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Urban Wind Field Real-time Reconstruction Based on Optimal Sparse Sensors and Deep Learning Model

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SUMMARY:
The urban wind environment contains many derived research directions, such as pedestrian comfort, heat island effect, pollutant dispersion, drone transportation, and wind energy harvesting. For most derived problems, complete urban wind field information can provide a solid basis for those researches. However, existing technologies such as Numerical Weather Prediction (NWP) are difficult to obtain real-time, high-resolution wind field data including details such as building disturbances. For solving this problem, this study proposes a real-time reconstruction system of urban wind field data based on the optimal sensor arrangement scheme and deep learning model. The former part can find the spatial locations that are easy to arrange from an engineering point of view and best reflect the characteristics of the wind field. These optimal sensors provide the most effective sparse real-time wind data for the deep learning model. Based on these data, the trained deep learning model can reconstruct the wind field data in the research area of specified resolution in real-time. In this study, the Computational Fluid Dynamics (CFD) results are used as ground truth to measure the performance of the deep learning model. The results show that deep learning model can accurately reconstruct the time-averaged characteristics of the wind field, and reconstruct the wind field fluctuating characteristics with excellent fidelity. This system has the ability to reconstruct the complex urban wind field in real time, and provide a solid data basis for the derived research of the urban wind environment.

Keywords: Multi-resolution Dynamic Mode Decomposition (mrDMD), Wind Environment, Deep Learning

1. MOTIVATIONS

Urban wind environment is a very important research topic in the field of wind engineering. The traditional directions in this field mainly include pedestrian comfort, heat island effect, urban pollutant diffusion and more recently wind energy harvesting in urban environment. With the development of advanced technologies, other emerging research directions such as drone route planning has also attracted intense research interests. For these studies, complete, detailed, and real-time urban wind field information can provide a solid data foundation, greatly reducing the difficulty of research. However, the current technologies that can obtain all wind field information in the study area are primarily based on Computational Fluid Dynamics (CFD) and Numerical Weather Prediction (NWP). The former can obtain detailed wind field information, but its calculation requires a lot of time and computing resources, which is almost impossible to achieve real-time data of wind field. Compared with CFD, NWP has a fast calculation speed, but what can be obtained is regional wind field information with relative lower resolution, and it is difficult to capture the local changes caused by buildings in the wind field based on this kind of data. This paper proposes a real-time urban wind field reconstruction system that combines the optimal sensor arrangement scheme in the city and deep learning methods.

2. METHODS

2.1. Optimal Sensor Placement Scheme in Urban

The optimal sensor placement selection scheme (mrDMD-SDF-PSO-RF, mrDSPR scheme) proposed in this paper is based on multi-resolution Dynamic Mode Decomposition (mrDMD) (Kutz et al., 2015), Signed Distance Function(SDF) (Guo et al., 2016) and Particle Swarm Optimization-Random Forest (PSO-RF) (Kennedy and Eberhart, 1995). Specifically, the mrDMD method is applied to analyze the spatial-temporal data of the research variables, such as wind magnitude and pressure to identify the primary optimal sensors for each wind attack angle. Then, the SDF method is used to remove the sensor positions that are difficult or even infeasible for real engineering applications. Finally, the PSO-RF method is introduced for secondary selection based on the result generated by SDF. The objective of the secondary selection is to select the sensor locations which are important when considering multiple wind angles. The procedure of this scheme is shown in Fig. 1.

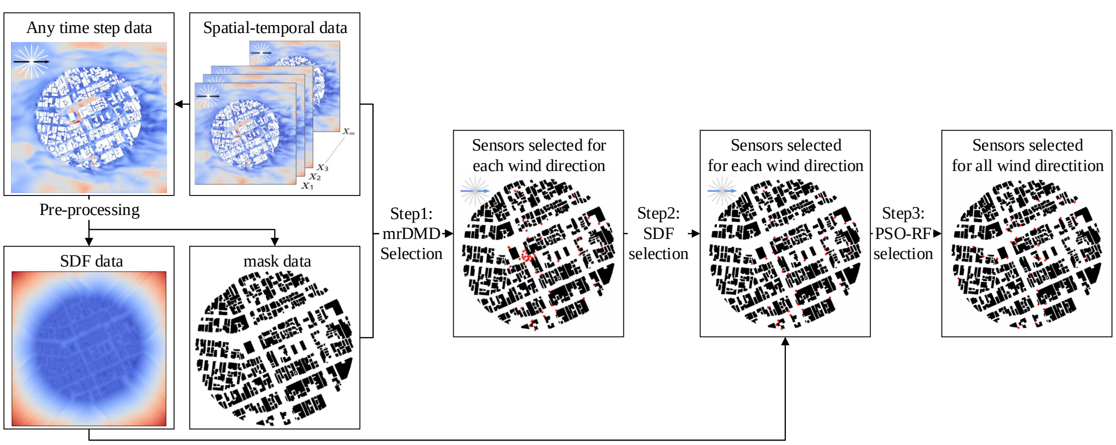


Figure 1. Overall procedure of the mrDMD-SDF-PSO-RF (mrDSPR) optimal sensor placement scheme

2.2. Wind Field Reconstruction deep learning model

The deep learning model used in this paper is a generative image-constrained model. Specifically, the model used is based on the UNet architecture, and modified by Ulyanov et al. (2018). Compared with the original UNet model (Ronneberger et al., 2015), our model is equipped with deeper convolution layers to improve the information extraction capabilities of the model, and the skip-connection technology inherited from UNet ensures that the information will not be lost in the process of passing through the deep network. The structure of our model is shown in Fig. 2.

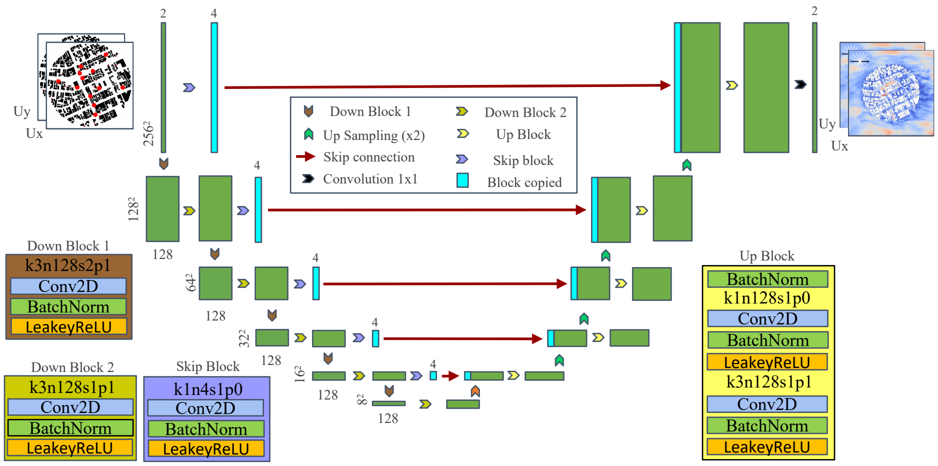


Figure 2. Structure of Wind Field Generation Model with corresponding kernel size (k), number of feature maps(n), stride (s) and number of padding (p)

3. RESULTS

3.1. Optimal Sensor Placement Scheme

The most effective sensor arrangement scheme based on mode decomposition often takes the mode reconstruction error as the criterion, as shown in the research of Kelp et al. (2022). The more the reconstruction error is close to 0, the more it indicates that the selected combination of sensor locations can reflect the characteristics of the wind field. The reconstruct error of mrDSPR method is shown in Fig. 3, which shows that the sensor locations selected by our algorithm are very effective at capturing the characteristics of the urban wind field.

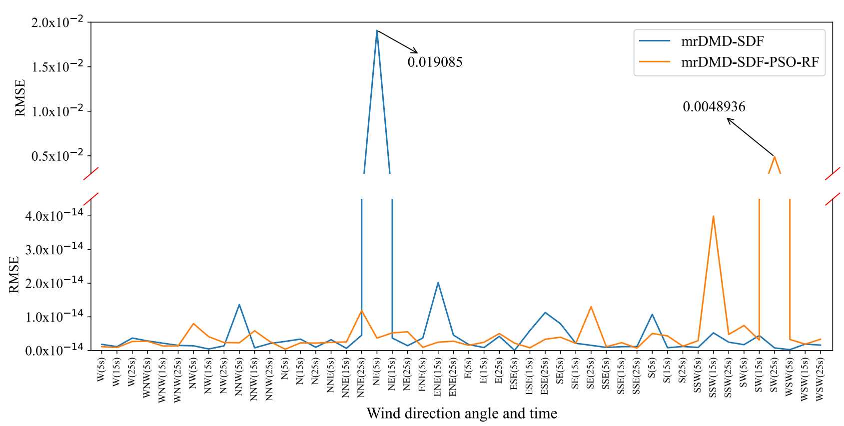
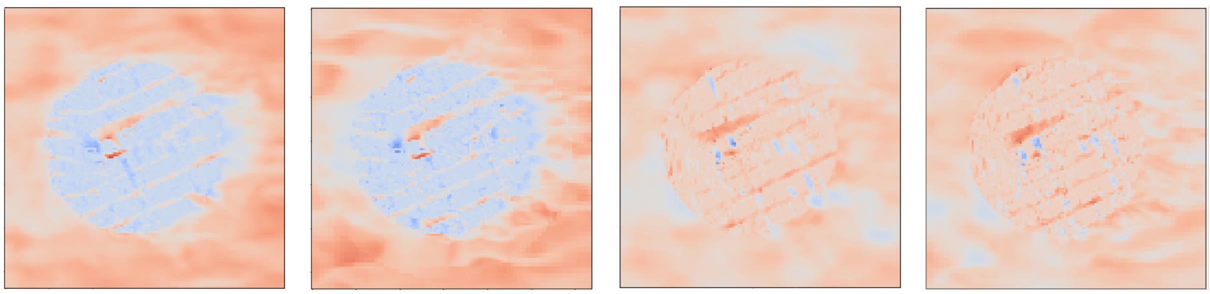


Figure 3. Comparison of mrDMD-SDF and mrDSPR reconstruction error

3.2. Wind Field Generation Model

After training, the deep learning model can perform real-time reconstruction of the wind field in the research area based on the sparse data returned by sensors. The experimental results of the test data set show that the average R^2 value of the model is greater than 0.8, which means good regression performance. One result in the test data set is shown in Fig. 4. According to the results predicted by the deep learning model, the urban wind field can be monitored in real time. With the help of this global information, we can know the areas where high wind speeds may occur based on the deduction of wind speeds in space. With the help of algorithms such as reinforcement learning (Wang et al., 2022), appropriate large-scale urban wind energy harvesting devices (Rezaeiha et al., 2020) can be intelligently started at appropriate wind speeds and shut down prior to when disruptive wind speeds are imminent, thus ensuring these devices operate safely to facilitate utilization of urban wind energy.



(a) Ux Prediction (b) Ux Ground Truth (c) Uy Prediction (d) Uy Ground Truth

Figure 4. Wind Field Reconstruction Result of Deep Learning Model

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