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A method to optimize sampling locations for measuring indoor air distributions

Yan Huang [a], Xiong Shen [a, *], Jianmin Li [a], Bingye Li [a], Ran Duan [a], Chao-Hsin Lin [b], Junjie Liu [a], Qingyan Chen [c, a]

[a] School of Environmental Science and Engineering, Tianjin University, Tianjin 300072, China
[b] Environmental Control Systems, Boeing Commercial Airplanes, Everett, WA 98203, USA
[c] School of Mechanical Engineering, Purdue University, West Lafayette, IN 47907, USA

HIGHLIGHTS

- Gradient-based sampling method is introduced for point measurements of indoor air.
- Ordinary Kriging method interpolated the point data to form field distributions.
- Gradient-based method reduced more interpolation errors than the grid method.

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ABSTRACT

Indoor air distributions, such as the distributions of air temperature, air velocity, and contaminant concentrations, are very important to occupants' health and comfort in enclosed spaces. When point data is collected for interpolation to form field distributions, the sampling locations (the locations of the point sensors) have a significant effect on time invested, labor costs and measuring accuracy on field interpolation. This investigation compared two different sampling methods: the grid method and the gradient-based method, for determining sampling locations. The two methods were applied to obtain point air parameter data in an office room and in a section of an economy-class aircraft cabin. The point data obtained was then interpolated to form field distributions by the ordinary Kriging method. Our error analysis shows that the gradient-based sampling method has 32.6% smaller error of interpolation than the grid sampling method. We acquired the function between the interpolation errors and the sampling size (the number of sampling points). According to the function, the sampling size has an optimal value and the maximum sampling size can be determined by the sensor and system errors. This study recommends the gradient-based sampling method for measuring indoor air distributions.

1. Introduction

In indoor air environments, the optimization of parameters such as air velocity, temperature, and contaminant concentrations is important for the health and comfort of occupants. To assess the detailed distributions of these parameters, two primary methods can be applied: numerical simulations by computational fluid dynamics (CFD), and in-situ measurements. CFD simulations are inexpensive, but they may not accurately predict the distributions because of the approximations used in turbulence modeling and numerical algorithms. In-situ measurements, although time-consuming and expensive, are more reliable. Furthermore, even in numerical simulations, a certain amount of experimental data is often needed for validating the computed results (Chen and Srebric, 2002; Liu et al., 2012a,b). Therefore, it is preferable to conduct in-situ measurements.

Both optical and point–wise measurement method can be applied to acquire the distributions of indoor air parameters. The optical measurement method uses optical anemometry techniques such as particle streak velocimetry, particle tracking velocimetry, and particle image velocimetry to measure air distributions by acquiring and processing the reflected signals of particles seeded in the flow. This method can determine air velocity distributions in a

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* Corresponding author.
E-mail address: shenxiong@tju.edu.cn (X. Shen).

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local field (Cao et al., 2014). However, in indoor spaces with complex geometry, occupants and other objects may block the light from the optical anemometer, which makes it difficult to measure an entire region (Liu et al., 2012a,b).

The point–wise method measures the air parameters with point sensors such as anemometers, thermocouples, and tracer-gas samplers (Liu et al., 2012a,b; Li et al., 2014). In comparison with the optical method, the point–wise method is more adaptable to a complex space because the sensors can be located flexibly in spaces where the optical anemometry cannot take measurements. However, the accuracy of the interpolated air distributions based on the point sensor data is highly dependent on the sampling size and locations (Swiler et al., 2006; Coetzee et al., 2012). The sampling size means the number of sampling locations and sampling methods means how the sampling locations were selected. In order to reduce the time requirement and labor costs for the measurements, the sampling size should be as low as possible, but the use of too few sampling points can result in poor spatial resolution. Laurenceau and Sagaut (2008) found that the grid method, which is the most commonly applied method in engineering fields, requires a large sampling size in order to provide good results. The grid method may not be optimal in determining the sampling locations.

This paper reports our effort in proposing a method for determining the optimal sampling location and sampling size. We have also investigated the relationship between sampling location and the accuracy of air parameter fields obtained in measuring indoor air environment.

2. Research methods

2.1. Sampling method

Several methods are available for determining sampling locations, including grid, unstructured triangular mesh, Latin hypercube sampling, sequential, and gradient-based methods. The grid method uses equal intervals along a sampling direction (Laurenceau and Sagaut, 2008; Carvajal et al., 2010; Coetzee et al., 2012). The unstructured triangular mesh method uses an unstructured mesh to spread the sampling points such that they are adapted to the boundary of the sampling domain (Persson and Strang, 2004; Coetzee et al., 2012). The sampling domain is the plane or volume where measurements were conducted in a2D or 3D indoor space, respectively. The Latin hypercube sampling method is an enhanced random sampling method that divides the sampling domain into cells with equal intervals and then sets one sampling point at a random position in each cell (Laurenceau and Sagaut, 2008; Nissenson et al., 2009; Coetzee et al., 2012). It is widely used in geo-statistics but does not seem to be useful for indoor air measurements. This is because indoor spaces are relatively small, and we can acquire the exact spatial coordinates easily. The sequential method sets a few initial sampling points and then adds points one by one to improve the interpolation accuracy, until the desired sampling size has been obtained (Jin et al., 2002). However, the sequential method is computationally expensive, as it sets only one point at a time, and the whole field interpolation must be calculated each time (Coetzee et al., 2012). Jouhaud et al. (2007) proposed a gradient-based sampling method that determines new sampling points in regions with a large gradient. The gradient-based method seems to be scientific, simple, and computationally inexpensive. It was therefore selected for this study.

The gradient-based method uses equal intervals along a direction if the gradient of air parameter is small. If the gradient is large, one or more points are added between the two original sampling points until the differences between two adjacent points are sufficiently small when compared with the maximum gradients in the sampling domain. However, it is difficult to determine the sampling locations for the gradient-based method because the gradient is unknown before the start of the experiment. One could estimate the gradient from experience, by identifying, for example, the regions with large velocity and temperature gradients. Such estimation may not be easy for an actual indoor space where the flow can be complex. Thus, this investigation recommends using a CFD simulation to identify the regions with large parameter gradients. The information required by CFD is typically known, such as the thermo-fluid boundary conditions. With the air distribution predicted by CFD, one can determine the sample x_i by calculating the gradient coefficient, α, as (Jouhaud et al., 2007):

$$\alpha = \frac{\|grad(\phi)\|}{\max\|grad(\phi)\|} \tag{1}$$

where, ϕ represents an air parameter such as velocity, temperature, or contaminant concentration.$\|grad(\phi)\|$ is the gradient of the flow parameter, while $\max\|grad(\phi)\|$ is the largest gradient of this flow parameter in the sampling domain.

If $\alpha > \alpha_0$, the gradient is considered to be sufficiently large to require the addition of more sampling points in the region. We chose $\alpha_0 = 0.15$which had been recommended to be the optimal choice to avoid the use of too numerous points in sampling domain with large gradient (Jouhaud et al., 2007). By starting with a coarse grid of sampling points, one can flag a sampling point if $\alpha > 0.15$. The percentage of flagged points is:

$$\eta = \frac{w_f}{w_t} \tag{2}$$

where, w_f is the number of flagged points in the sampling domain and w_t the total number of points in the domain. If $\eta \le \eta_0$, then a point is refined into two points. This process is repeated for all sampling points until $\eta > \eta_0$. The recommended value of η_0 was in the range of 0.5–0.75. Here we chose $\eta_0 = 0.6$ (Quirk, 1996).

It should be noted that in order to compare the grid and gradient-based sampling methods, the total grid number (sampling size) should be the same in both methods. However, since the gradient-based method splits points for regions with a large gradient, the starting sampling size for this method should be smaller than that for the grid method.

2.2. Kriging interpolation method

The data obtained from the sampling positions by the grid or gradient-based method can be interpolated to form field distributions. Several interpolation methods are available, such as polynomial methods, radial basis function methods, inverse distance weighting methods, Kriging methods, etc.

The polynomial method uses Taylor expansion equations to express the values at places not measured by the values at the measured points. The coefficients of the polynomial are estimated by minimizing the mean square error of the expansion equations (Shen et al., 2013). This is the most mature method for interpolation and requires the lowest number of sampling points for modeling; however, it may not as accurate as Kriging methods (Wang and Shan, 2006).

The radial basis function method estimates the value at places not sampled, by use of a basis function (such as linear, cubic, thin plate spline, multiquadric, and Gaussian functions) (Gutmann, 2001). However, the radial basis function method cannot be used to determine measurement errors (Jin et al., 2002).

The inverse distance weighting method determines the value between the measured points as the weighted sum of the measured