Mega-nourishment morphology evolution prediction combining spatial and temporal features

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ABSTRACT

To protect coastal areas and ecology environment, Sand nourishment is widely used as an effective method. The morphology evolution and prediction is needed for sand nourishment and maintenance. Based on the observations of a mega-nourishment, a data-driven approach combining temporal and spatial features for the prediction of nourishment morphology evolution is proposed in this paper. The sequence grids from the survey data are used to extract the spatial features of nourishment beach by CNN, which can reduce the complexity of the network and extract the spatial features. And then LSTM is employed to derive the temporal relationship from past time-series features for predicting future nourishment terrain. Finally, the final prediction result is obtained through decoding the LSTM output by the fully connected layer. The complex spatiotemporal correlations of the sand nourishment evolution can be derived by training the proposed model effectively. The proposed model achieved the best performance for nourishment morphology evolution prediction compared with other methods as shown by the experimental results.

Keywords: Mega-nourishment, nourishment morphology evolution prediction, long short-term memory, convolutional neural network

1. INTRODUCTION

A number of coastal areas in the world are threaten by the increasingly environmental problems such as storm surge and sea level rise[1]. The effectively approaches of intervention are required to provide sustainable protection against the risk of flooding[1, 2].

Sand nourishment belongs to a kind of soft approaches which is to place the sand imported for strengthening the beach[1,3]. Sand nourishment is considered as a more environmentally friendly, economical, and efficient counter measure against sea flooding. Moreover, an additional appealing area can be created by the nourishment for the coast tourism[4]. So sand nourishments are widely applied to protect coastal areas[5,6]. With beach nourishment increasing worldwide[3], the morphological evolution prediction is of major importance[7,8]. However, previous studies are limited due to the lack of the terrain observations of sand nourishment[3,7,9].

The nourishment morphology prediction output the future data by inputting the historical data, which is actually a sequence prediction problem. The deep learning methods are capable of considering spatiotemporal changes from historical data and obtain the predicted data by the time-series monitoring data. The prediction model can be gradually trained and adjusted to reduce prediction error and achieve optimal performance[10,11]. The deep learning has many applications such as predicting sea surface temperature, sea level changes, precipitation distribution, air quality and et al.[10,12-15].

To make use of the temporal and spatial information from the survey data, a data-driven method combining the long short term memory (LSTM) network and convolutional neural network (CNN) is proposed to predict the nourishment morphology evolution. Section 2 describes the survey data and the model combining LSTM and CNN. Section 3 describes and analyses the experimental data and the results. Finally, the conclusion is drawn in Section 4.

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2. DATA AND METHODOLOGY

2.1 Study data

The mega-nourishment known as the Sand Engine comprising 21.5 million m^3 sand nourishment in the Netherlands was constructed in 2011 for coastal protection and coastline maintenance as well as for ecology and recreational purposes[2,4]. The nourishment terrain is observed monthly since summer 2011[2]. The surveyed area was 4.7 by 1.6 km as shown in Figure 1a.

The observed data are realigned to shoreline orientation as Figure 1b. As can be seen in Figure 1c, the collected x, y, z point data are transformed to a 20 by 20 m grid through the Inverse Distance Weighting (IDW) interpolation.

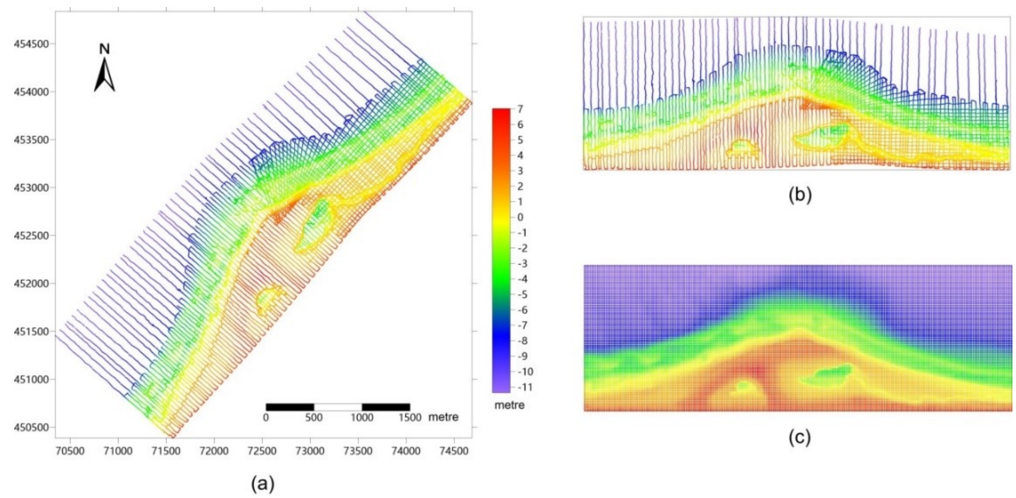

Figure 1. The data of study area.

2.2 Nourishment morphology prediction by combining CNN and LSTM

The spatial correlation of nourishment terrain is acquired by the CNN model. The deep neural layers are capable of being used to obtain the spatial correlation features. This architecture makes CNN perform well for obtaining features because it has the strengths of local connectivity and spatial arrangement between layer nodes. The CNN mainly consists of two kinds of layers. The first is the convolutional layers, which is used for obtaining the spatial feature. The second is the pooling layers, which is employed to reduce the number of layer links and improve computing efficiency.

The spatial features extracted by the above network are put into the LSTM model after flattening to one-dimensional vector. The LSTM network has the structure of memory units, which is capable of storing long term dependencies. The memory unit contains three kinds of gates. The input gate can be used to determine what new features to store. The output gate can control how to deliver output information. The forgotten gate is adopted for reducing some features.

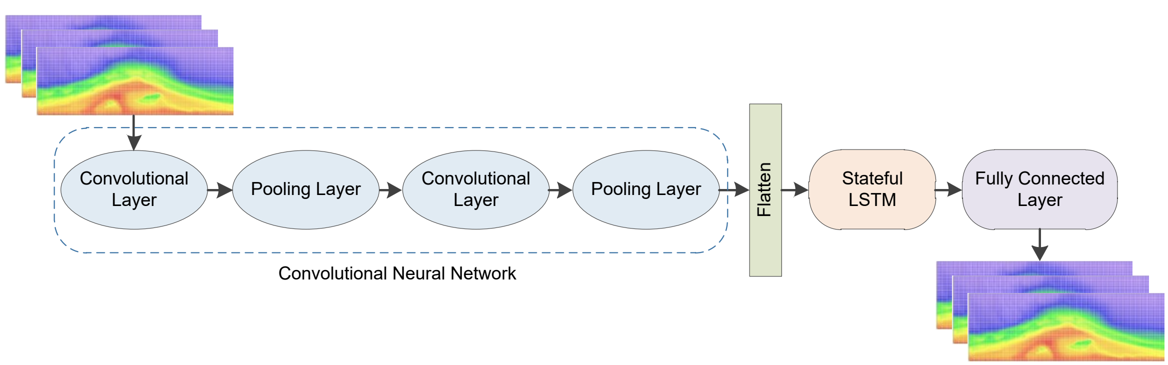

Figure 2. The model combining CNN and LSTM for predicting nourishment terrain.

2.3 Predicting nourishment terrain

The nourishment prediction result is obtained by the fully connected layer following the above CNN and LSTM. The prediction framework is shown as Figure 2. The convolutional kernel size is 3×3 with stride 1×1. ''Same-Padding'' is performed during the convolution processes. The activation function of ReLU is used for convolutional layers and LSTM layer.

The stateful LSTM has the ability of maintaining the information through long time series[16]. The time lag is set to three. Mean squared error (MSE) is employed as loss function during the training process.

3. RESULTS

The nourishment observations from August 2011 to September 2015 are used in this research. Twenty-three data from August 2011 to April 2014 is used to train the model. The remaining nine data in July 2014 to September 2015 is used to test the model.

Each three past grid data is used as one input sample. A predicted next terrain grid is the output. A one-step prediction model based on the observations is created. A total of 30 epochs is run for training model. The recursive method is used for multiple-step prediction.

Figure 3 shows the root of mean squared error (RMSE) variation of each model over prediction time. And the proposed model results are compared with four classic models, namely, CNN, RNN, LSTM, and the BP neural network. The same dataset and the recursive prediction process are adopted by each model as the proposed model. The average RMSE of the five models are shown as figure 4. The best performance is achieved by the proposed model in this paper as shown in Figures 3 and 4.

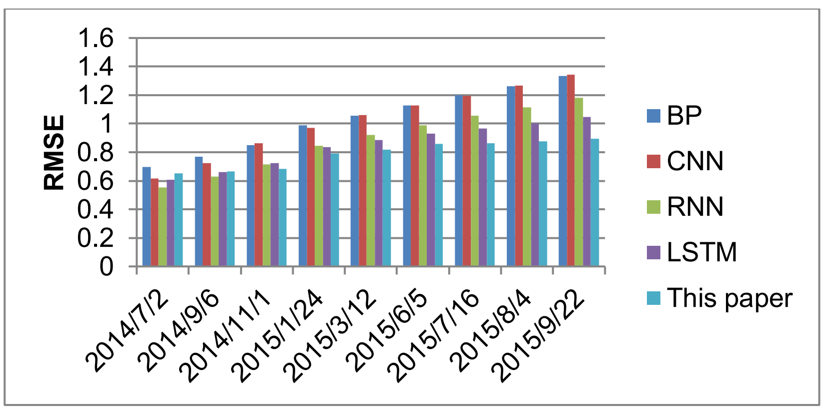

Figure 3. Corresponding RMSE of different models on prediction over time.

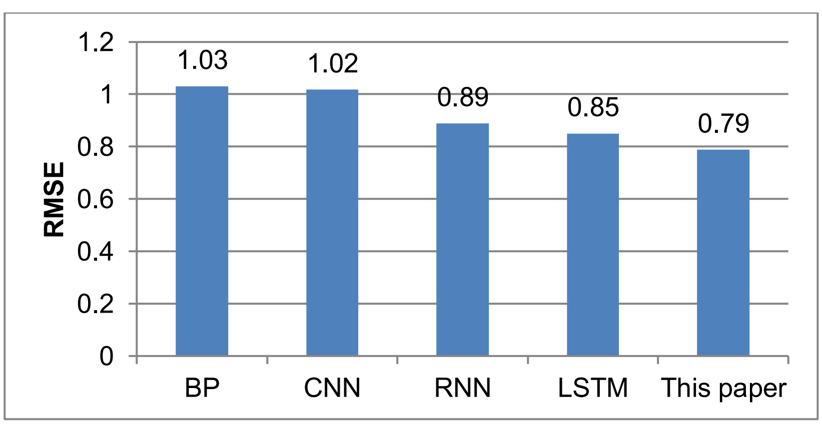

Figure 4. The average RMSE of different models on prediction over time.

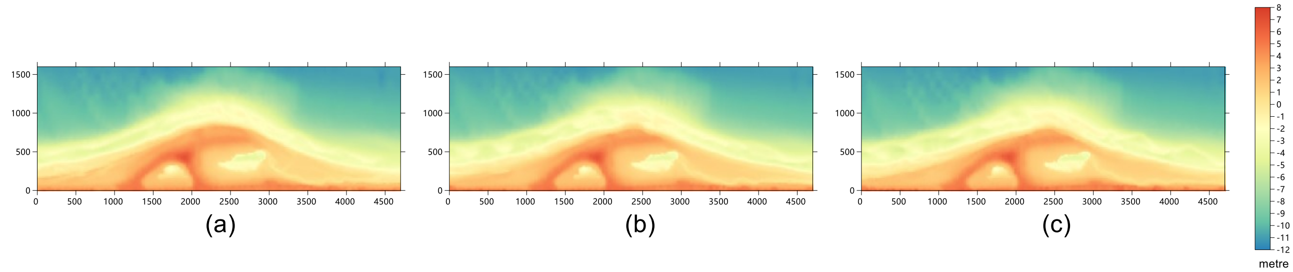

Figure 5. The true nourishment terrains. (a): July 2014; (b): March 2015; (c): September 2015.

Figure 5-7 show the observations and predictions of this proposed model at three different dates for comparison. The measurements and the predicted terrain are generally consistent. The differences mainly exist at steep slope.

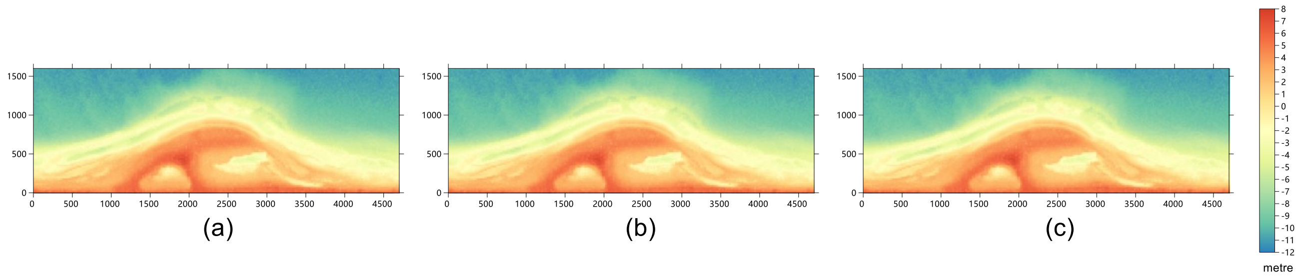

Figure 6. The nourishment predictions. (a): July 2014; (b): March 2015; (c) September 2015.

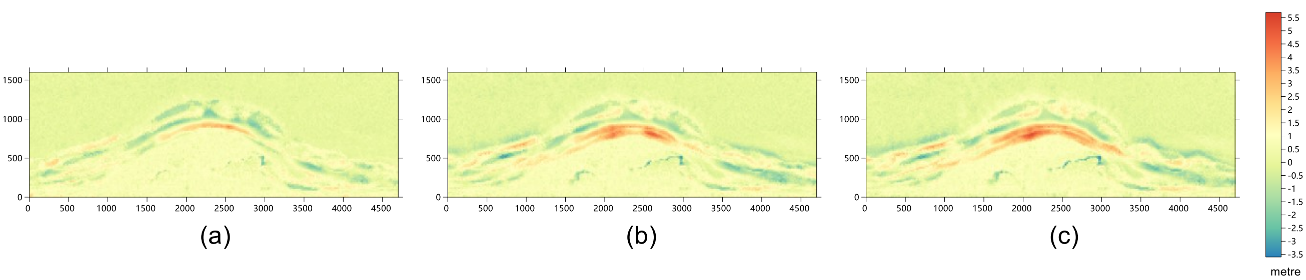

Figure 7. Error maps of predicting nourishment. (a): The differences between the observation and prediction in July 2014; (b): The differences between the observation and prediction in March 2015; (c): The differences between the observation and prediction in September 2015.

4. CONCLUSION

Sand nourishment is widely used for protecting coastal areas against the flooding risk. The nourishment prediction is important because of increasingly nourishments worldwide. To make use of temporal and spatial information, we carry out nourishment prediction by combining LSTM and CNN. The spatial features of nourishment are obtained by CNN from the observation grids. The time dependency is tackled by LSTM. The nourishment prediction result is obtained by the fully connected layer following the above CNN and LSTM. The results show that the best performance is achieved by the proposed model in this paper compared with other methods.

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