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Predicting the wind using spatial correlation

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Abstract—When we attempt to generate more electricity by controlling wind turbines, the first step is to predict the wind. However, it is difficult to predict the wind just from the past observations at that point because the wind does not have temporal correlation much. Here we set up an experimental observation and tried to predict the wind using spatial correlation. By constructing an embedding for multivariate time series and building a nonlinear model, we found that the wind is better predicted from the past observations at neighboring points rather than from those at the predicted point only.

1. Generating more electricity using the same wind turbines by control — motivation

Every year, more attention has been paid to wind farms because the wind is a clean energy. The number of wind turbines is also increasing. Here an important question is whether we can use these wind turbines more effectively. To answer this question, we are proposing a general idea under which we try to produce more electricity by adjusting the turbines to the future wind.

2. The wind cannot be predicted well from the past observations at that point only — problem

When we try to adjust the wind turbines to the future wind, the first step is to predict the wind. However, predicting the wind is difficult. As shown in Table 2, making a predictive model using the past observations at that point shows a predictive ability that is almost similar to letting the values 1 second before be the predictions.

This poor result may come from the weak serial dependence and nonlinearity of the time series. We applied the surrogate data for testing the serial dependence [1] and nonlinearity [2, 3]. We used data of the wind we observed with 50 Hz for about 1 hour on Komaba campus at The University of Tokyo on 25 August 2004. Although the data are 3 dimensional including the east wind (component from the east to the west), the north wind, and the upward wind, we used the east and the north winds as a scalar time series. The surrogate test was the following procedure:

1. We initially took the moving average of 0.5 seconds.
2. Second we split the two scalar time series into segments of length 10000. Therefore, the number of segments is 36.
3. Third we matched the ends so as to avoid artificial high frequencies which may be produced during the discrete Fourier transforms [4].
4. Fourth for each segment, we applied the method of Kennel [5] and confirmed its stationarity.
5. Fifth we generated 39 random shuffle surrogates [1] and tested the serial dependence. For the test statistic, we used the prediction errors.
   (a) We split the segment into two sub-segments. The last 500 points were used for evaluating the prediction, and the remaining points, for building a predictive model.
   (b) We embedded the time series using the methods of Fraser [6] and Kennel [7] and predicted τ steps ahead, where τ is selected from the first minimum of the mutual information [6].
   (c) The prediction was evaluated with the root mean square errors.

   Then only 16 out of 36 segments have shown the serial dependence.
6. Lastly for each segment which showed the serial dependence, we generated phase-randomized surrogates [2] and iterative amplitude adjusted Fourier transform surrogates [3] for testing the nonlinearity. Out of 16, only 3 segments have passed the test of nonlinearity.

3. From temporal correlation to spatial correlation — hypothesis

As shown in the previous section, predicting the wind using temporal correlation is hard because there is not much temporal correlation. However, to control the wind turbines, we need to predict the wind somehow. Here we pay attention to spatial correlation.

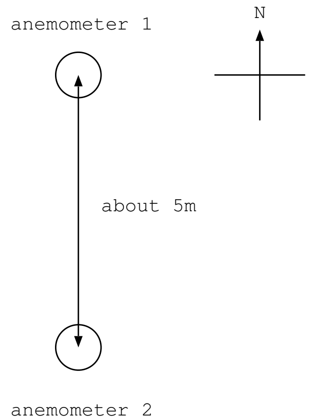

Figure 1: Setting of observation.

The wind blows from the upstream. Therefore, if we observe the wind at the upstream some time before, we may be able to predict the wind at the downstream better.

Figure 2: Scene of observation.

4. Observing the wind using two anemometers — experiment

To test the hypothesis, we set up an experimental observation. This observation was done on 24 March 2005 on Komaba campus at The University of Tokyo for about 1 hour. An anemometer was located about 5m north from another (Fig. 1). The scene of observation was shown in Fig. 2. We call the north one as anemometer 1, and the south as anemometer 2.

During the observation, the southward wind was dominant.

5. Correlation between two anemometers — analysis

Before doing any analyses, we took the moving average of length 1 second and resampled it every 1 second. We call the east wind, north wind, and upward wind of anemometer 1 at time t as $x_1(t)$, $x_2(t)$, and $x_3(t)$, respectively, and those of anemometer 2 as $y_1(t)$, $y_2(t)$, and $y_3(t)$, respectively. We calculated the correlation coefficient between the north winds x_2 and y_2 at the two anemometers. The result is shown in Fig. 3. We found a peak at 1–2 seconds, meaning that there is a strong correlation between the current north wind at anemometer 1 and the north wind 1–2 seconds before at anemometer 2.

We also made two scatter plots in Fig. 4. The figure shows that when the future north wind $x_2(t + 1)$ at anemometer 1 is soft, the current north wind $x_2(t)$ at anemometer 1 gives a smaller variance, while the current north wind $y_2(t)$ at anemometer 2 gives a smaller variance when the future north wind $x_2(t + 1)$ at anemometer 1 is strong. This means that when $x_2(t + 1)$ is soft, the current observation $x_2(t)$ at anemometer 1 may give the better prediction, while when $x_2(t + 1)$ is strong, the current observation $y_2(t)$ at anemometer 2 may provide the superior prediction.

These are supportive evidence that the spatial correlation can help predicting the wind.

6. Predicting the wind — method

Using the observation obtained in Section 4, we built nonlinear predictive models for predicting $x_2(t + 1)$ using the past observations up to time t. We split the data into two segments: the last 500 points for evaluation and the remaining points for modeling.

Firstly we obtained an embedding, or state to predict, using the modeling segment. Here we used the following cross validation: Let C be the set of candidate delays. For example, if we consider the maximum of 30 delays for each of $x_i(t)$ and $y_j(t)$, we have $C = \{x_i(t - d_x), y_j(t - d_y) | i, j = 1, 2, 3, d_x, d_y = 0, 1, \cdots, 29\}$.

1. From the modeling segment, we randomly select 1000 points for modeling, and other 1000 points for evaluation.

2. For each possible non-uniform embedding, or each possible combination of candidate delays,

   (a) by following the method of Judd and Mees [8] with the normalized maximum likelihood [9] as a model selection criterion, construct a radial basis function model using the points for modeling, and

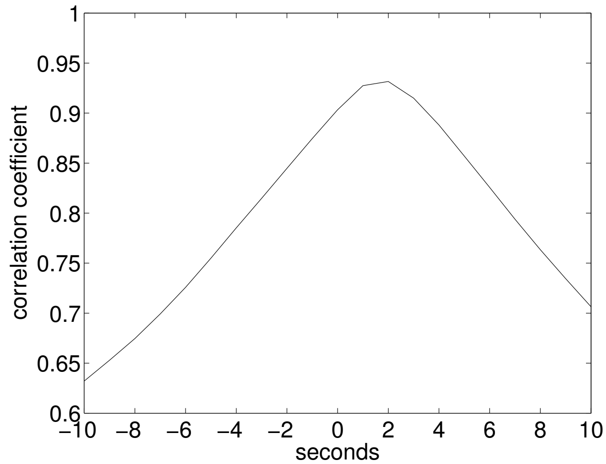

Figure 3: Correlation coefficient between the north winds. The horizontal axis shows the time difference of the north wind at anemometer 1 from that at anemometer 2.

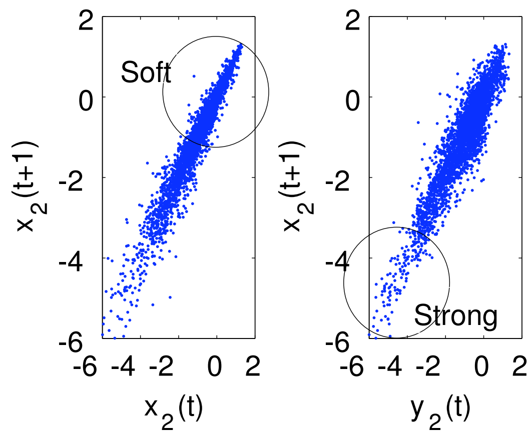

Figure 4: Scatter plot between the current north wind $x_2(t)$ and its future $x_2(t+1)$ at anemometer 1 (left) and that between the current north wind $y_2(t)$ at anemometer 2 and the future north wind $x_2(t+1)$ at anemometer 1.

(b) evaluate the prediction error (root mean square error) using the points for evaluation.

3. Minimize the prediction error over possible non-uniform embeddings.

After obtaining the optimal embedding, we built a radial basis function model by using the method of Judd and Mees [8] with the normalized maximum likelihood [9] as a model selection criterion.

We considered three sets of candidate delays. When $C = \{x_i(t-d_x), y_j(t-d_y)|i, j = 1, 2, 3, d_x, d_y = 0, 1, \cdots, 29\}$, we predict the future north wind $x_2(t+1)$ at anemometer 1 using the past observations at the two anemometers. When $C = \{x_i(t-d_x)|i, j = 1, 2, 3, d_x = 0, 1, \cdots, 29\}$, it corresponds to the case where we predict $x_2(t+1)$ just using the past observations at anemometer 1. Even we considered the case $C = \{y_j(t-d_y)|i, j = 1, 2, 3, d_y = 0, 1, \cdots, 29\}$, where we predict $x_2(t+1)$ with the past observations at anemometer 2 only.

In the method of Judd and Mees [8], the centers of radial basis functions are selected using points in the embedded time series perturbed with Gaussian noise. Therefore, the performance may vary according to a set of the centers. Hence, for each case, we built 10 different radial basis function models and obtained the average and standard deviation of the prediction errors.

7. The wind was better predicted using the the past observations at the upstream — results

Firstly we listed in Table 1 the delays selected for each case. We can see that when using the observations at the single anemometer, the delays were selected such that we can reconstruct the dynamics using the temporal correlations, while when using the observations at the two anemometers, the delays were selected so that we use the spatial correlations between them.

The prediction performances were compared in Table 2. When using the past observations at anemometer 1 only, the performance was comparable with the case where the values 1 second before were regarded as the predictions. When using the past observations at the two anemometers, the prediction was 20 % better than using the past observations at anemometer 1 only. When using the past observations at anemometer 2 only, the performance was worst. It seems that the past observations at anemometer 2 themselves do not contain enough information to predict the future at anemometer 1 effectively, but they help the prediction well with those at anemometer 1.

The predicted time series were shown in Fig. 5. The prediction using the observations at the two anemometers is better than that at anemometer 1 only in most time, especially when the wind is strong. This observation will coincide with the statement of Kantz *et al.* [10, 11], which says that we can predict the turbulent gusts from a time series in a meaningful way.

8. Conclusions

We showed that predicting the wind using temporal correlation is difficult due to the weak serial dependence and nonlinearity. Therefore, instead of temporal correlation, we proposed to predict the wind using spatial correlation. The experimental observation of the wind illustrated that the wind at the upstream gives supplementary information when the wind is strong. Thus the wind was better predicted using the past observations at both the predicted point and the upstream than when using those at the predicted point only.

Since the affirmative evidence was obtained, we are

Table 1: Selected delays for optimal embeddings.

method	selected delays
with observations at anemometer 1	$x_2(t)$, $x_2(t-4)$, $x_3(t-3)$, $x_3(t-4)$, $x_3(t-16)$
with observations at anemometer 2	$y_1(t-20)$, $y_2(t)$, $y_2(t-1)$, $y_2(t-6)$
with observations at anemometers 1 and 2	$x_2(t)$, $y_2(t)$, $y_3(t-15)$

Table 2: Root mean square errors when predicting the north wind at anemometer 1 using various methods.

method	prediction errors
the values 1 second before	0.3461
with observations at anemometer 1	0.3415 ± 0.0012
with observations at anemometer 2	0.4201 ± 0.0025
with observations at anemometers 1 and 2	0.2722 ± 0.0070

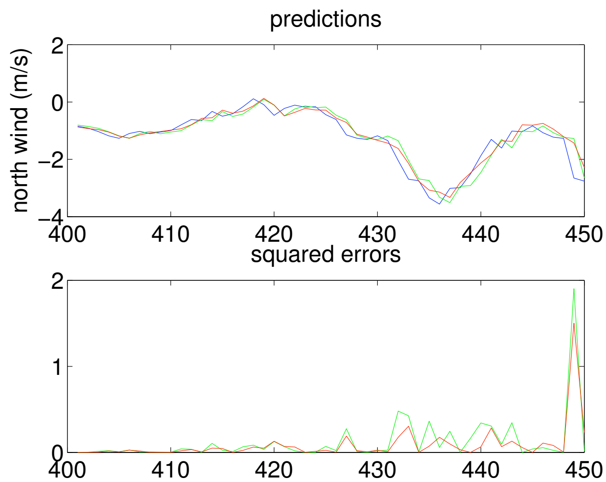

Figure 5: Time series predicting 1 second ahead (top) and its prediction errors (bottom). The blue line shows the observed series, the red line corresponds to the prediction using the observations at the two anemometers, and the green line is the prediction using the observations at anemometer 1 only.

looking forward to moving on to more practical experiments.

Acknowledgment

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