)	3.2	0.39(0.37,0.41)	3.8	0.47(0.43,0.50)
5	Used	6.0	0.54(0.50,0.59)	7.4	0.63(0.58,0.67)	10.3	0.76(0.68,0.83)
	Not used	2.8	0.20(0.17,0.24)	3.2	0.25(0.21,0.29)	3.8	0.38(0.34,0.42)

Table A.3: Medians (1st quartiles, 3rd quartiles) of PMV values in Figure 2.9

Test positions	Mapping scheme	26 °C: desired PMV - 0.00		27.5 °C: desired PMV - 0.15		29 °C: desired PMV - 0.30 m/s	
		Fan power (W)	PMV	Fan power (W)	PMV	Fan power (W)	PMV
1	Used (baseline data)	2.8	0.00(-0.01,0.02)	3.2	0.15(0.14,0.16)	3.8	0.30(0.29,0.32)
2	Used	3.3	-0.03(-0.04,-0.01)	3.8	0.11(0.10,0.13)	4.8	0.30(0.29,0.31)
	Not used	2.8	0.09(0.07,0.11)	3.2	0.27(0.25,0.30)	3.8	0.38(0.36,0.42)
3	Used	4.0	0.00(-0.02,0.04)	4.7	0.14(0.12,0.16)	6.2	0.34(0.31,0.37)
	Not used	2.8	0.16(0.14,0.20)	3.2	0.32(0.29,0.34)	3.8	0.49(0.46,0.54)
4	Used	4.5	-0.01(-0.04,0.02)	5.4	0.13(0.11,0.16)	7.3	0.31(0.29,0.34)
	Not used	2.8	0.25(0.20,0.30)	3.2	0.41(0.38,0.44)	3.8	0.57(0.55,0.64)
5	Used	6.0	0.01(-0.03,0.04)	7.4	0.16(0.13,0.19)	10.3	0.31(0.27,0.37)
	Not used	2.8	0.51(0.40,0.61)	3.2	0.66(0.58,0.79)	3.8	0.71(0.64,0.78)

Appendix B

Supplementary Information for Chapter 3

The relationship between air speed and fan speed setting, which is assumed to be linear in Eq. (3.12), was investigated. As a comparison, a natural logarithm relationship was also tested. During the testing process, the air speed sensor was placed at 1.1 m above the ground, which refers to the head height of a seated person. Eight positions being away from the fan from 0.5 m to 4.0 m in a step of 0.5 m were considered. At each position, the air speed generated by the fan was measured when the fan speed setting was gradually increased from level 1 to level 32. For each speed setting, 90 samples were taken and the average values for all speed settings were used to fit the linear and natural logarithm curves, respectively, for this position using least-squares estimation. The fan speed setting, fan power and the corresponding average air speed at each position are given in Table B.1.

The fitted curves for both linear and natural logarithm models at selected distances are plotted in Figure B.1, where the average values of measured air speed are shown as scatter plots. It can be seen that the logarithm model does not represent the measured air speed well at nearer distances, e.g., at the distance of 0.5 m. The two

Figure B.1: Models between air speed and fan speed setting: (A) linear model; (B) natural logarithm model

models are then compared by calculating the mean absolute error e_{ma} and the root means square error e_{rms} between the measured air speed and the fitted curve. The results are summarized in Table B.2. At nearer positions up to 2 m, the straight lines fit the measured data better than the logarithmic curves. Especially, at the distance of 0.5 m, the errors e_{ma} and e_{rms} can be as high as 0.21 m/s and 0.26 m/s respectively for the natural logarithm model. Even though at farther distances beyond 2.5 m, the errors of the straight lines are slightly bigger than those of the logarithm curves, they are still limited within 0.1 m/s. In summary, the assumed linear relationship between air speed and fan speed setting is valid.

Figure B.2: Fan speed setting obtained by the proposed algorithm: (A) Fan 1 to 5 and (B) Fan 6 to 10.

Table B.1: Fan speed settings, fan power and the corresponding air speed at tested distances.

Speed setting	Power (W)	Average air speed (m/s)							
		0.5 m	1.0 m	1.5 m	2.0 m	2.5 m	3.0 m	3.5 m	4.0 m
1	3.8	0.96	0.77	0.67	0.58	0.46	0.39	0.32	0.31
2	4.4	1.13	0.93	0.81	0.69	0.54	0.46	0.38	0.37
3	4.7	1.30	1.07	0.94	0.79	0.65	0.57	0.46	0.44
4	5.2	1.51	1.20	1.03	0.85	0.72	0.66	0.54	0.51
5	5.7	1.67	1.29	1.12	0.92	0.79	0.72	0.57	0.55
6	6.4	1.79	1.38	1.18	0.96	0.84	0.76	0.59	0.58
7	6.8	1.87	1.44	1.24	1.01	0.85	0.76	0.60	0.59
8	7.9	2.06	1.53	1.32	1.06	0.94	0.84	0.68	0.64
9	8.6	2.21	1.64	1.42	1.17	0.98	0.90	0.73	0.69
10	9.1	2.21	1.66	1.45	1.21	1.00	0.91	0.75	0.71
11	9.6	2.33	1.73	1.50	1.24	1.02	0.92	0.75	0.69
12	10.9	2.44	1.81	1.59	1.31	1.04	0.95	0.80	0.73
13	11.8	2.56	1.87	1.63	1.35	1.13	1.03	0.84	0.78
14	13.0	2.57	1.85	1.63	1.38	1.14	1.02	0.83	0.77
15	14.2	2.82	2.00	1.76	1.45	1.16	1.04	0.89	0.80
16	15.4	2.90	2.05	1.80	1.48	1.28	1.13	0.95	0.85
17	16.4	3.02	2.11	1.88	1.59	1.33	1.19	1.02	0.92
18	17.6	2.98	2.11	1.89	1.58	1.30	1.16	1.00	0.90
19	18.4	2.98	2.05	1.85	1.58	1.32	1.17	0.99	0.85
20	19.3	3.04	2.15	1.93	1.63	1.37	1.22	1.06	0.93
21	19.9	3.30	2.28	2.05	1.69	1.22	1.09	0.93	0.81
22	20.6	3.35	2.29	2.07	1.73	1.35	1.21	1.03	0.92
23	21.2	3.22	2.14	1.96	1.68	1.35	1.22	1.01	0.87
24	22.4	3.55	2.36	2.12	1.77	1.27	1.12	0.96	0.84
25	23.2	3.40	2.30	2.05	1.74	1.34	1.19	1.01	0.88
26	24.1	3.58	2.39	2.16	1.83	1.45	1.29	1.08	0.96
27	25.2	3.69	2.49	2.24	1.86	1.38	1.24	1.08	0.95
28	26.0	3.78	2.52	2.26	1.87	1.47	1.33	1.12	0.99
29	27.3	3.82	2.58	2.29	1.90	1.45	1.30	1.11	1.00
30	29.2	3.98	2.60	2.32	1.96	1.57	1.41	1.18	1.04
31	30.9	4.10	2.69	2.39	1.96	1.54	1.39	1.21	1.03
32	32.5	4.20	2.78	2.46	2.01	1.37	1.25	1.00	0.98

Introduction

1. To control the fan, send the **5-character** command via SMS to 77577:

format:

0 **X** **X** **+** or **0** **X** **X** **-**

example:

where XX is your Seat No.

- a. If you sit at position **05** and want to **increase** air movement, your command is:

0 05+
 ↑ ↑ ↑
 0 <Space> 05 +
 (Seat NO.) (Indicator)

- b. If you sit at position **28** and want to **decrease** air movement, your command is:

0 28-
 ↑ ↑ ↑
 0 <Space> 28 -
 (Seat NO.) (Indicator)

Please note it will take some time for the commands to take effect (typically 1 minute). Please strictly follow the 5-character format.

2. Complete the survey, when prompted, by drawing lines at any appropriate positions where your feelings can be best described.

example:

<p>1. Rate your acceptance of current thermal environment</p>	<p>2. Rate your current thermal sensation</p>	<p>3. Rate your acceptance of air movement</p>
--	--	---

Introduction ends here.

Figure B.3: Survey questionnaire page 1 of 3

Personal Information

1. Seat No.: _____ (e.g. 05)
2. Gender: _____ (male/female)
3. Age: _____ (e.g. 29)
4. Height: _____ (e.g. 175 cm)
5. Weight: _____ (e.g. 75 kg)
6. How many months in total have you lived in tropical (hot/humid) countries (e.g. Singapore, Hong Kong, Miami, Kuala Lumpur, etc.):
_____ (e.g. 12 months)
7. Please indicate on the scale below how sensitive you think you are to indoor thermal conditions (temperature, humidity, draft, etc.):
Non sensitive ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 Very sensitive
8. How much do you usually perspire (sweat):
☐ Not at all ☐ Very little ☐ Somewhat ☐ Very much
9. If you are warm, do you prefer to cool down with an air conditioner or a fan:
☐ Air conditioner
☐ Fan

Finish this page at the beginning.

Figure B.4: Survey questionnaire page 2 of 3

Survey 1

<p>1. Rate your acceptance of current thermal environment</p>	<p>2. Rate your current thermal sensation</p>	<p>3. Rate your acceptance of air movement</p>
--	--	---

Please draw a horizontal line on each bar graph to indicate your answers.

Survey 2

<p>1. Rate your acceptance of current thermal environment</p>	<p>2. Rate your current thermal sensation</p>	<p>3. Rate your acceptance of air movement</p>
--	--	---

Please draw a horizontal line on each bar graph to indicate your answers.

Finish the specific survey only after you've been prompted.

Figure B.5: Survey questionnaire page 3 of 3

Table B.2: Errors between measured air speed and fitted curves

Distance (m)	Linear model		Natural logarithm model	
	e_{ma} (m/s)	e_{rms} (m/s)	e_{ma} (m/s)	e_{rms} (m/s)
0.5	0.11	0.13	0.21	0.26
1.0	0.09	0.11	0.10	0.13
1.5	0.07	0.09	0.10	0.12
2.0	0.06	0.07	0.08	0.10
2.5	0.08	0.10	0.06	0.07
3.0	0.07	0.09	0.05	0.06
3.5	0.06	0.08	0.05	0.06
4.0	0.05	0.07	0.04	0.04

Table B.3: Gain matrix K used in Subsection 3.3.1

0.0140	0.0010	0	0	0	0	0	0	0	0
0.0123	0.0010	0	0	0	0	0	0	0	0
0.0100	0.0020	0	0	0	0.0020	0	0	0	0
0.0090	0.0020	0	0	0	0.0030	0	0	0	0
0.0060	0.0010	0	0	0	0.0040	0	0	0	0
0.0040	0	0	0	0	0.0060	0.0010	0	0	0
0.0030	0	0	0	0	0.0090	0.0020	0	0	0
0.0020	0	0	0	0	0.0100	0.0020	0	0	0
0	0	0	0	0	0.0123	0.0010	0	0	0
0	0	0	0	0	0.0140	0.0010	0	0	0
0.0165	0.0084	0	0	0	0	0	0	0	0
0.0157	0.0064	0	0	0	0	0	0	0	0
0.0145	0.0064	0	0	0	0.0020	0	0	0	0
0.0131	0.0062	0.0013	0	0	0.0050	0	0	0	0
0.0111	0.0043	0.0013	0	0	0.0080	0.0020	0	0	0
0.0080	0.0020	0	0	0	0.0111	0.0043	0.0013	0	0
0.0050	0	0	0	0	0.0131	0.0062	0.0013	0	0
0.0020	0	0	0	0	0.0145	0.0084	0	0	0
0	0	0	0	0	0.0157	0.0084	0	0	0
0	0	0	0	0	0.0165	0.0104	0	0	0
0.0165	0.0140	0.0070	0	0	0	0	0	0	0
0.0158	0.0127	0.0080	0	0	0	0	0	0	0
0.0139	0.0105	0.0060	0	0	0	0.0020	0	0	0
0.0136	0.0090	0.0050	0.0010	0	0.0010	0.0030	0	0	0
0.0105	0.0070	0.0030	0.0010	0	0.0050	0.0050	0.0020	0	0
0.0050	0.0050	0.0010	0	0	0.0105	0.0070	0.0040	0.0010	0
0.0010	0.0030	0	0	0	0.0136	0.0090	0.0060	0.0010	0
0	0.0020	0	0	0	0.0139	0.0105	0.0060	0	0
0	0	0	0	0	0.0158	0.0107	0.0070	0	0
0	0	0	0	0	0.0165	0.0100	0.0070	0	0
0.0120	0.0160	0.0153	0.0080	0.0007	0	0	0	0	0
0.0102	0.0142	0.0138	0.0080	0.0012	0	0	0	0	0
0.0083	0.0130	0.0119	0.0069	0.0013	0	0.0010	0.0020	0	0
0.0060	0.0101	0.0100	0.0050	0.0016	0	0.0030	0.0040	0.0010	0
0.0044	0.0090	0.0080	0.0041	0.0012	0.0020	0.0050	0.0060	0.0030	0.0010
0.0020	0.0070	0.0060	0.0020	0.0010	0.0044	0.0070	0.0080	0.0041	0.0012
0	0.0050	0.0040	0.0010	0	0.0060	0.0081	0.0100	0.0050	0.0016
0	0.0020	0.0020	0	0	0.0083	0.0100	0.0119	0.0069	0.0013
0	0	0	0	0	0.0082	0.0122	0.0138	0.0070	0.0012
0	0	0	0	0	0.0100	0.0140	0.0153	0.0060	0.0007
0.0080	0.0140	0.0160	0.0140	0.0080	0	0	0	0	0
0.0067	0.0133	0.0145	0.0134	0.0080	0	0	0	0	0
0.0044	0.0111	0.0134	0.0126	0.0069	0	0	0.0020	0.0010	0
0.0030	0.0101	0.0104	0.0106	0.0050	0	0.0020	0.0040	0.0030	0.0010
0.0023	0.0080	0.0080	0.0090	0.0041	0.0013	0.0050	0.0060	0.0070	0.0030
0.0013	0.0050	0.0060	0.0070	0.0030	0.0023	0.0080	0.0080	0.0090	0.0041
0	0.0020	0.0040	0.0030	0.0010	0.0030	0.0101	0.0104	0.0106	0.0050
0	0	0.0020	0.0010	0	0.0034	0.0101	0.0134	0.0126	0.0069
0	0	0	0	0	0.0047	0.0133	0.0145	0.0134	0.0080
0	0	0	0	0	0.0030	0.0100	0.0160	0.0140	0.0080
0.0010	0.0070	0.0130	0.0160	0.0140	0	0	0	0	0
0.0010	0.0080	0.0117	0.0149	0.0134	0	0	0	0	0
0.0010	0.0080	0.0100	0.0134	0.0126	0	0	0	0.0040	0.0010
0.0010	0.0070	0.0080	0.0122	0.0106	0	0	0.0020	0.0060	0.0030
0	0.0050	0.0060	0.0100	0.0090	0	0.0030	0.0040	0.0080	0.0070
0	0.0030	0.0040	0.0080	0.0070	0	0.0080	0.0060	0.0100	0.0090
0	0	0.0020	0.0060	0.0030	0	0.0080	0.0090	0.0122	0.0106
0	0	0	0.0040	0.0010	0	0.0070	0.0110	0.0134	0.0126
0	0	0	0	0	0	0.0060	0.0127	0.0149	0.0134
0	0	0	0	0	0	0.0040	0.0110	0.0160	0.0140
0	0	0.0080	0.0140	0.0160	0	0	0	0	0
0	0	0.0070	0.0131	0.0149	0	0	0	0	0
0	0	0.0070	0.0115	0.0134	0	0	0	0	0.0040
0	0.0013	0.0064	0.0094	0.0122	0	0	0.0010	0.0020	0.0060
0	0.0017	0.0056	0.0073	0.0100	0	0	0.0030	0.0040	0.0080
0	0	0.0030	0.0040	0.0080	0	0.0017	0.0056	0.0083	0.0100
0	0	0.0010	0.0020	0.0060	0	0.0013	0.0064	0.0104	0.0122
0	0	0	0	0.0040	0	0	0.0070	0.0115	0.0134
0	0	0	0	0	0	0	0.0050	0.0131	0.0149
0	0	0	0	0	0	0	0.0030	0.0140	0.0160
0	0	0.0010	0.0040	0.0140	0	0	0	0	0
0	0	0.0012	0.0070	0.0131	0	0	0	0	0
0	0	0.0024	0.0080	0.0115	0	0	0	0	0
0	0	0.0021	0.0061	0.0104	0	0	0	0	0.0020
0	0	0.0022	0.0040	0.0083	0	0	0.0010	0.0010	0.0040
0	0	0.0010	0.0010	0.0040	0	0	0.0022	0.0020	0.0083
0	0	0	0	0.0020	0	0	0.0021	0.0041	0.0104
0	0	0	0	0	0	0	0.0014	0.0080	0.0115
0	0	0	0	0	0	0	0.0012	0.0070	0.0131
0	0	0	0	0	0	0	0.0010	0.0030	0.0140

Table B.4: Measured air temperature and relative humidity in Figure 2.5

HOBO	Air temperature ($^{\circ}\text{C}$)			Relative humidity (%)		
	Session 1	Session 2	Overall	Session 1	Session 2	Overall
1	26.6 ± 0.2	26.9 ± 0.1	26.8 ± 0.2	61.0 ± 0.5	60.0 ± 0.6	60.5 ± 0.7
2	26.2 ± 0.3	26.9 ± 0.1	26.6 ± 0.4	61.5 ± 0.8	59.5 ± 0.7	60.5 ± 1.2
3	26.0 ± 0.2	26.4 ± 0.1	26.2 ± 0.3	62.5 ± 0.6	60.8 ± 0.6	61.7 ± 1.0
4	25.8 ± 0.1	26.1 ± 0.1	25.9 ± 0.2	62.4 ± 0.9	61.4 ± 0.5	62.0 ± 0.8
Overall	26.1 ± 0.4	26.6 ± 0.4	26.4 ± 0.4	61.8 ± 1.0	60.4 ± 1.0	61.1 ± 1.2

Appendix C

Derivation of the Filter with GT Noise Model in Table 4.2

Instead of estimating $\hat{x}(1|N)$ in Eq. (4.30) we can estimate $\hat{x}(N|N)$ directly as shown in Eq. (4.31). The recursive filter algorithm in Table 4.2 can be derived as follows.

First, notice that Eq. (4.10) gives Eq. (4.32).

Second, multiplying Eq. (4.30) by Φ^{N-1} and then adding $\bar{x}(N)$ to both sides of the equation gives

$$\begin{aligned} & \Phi^{N-1}\hat{x}(1|N) + \bar{x}(N) \\ = & \Phi^{N-1}\hat{x}(1|N-1) + \bar{x}(N) + \Phi^{N-1}K(N) \\ & \times [W(N) + H\bar{x}(N) - H\Phi^{N-1}\hat{x}(1|N-1) - H\bar{x}(N)] \end{aligned} \quad (\text{C.1})$$

Using Eq. (4.12), Eq. (C.1) can be written as

$$\begin{aligned} \hat{x}(N|N) = & \hat{x}(N|N-1) + \Phi^{N-1}K(N) \\ & \times [W(N) + H\bar{x}(N) - H\hat{x}(N|N-1)] \end{aligned} \quad (\text{C.2})$$

Defining

$$K_f(N) = \Phi^{N-1}K(N) \quad (\text{C.3})$$

in Eq. (C.2) gives Eqs. (4.31) and (4.35).

Third, substituting Eq. (4.29) into Eq. (C.3) gives

$$\begin{aligned} K_f(N) &= \Phi^{N-1}P(1|N-1)(H\Phi^{N-1})^T \\ &\quad \times [\lambda S^{-1} + H\Phi^{N-1}P(1|N-1)(H\Phi^{N-1})^T]^{-1} \\ &= P(N|N-1)H^T \\ &\quad \times [\lambda S^{-1} + HP(N|N-1)H^T]^{-1} \end{aligned} \quad (\text{C.4})$$

where

$$P(N|N-1) = \Phi^{N-1}P(1|N-1)(\Phi^{N-1})^T \quad (\text{C.5})$$

Notice that Eq. (C.4) is also Eq. (4.34).

Finally, replacing N by $N+1$ in Eq. (C.5) gives

$$P(N+1|N) = \Phi^N P(1|N)(\Phi^N)^T \quad (\text{C.6})$$

and substituting Eq. (4.28) into Eq. (C.6) gives

$$\begin{aligned} &P(N+1|N) \\ &= [\Phi P(N|N-1)\Phi^T - \Phi K_f(N)HP(N|N-1)\Phi^T] \frac{1}{\lambda} \\ &= \Phi[I - K_f(N)H]P(N|N-1)\Phi^T \frac{1}{\lambda} \end{aligned}$$

which is Eq. (4.33).

Appendix D

Sample Calculation for the Variances in Section 4.5.3

The integral in Eq. (4.54) can be viewed as an expectation and calculated as a sample average. For $p_1 = p_2 = 2$, $v_1 = v_2 = 1.5$, $\sigma_1 = \sigma_2 = 0.42$, $\lambda = 0.5$, Eq. (4.54) gives

$$\begin{aligned}\gamma_1 &= \int_{-\infty}^{\infty} \left(\frac{4\varepsilon_1}{0.265 + \varepsilon_1^2} \right)^2 f_1(\varepsilon_1) d\varepsilon_1 \\ &= \frac{1}{2600} \sum_{k=1}^{2600} \left(\frac{4\varepsilon_1(k)}{0.265 + \varepsilon_1(k)^2} \right)^2 \\ &= 8.706\end{aligned}$$

where $f_1(\varepsilon_1)$ is given by the empirical discrete distribution obtained from the 200 experiments $\times$ 13 samples = 2,600 data samples i.e. $\varepsilon_1(k)$ and $k = 1, 2, \dots, 2600$. Similar calculations for γ_2 gives

$$\Gamma = \begin{bmatrix} 8.706 & 0 \\ 0 & 8.692 \end{bmatrix}$$

for Eq. (4.53). For $N = 2$, Eq. (4.52) gives

$$M_2 = \Phi (H^T \lambda S H + (H\Phi)^T S H \Phi)^{-1}$$

$$= \begin{bmatrix} 0 & 0 & 0.441 & 0 \\ 0 & 0 & 0 & 0.441 \\ -0.637 & 0 & 2.957 & 0 \\ 0 & -0.637 & 0 & 2.957 \end{bmatrix}$$

where from Eq. (4.39)

$$S = \begin{bmatrix} 7.559 & 0 \\ 0 & 7.559 \end{bmatrix}$$

Finally, Eq. (4.51) gives

$$\text{Var } \tilde{x}(2) = \lambda^2 M_2 H^T \Gamma H M_2^T + M_2 (H\Phi)^T \Gamma (H\Phi) M_2^T$$

$$= \begin{bmatrix} 0.152 & 0 & 0.508 & 0 \\ 0 & 0.152 & 0 & 0.507 \\ 0.508 & 0 & 2.577 & 0 \\ 0 & 0.507 & 0 & 2.573 \end{bmatrix}$$

where the first two diagonal elements of 0.152 are the variances of the x-position and y-position estimation errors shown in Fig. 4.8 by the crosses at $N = 2$.