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Two-stage indoor physical field reconstruction from sparse sensor observations

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ABSTRACT

CFD simulation is a powerful tool to estimate an indoor physical field of interest but it is computationally expensive. The simulation has to be repeated if the environment (e.g., heat sources) changes. In this work, we propose a two-stage physical field reconstruction (TSPFR) approach to directly estimate an indoor physical field without rerunning the CFD simulation. Current methods for physical field reconstruction separately used the observed input parameters of the CFD simulation and the sparse sensor observations. We fuse both of them. Using the principle component analysis (PCA) technique, the physical field can be reconstructed by estimating the PCA components. In this paper, we estimate the physical field in two stages. In the first stage, we proposed a scaled extreme learning machine (sELM) algorithm to train a regression model with which we can estimate PCA components from the observed input parameters and reconstruct an approximated physical field. In the second stage, we correct the physical field reconstructed in the first stage with the sparse sensor observations. We theoretically show that the proposed approach outperforms the current one stage methods. When using current methods, the number of sensor observations cannot be less than that of the dominant PCA modes. We show how the proposed method can reduce the number of required sensor observations. Finally, we provide an indoor thermal map estimation problem to show the effectiveness of the proposed method.

1. Introduction

Energy usage is continuously growing worldwide as nations pursue economic growth and infrastructure development. Around one-third of energy is consumed in buildings, and it is still increasing [1]. In the US, the heating, ventilating and air-conditioning systems (HVACs) account for around half of energy consumption in buildings [2]. The estimation of indoor physical fields, such as the estimation of indoor thermal map and airflow patterns is significant for energy efficient thermal and airflow management [2–8]. One 'perfect' HVAC system should be able to maintain the occupants' thermal comfort sensation while being energy efficient. On one hand, the indoor physical fields, e.g., thermal map and airflow patterns, have been widely used to estimate the distribution of indoor human thermal comfort index [9–13]. On the other hand, the physical fields can be used to analyze the indoor air for localized air-conditioning [5,14–16] and can be used as the feedback information for airflow control [17–19], which can maintain the thermal comfort and reduce energy consumption of HVACs.

However, it is not easy to observe environmental physical fields because sensor networks can only observe the data at particular sparse locations. Some special sensors can provide dense observations. For example, the thermal-infrared camera, it can provide 2-dimensional thermal map of the surface of an object but cannot provide environmental temperature field. The computational fluid dynamics (CFD) simulation is the most popular tool to predict indoor physical fields [20]. From a CFD simulation we can obtain the global information of one indoor physical field, which is very expensive from experiments. However, CFD simulations suffer from three issues: (1) the simulations require experts to carefully calibrate the CFD model, (2) the simulation results are usually inaccurate compared with sensor observations, and (3) the simulation is computationally very expensive and time-consuming, especially for large scale 3-dimensional cases.

For many CFD applications, to produce reliable simulation results, we need to adjust the input parameters of the simulation to amend the agreement between the simulated results and the corresponding experimental data [21–23]. The input parameters can be model parameters [23], boundary condition parameters

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[24–28], Rayleigh number [28,29], Mach number [30,31], etc. Tens of simulation runs are required for the calibration process of finding acceptable parameters.

In addition, for the indoor environment, the input parameters are commonly varying due to the change of heat source distribution, the change of radiation condition, the change of the set-point of air-conditioning system, etc. If the environment (e.g., heat sources) changes, which leads to the change of both the physical field and the input parameters of the CFD simulation, to estimate the physical field we have to repeat the simulation. Many efforts to speed up CFD simulations were made in recent years, such as the fast fluid dynamics (FFD) model [32,33]. For many cases, however, the cost to rerun the simulation for the varying parameters is still very expensive. Therefore, a new method which can quickly predict a physical field is highly desirable.

1.1. Related prior work

Indoor physical fields are with dense data. Directly estimating a physical field from sparse sensor observations is an ill-posed problem. Model-order-reduction techniques can be used to solve this ill-posed problem. Principle components analysis (PCA), also known as proper orthogonal decomposition in fluid mechanics community, is a powerful model-order-reduction technique to represent physical fields by a linear combination of their dominant PCA modes [27,34–36]. The number of the dominant PCA modes is far less than that of the mesh points in the CFD simulation. By finding the dominant PCA coefficients we can easily estimate an indoor physical field.

Currently, there are two popular methods to estimate the PCA coefficients of one physical field of interest.

- One approach is to find regression models to estimate the PCA coefficients from the observed input parameters of interest [28–31]. Most of current works [29–31] used the spline interpolation technique to train the regression models, which are multi-input-single-output (MISO) functions. For each PCA coefficient, we need to train a regression model. The spline interpolation technique has been widely used for regression problems. It can provide very good fitting performance if the number of input variable is less than four, while if the input variable are more than three, this technique may not be a good choice [37].
- The other approach is to solve the linear measurement equation of the physical field of interest [27,34,38,39]. With the PCA modes, we can easily find a linear measurement model for every single point of the physical field in terms of the PCA coefficients. If enough sensor observations are available, we can easily estimate the dominant PCA coefficients. To solve this linear inverse problem, the number of sensor observations cannot be less than that of the dominant PCA modes, and the sensing locations are very important in terms of the estimation performance [40].

The two approaches find the PCA components from the input parameters and the sparse sensor observations, respectively. In the case that both input parameters and sparse sensor observations are known, how to fuse them to better estimate the indoor physical field? If the number of sensor observations is less than that of the dominant PCA modes, how to estimate the physical field? It is very interesting to answer the two questions.

1.2. Our method

In this work, we consider the case that both the input parameters of interest and some locations of an indoor physical field are observed. We fuse both types of information to achieve better estimation of the field. We present a two-stage physical field reconstruction (TSPFR) method by combining the two current approaches. The block diagram of the TSPFR is given in Fig. 1.

To reconstruct one physical field based on sparse observations, we need to firstly build up the dominant PCA modes of the physical fields of interest. Using the method of snapshots [41], we can easily find the PCA modes from the known physical field database obtained from off-line CFD simulations under various input parameters.

In the first stage, we train a regression model to estimate the PCA coefficients from the input parameters. In previous work, spline interpolation [29–31] and extreme learning machine (ELM) [26] were used to train the regression models. To find a better regression model, we propose a variation of the ELM and name it as the scaled extreme learning machine (sELM). Here, sELM is a powerful approach to train a neural-network, which is a multi-input-multi-output (MIMO) regression model. When using the spline interpolation, we need to train many MISO regression models. If using sELM, we train only one MIMO regression model. With the observed input parameters and the PCA modes, we can estimate all the PCA components from which the indoor physical field can be easily reconstructed.

Compared with the physical field reconstructed in the first stage, sensor observations of the field are considered to be more accurate. However, the observations only provide information of the sensing locations. For simplicity, we introduce an error field, i.e., the difference between the indoor physical field reconstructed in the first stage and the real field. With the sensor observations, we can obtain a linear measurement model of the error field.

In the second stage, we can obtain the dominant PCA coefficients of the error field from the measurement model by solving a least square problem. Then, we can reconstruct the error field with which we can modify the physical field estimated in the first stage. Such a modification is to correct the dominant PCA components of the physical field reconstructed in the first stage. We then theoretically show why the proposed TSPFR approach outperforms the two current one stage approaches.

In addition, some of the PCA components may be well estimated in the first stage, which are not required to be corrected in the second stage. The leave-one-out-cross-validation (LOOCV) technique can be used to test the regression model and determine the PCA components which can be well-estimated in the first stage. We can simply remove the PCA components that are well-estimated in the first stage from the low dimensional approximation of the error field in the second stage. As mentioned before, the number of sensor observations cannot be less than the number of PCA modes used in the second stage. In this case, the number of PCA modes used in the second stage is reduced. Hence, we can reduce the number of sensor observations.

1.3. Statements of our contributions

We apply the proposed TSPFR approach to estimate the indoor thermal maps of one air-conditioned room. The results demonstrate that compared with the current one-stage methods, the proposed two-stage method can provide better estimation of the thermal map with less sensor observations.

In this work, we fuse the information of observed input parameters of the CFD simulation and the sparse observations of the indoor physical field to achieve better physical field estimation. The brief idea of the two stage method was previously presented in [26]. This paper can be viewed as a update version of [26]. We have greatly improved the two stage method. Compared with previous work and [26], we summarize the contributions of this paper as follows:

- We provide a sELM algorithm which is shown better and more convenient than the commonly used spline interpolation method