Improving Accuracy of Airflow Measurement around Buildings by Machine Learning

Cross-sensor domain adaptation (CSDA) for data-driven correction of wind measurement around buildings using cup anemometers



Introduction: Data-driven correction fits the instantaneous cup anemometer (CA) samples to ultrasonic anemometer (UA) samples by artificial neural networks (ANN).

- <u>Aim:</u> Improve the model generalization ability. Develop an accurate and low-cost sensor system.
- <u>Problem-1 (Cross-sensor (CS) correction)</u>: due to the sensor health state or lifetime, the differences in response between the multiple CAs below the U_{start} can cause the correction error to increase.
- Problem-2 (Cross-condition correction): the differences in the inside-feature of wind speed samples between different locations or measuring period can cause the correction error to increase.

Data: Two source (S) domain samples were collected at open space (OS), building side (BS) for two weeks with CA1 · UA1. Target (T) domain samples was collected at BS for three days with CA2 · UA2. As for the correction, in the single-sensor (SS) case, the S BS CA2

was used to correct T_BS_CA2. In the CS case, S_OS_CA1 is expected to display a correction effect like S_BS_CA2 on T_BS_CA2.



Methodology:

Source domain samples (training dataset)

T_BS_CA2 samples: $S(t_i)$



label



I. EMD-based preprocess (for solving cross-sensor problem):

CSDA aligns the CA1 · CA2 response below U_{start} by decomposing their samples, deleting high-frequency components, and extracting low-frequency components. This filters the different short-term responses of CA1 · CA2.

• Clustering-based ANN (CANN)

(a) Stage 1: Feature-based Clustering	(c) Stage 2: Clustering-based UDA (d)	Stage 3: Modeling and Prediction
Wind Measuring Database	Cluster 1 Label Divided Sour.	Cluster 1 ANN model
 Source domain samples (S_OS_CA1, S_OS_UA1), or (S_BS_CA2_S_BS_UA2) 	Features → 10-min samples Divided Tar.	Cluster 2 ANN model



Target domain samples (test dataset)



II. Clustering-based domain adaptation (for solving cross-condition proble.):

In the CANN, the corrected CA samples are predicted using multiple ANN models trained from divided source and target domain samples cluster by cluster. This multi-modeling method has a higher generalization performance than single modeling method (ANN model) for transferring the knowledge of the source domain toward the target domain to adapt the cross-location case.

Result and conclusion:

- Fig. 4: The CSDA can reduce the distance between the probability density function of the weak wind speed response in the CS case.
- Fig. 5: The CSDA can suppress the correction error increase caused by the CS case in ANN or CANN models compared to the SS case.
- The correction effect of CSDA_CANN is superior to other baselines used. The existing database consisting of one CA and one UA measurement in an open space can potentially correct multiple CAs of the same type at different locations around the buildings.



4 Differences in response between sensors below U_{start} (0.5 m/s)

5-a ANN models: mean relative errors of wind statistics 5-b CANN models: mean relative errors of wind statistics

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