A Novel Method for Monitoring Air Speed in Offices Using Low Cost Sensors

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ABSTRACT

Even though HVAC systems consume around 40% of total building energy, they often fail to provide satisfactory thermal conditions to occupants in commercial buildings. Personalized Environmental Control Systems (PECS) such as local fans and heaters have the potential to control the local environment around the occupant to improve occupant satisfaction. Existing methods for modeling thermal preferences primarily rely on temperature measurements and often neglect air speed. Current methods for monitoring air speeds are either too expensive or too bulky to be used in real office environments. We present our preliminary results on predicting air speeds using alternate environmental parameters such as air pressure, temperature and humidity using low cost miniature sensors. The results show that we can accurately predict air speeds with a mean absolute error of 0.056 m/s for conditions investigated in this study. Although the results are promising, further studies are needed to improve the system before it can be used in real world environments.

INTRODUCTION

In the U.S., HVAC systems consume around 43% of the total building energy consumption (U.S. Department of Energy 2010), yet they often fail their primary purpose of providing comfortable indoor conditions. A large scale study, collected occupant satisfaction survey in commercial buildings in North America over 10 years, showed that only 38% of the occupants are thermally satisfied, with only 2% of buildings meeting the ASHRAE requirement of satisfying at least 80% of occupants (Karmann et al. 2018). Poor occupant satisfaction stems from two main reasons: the differences in comfort preferences among occupants, and the inability of centralized HVAC systems to provide personalized environmental conditioning and control opportunities. A recent simulation study showed that even when thermal comfort preferences of occupants are known, it is very difficult to achieve 80% occupant satisfaction using centralized HVAC systems due to lack of capability of controlling the environment at a granular level to meet individual occupant requirements (Aryal and Becerik-Gerber 2018).

Personalized Environmental Control Systems (PECS) have recently received interest from the research community as solutions to provide more comfortable environments while reducing building energy consumption. PECS, such as local fans and heaters, have the potential to provide local cooling and heating to maintain comfortable conditions around each occupant while enabling central HVAC systems to be controlled over a wider range of temperatures, thereby reducing overall energy consumption while improving occupant satisfaction. For example, a recent study demonstrated that extending HVAC setpoints could reduce CO_2 emissions up to 21.4% per year, and the use of personal cooling systems can result in cooling energy savings of 10% to 70% depending on the location (Heidarinejad et al. 2018). Thermal comfort depends on several factors, such as air temperature, radiant temperature, relative humidity, air speed, metabolic rate and clothing. There have been several recent efforts to learn individual thermal comfort preferences of building occupants by leveraging recent advancements in Internet of Things (IoT) and machine learning techniques (Kim et al. 2018). Once individual comfort preferences are modeled, these models could be used to automatically control HVAC systems and PECS to improve occupant comfort and satisfaction (Aryal et al. 2018). However, current methods of modeling thermal comfort preferences primarily rely on environmental temperature measurements, and physiological measurements using wearable devices, however they do not often consider air speeds due to the difficulty in monitoring air speed using existing methods (Kim et al. 2018).

Traditionally, it was believed that air movement has a negative effect of causing draft that can lead to discomfort. However, there has been a recent shift in focus towards the positive effects of air movement and its ability to improve thermal comfort of occupants and even provide thermal pleasure or thermal alliesthesia (Parkinson and de Dear 2017; Zhai et al. 2017). Air speeds around an occupant could be affected by several factors, such as the fan size, fan location and orientation, furniture in the room, and so on. For example, a recent study mapped the influence of desks and office partitions on the air flow patterns inside a room with a ceiling fan to provide a better understanding of how furniture affects air movement in a room (Gao et al. 2017). Climate chamber studies have also been conducted to identify suitable air speeds for improving comfort in a typical office layout (Zhai et al. 2017). However, such studies utilize bulky sensing methods, such as an array of anemometers mounted on a rod for monitoring air speed around an occupant, which would be impractical for monitoring air movement in an actual office due to the large space requirements. Other methods, such as hot wire anemometer (~$100 - $500) and ultrasonic anemometers (~$100 - $2500) are expensive to be utilized at a large scale. A more practical approach would be to utilize sensing methods that are low cost, and small in size so they could easily be embedded in an existing office space (e.g., on desks, chairs, and other furniture) to monitor air movement around an occupant to provide real time measurements of air speed even when other conditions change in the environment. In this paper, we present our preliminary results from our attempt to find an alternate way to monitor air speeds in indoor spaces.

METHODOLOGY

Moving air exerts pressure on objects as we experience in everyday life, such as trees swaying in the wind. Pitot tubes, a common instrument, used to measure air speeds in aircrafts, rely on measuring the dynamic pressure caused by moving air to evaluate the air speed. Moving air also has a cooling effect as it can take away some of the thermal energy from a body by conduction and convection. Moving air can also change relative humidity by causing a change in the density of air. Analytical modeling of the underlying physical relationships among temperature, pressure, humidity and air speed for turbulent flows of open air is a complicated task. However, machine learning algorithms can model complex relationships solely from the provided data. Thus, we utilize inexpensive sensors to monitor environmental parameters, such as air pressure, temperature and humidity, and utilize machine learning algorithms to predict the air speed. The sensors utilized in this study are low-cost (2 sensors, $20 each) and small in size (2cm*2cm), which can be easily embedded in office spaces and deployed at a large scale.

Figure 1: Left- Data Collection Setup. Right- Top: Main sensor, Bottom: Reference sensor

Data Collection: For this study, air movement was generated using a typical desk fan (Honeywell HT-908) with three different speed settings. A cup-based anemometer connected to an Arduino Uno was used to monitor the air speed and provided the training labels for our model. Environmental measurements for pressure, temperature and humidity were taken using two BME280 sensors connected to the Arduino Uno. One of the BME280 sensor was directly facing the fan (referred hereafter as the main sensor), and another BME280 sensor (referred hereafter as reference sensor) was placed in a location that was not directly influenced by the fan to serve as a reference measurement of the ambient conditions in the room. The anemometer, as well as the BME280 sensors were mounted on an office chair, with the anemometer and the main sensor placed roughly at the location of the head of a person sitting on the chair, while the reference sensor was mounted at the back of the chair as shown in Figure 1. The three fan speeds as measured by the anemometer were around 3.2 m/s, 3.5 m/s, and 4 m/s.

Since ambient conditions in the room change throughout the day due to several factors, such as HVAC operations, occupants in the room, outside climate etc., we utilized the reference sensor to gather background changes that can be removed from the measurements collected by the main sensor directly facing the fan. It is important to note that the office space was occupied during the data collection period where occupants were in the office during the day, and the temperature setpoint of the HVAC system was set by the occupants as desired. For this pilot study, the fan was placed roughly 2 feet from the sensors, with the center of the fan aligned to the sensors. We also utilized a smart plug that can be remotely controlled to switch the fan on or off. The fan was switched on or off at a random interval between 5 to 15 minutes while the measurements were taken from all the sensors. The data was collected for a period of 115 hours (4 days and 19 hours) with sensor measurements taken every second resulting in approximately 416,000 data points. A portion of the collected data for a 6-hour window is shown in Figure 2, where the large fluctuation is caused by the HVAC being turned on when an occupant entered the office, and the smaller fluctuations are related to the fan operation.

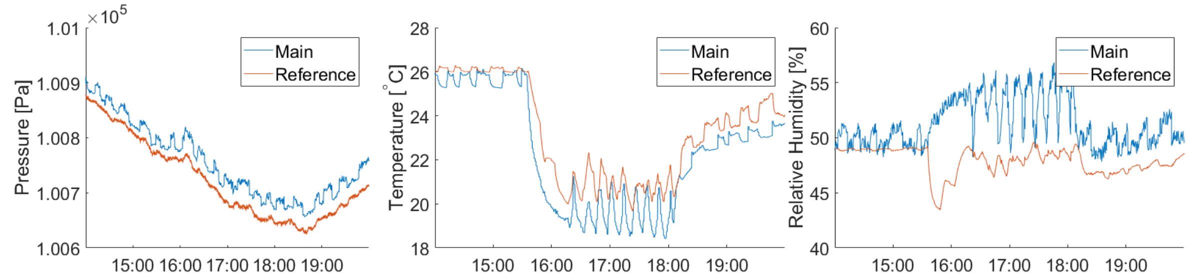

Figure 2: Pressure, temperature and humidity readings from main and reference sensors

Data pre-processing: The data collected, from the reference sensor, provided information regarding the changes in the background - not affected by the fan. The background trend was removed by subtracting the readings of pressure, temperature and humidity obtained by the reference sensor from the readings obtained by the main sensor. The data was then normalized by subtracting the mean from each data point and dividing it by the standard deviation. The cleaned data, after removing the background trend and normalization, is shown in Figure 3 along with the airspeed measurements obtained from the anemometer. Turning the fan on corresponds to increase in pressure and decreases in temperature and humidity, as seen in Figure 3. This trend can be observed strongly when the HVAC system is not operating but becomes weaker when the HVAC system is operating, around time 16:00 in Figure 3, due to additional background variation caused by the system.

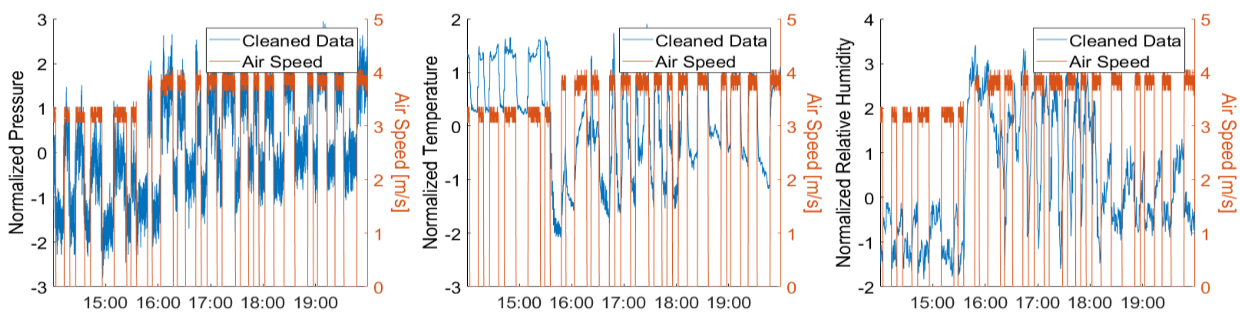

Figure 3: Cleaned and normalized data along with air speed measured by an anemometer

Among the three data streams shown in Figure 3, pressure seems to be more robust against the changes caused by HVAC operation as it does not abruptly change when the HVAC is turned on (around time 16:00) compared to other measurements. Since the changes observed in the pressure seemed to be more robust, a new variable that provides the information regarding whether the fan was on or off (fan state) was derived from the pressure data. An algorithm that finds the points where there is an abrupt change in the average of data was utilized to detect the points of change in the cleaned data. Since we know that the pressure increases correspond to the fan being turned on, the fan state was then calculated by evaluating the direction of change between two change points. After including this derived measurement, the data was used to train different regression models using supervised learning techniques.

Model Training: The sensor measurements for pressure, temperature and humidity from the main and reference sensors, the cleaned data stream for pressure, temperature and humidity, and the derived fan state, resulting in a total of 10 predictors, were used as predictors for training the regression models. The target variable (response) was the air speed measured by the anemometer. The dataset was split into training set (60%), and testing set (40%). We evaluated the common regression algorithms to determine which algorithm performed well for predicting air speeds.

RESULTS

The algorithms were evaluated using 5-fold cross validation on the training set in order to pick the best algorithm. The Root Mean Square Error (RMSE) for each of the algorithms in the 5-fold cross validation is shown in Table 1. Bagged trees outperformed other algorithms that were evaluated with the lowest RMSE of 0.15 as seen in Table 1. Bagged trees consist of a collection of decision trees trained on separate subsets of the data, which are later combined together to provide a more robust prediction. Since all the sensor signals in this case are inherently noisy, bagged trees seem to outperform other algorithms due to their robust nature.

Table 1: RMSE for different algorithms using all predictors

Algorithm	RMSE using all predictors
Linear Regression	0.91
Decision Trees (Large – minimum leaf size = 4)	0.21
Decision Trees (Small – minimum leaf size = 36)	0.49
Bagged Trees	**0.15**
Boosted Trees	0.84

Furthermore, to evaluate which of the physical measurements were most useful in predicting the air speed, we trained different bagged tree models using one physical measurement (pressure, temperature, or humidity) at a time. In addition, we also evaluated the usefulness of adding fan state, which was derived from changes in pressure readings, as a predictor by including fan state with one physical measurement at a time. The RMSE in the 5-fold cross validation for bagged trees, trained using a single type of physical measurement, is shown in

Table 2. We see that pressure was the most useful physical measurement that resulted in the lowest RMSE, followed by temperature and humidity respectively. In

Table 2, we also see that fan state was a useful predictor in the model as it reduced the RMSE by roughly 50% compared to using one of the physical measurements alone.

Table 2: RMSE when using data from single type of physical measurement

Predictors used	RMSE with Bagged Trees
Temperature	0.85
Pressure	0.64
Humidity	0.9
Temperature, fan state	0.42
Pressure, fan state	0.35
Humidity, fan state	0.41

Using all of the predictors together to train a bagged tree model yielded the best prediction with an RMSE of 0.15 as seen in Table 1. After selecting bagged trees as the preferred algorithm, we evaluated its prediction error in the testing set (40% of the data) using all the predictors. The RMSE in the testing set was 0.15, which is the same as the RMSE obtained from cross validation, which indicates that there was no overfitting on the training set. The measured vs. predicted airspeeds from the testing set are shown in Figure 4 for a 6-hour window. The coefficient of determination (r-squared) was 0.9934 and Mean Absolute Error (MAE) was 0.056m/s between the measured and predicted airspeeds in the test set. MAE, in contrast to RMSE, provides a better reflection of the average error that can be expected because it does not square the errors to penalize outliers. The low MAE of 0.056m/s provides a strong evidence that airspeed can be accurately predicted using other physical measurements.

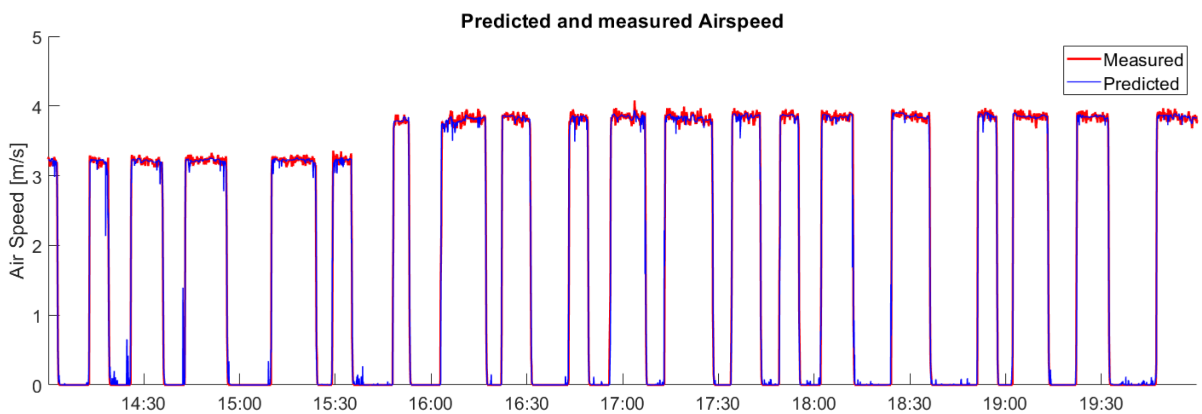

Figure 4: Airspeed measured from anemometer and predicted from bagged trees model.

DISCUSSION

Our results from this preliminary investigation strongly supports the idea of monitoring air speed using alternative measurements for pressure, temperature and humidity. This could provide a low-cost alternative to existing methods of monitoring air speed, such as the ones currently used, e.g., hot-wire anemometer or ultrasonic anemometers. Furthermore, the BME280 sensor used in this study is only 2cm*2cm in size, which makes it possible to embed these sensors into everyday objects, such as office furniture, which is not practical with bulky cup-based anemometers. In addition to monitoring airspeed, the data collected from the BME280 sensor is also useful for other purposes, such as ensuring temperature and humidity in the environment are within the desired ranges. This increases the usefulness of using our approach to monitor air speed compared to using different sensors for monitoring different parameters.

In this study, we collected air speeds under three fan speed settings, which were around 3.2 m/s, 3.5 m/s, and 4 m/s. Air speeds in offices tend to be lower than the air speeds used in this study, typically lower than 0.8m/s due to current guidelines to avoid draft. However, several studies have shown that higher air speeds such as 1.4m/s (Zhai et al. 2017) or even as high as 3m/s (Fong et al. 2010) can be effective ways to maintain thermal comfort at higher temperatures. Since this study was intended to provide a proof of concept, a higher air speed was used to improve the signal to noise ratio. Lower air speeds need to be considered in future studies.

Improved air quality is another added benefit that may result from using higher air speeds indoors. A recent study showed that using air movement devices such as a desk fan can significantly reduce the CO_2 inhaled by the occupant (Ghahramani et al. 2019). Since most existing methods to model individual thermal comfort preferences rely only on temperature and humidity measurements, having a convenient method to monitor air movement in real time can be useful in developing new methods that can include air movement as an additional parameter in individual comfort models. Ultimately, the actual effectiveness of using real time air speed measurements for thermal comfort prediction needs to be evaluated after the system is fully developed.

There are several limitations in this preliminary investigation that need to be overcome before air speed can be monitored in real offices using the approach. In our study, only one type of fan was used to generate air movement, but the changes observed in the sensor signals might vary with different types of fans. The air speed also depends on the distance from the fan and the angle that the fan is positioned in, which was fixed in this study. Future studies need to consider different types of fans or air terminals positioned at different distances and orientations to develop more robust models that can work under different conditions. For real world implementation, the impact of an occupant sitting on a chair where the sensor is placed also needs to be considered. The ideal location for sensor placement needs to be investigated by considering the occupant, and methods to filter out additional noise caused by occupant's presence need to be developed.

CONCLUSION

In this study, we presented our preliminary results for monitoring air speed in office environments using alternate measurements of air pressure, temperature and humidity. The presented approach resulted in a mean absolute error of 0.056m/s in air speed prediction, which indicates the possibility of using this approach for real time monitoring of air speed in indoor environments. The approach provides a low-cost alternative to existing methods, such as hot wire anemometers and ultrasonic anemometers, and is much smaller in size compared to cup-based anemometers. Although this preliminary investigation has several limitations and there is additional work needed to develop a robust method to monitor air speeds around an occupant, the results are promising and warrant further investigation. We believe that with a convenient method to monitor air speeds, we can better understand the impact of air speed on thermal comfort by being able to obtain real time air speed measurements and comfort feedback from occupants. Current methods of learning thermal comfort preferences of individual occupants mostly rely on temperature measurements alone to infer thermal comfort of occupants and including air speed measurements could potentially improve the modeling of thermal comfort preferences. Furthermore, with real time monitoring of temperature and air speed, and by modeling individual comfort preferences, the local environment around the occupant could be automatically controlled to improve occupant comfort and satisfaction using PECS.

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