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Deep Neural Network for Runway Visual Range Estimation

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Abstract

The runway visibility affected by weather conditions such as fog is one of the main indicators that determine aircraft taking offs and landings at airfields. Airports operating transport aircraft provide a key local weather forecast including runway visibility and ensure that pilots check the forecast. This study developed an estimation model of runway visibility for a local airport and estimated visibility using the model by applying deep neural network that has been applied to various fields such as image processing, speech recognition and natural language processing to the estimation of runway visibility.

Keywords : Runway visual range, Deep neural network, Aviation weather, Weather forecast,

INTRODUCTION

There are weather factors affecting aircraft safety such as thunder storm, icing, turbulence, mountain waves, wind shear, microburst, visibility and etc [1]. Runway visual range has a direct impact on a pilot's decision to taking off and landing on the runway.

This study used deep neural network (DNN) to develop a runway visual range estimation model. The DNN as an artificial neural network with deeper networks using more than two hidden layer can generate a learning model for inputs and outputs with a nonlinear relationship. We aimed to generate a learning model inputting the previously measured time series weather data such as wind speed, humidity, temperature and to confirm whether the local information of a specific airfield could be generated by estimating runway visual range through the generated model.

DEEP NEURAL NETWORK AND WEATHER FORECAST

Deep neural network

An artificial neural network is an algorithm that simulates learning through interactions of neurons and experiences in the brain, and it has been developed in various forms starting with the perceptron learning model or a single-layer neural network proposed by Rosenblatt in 1958[2]. The early single-layer artificial neural network could solve only limited problems such as linear separability, and the amount of computation needed to be increased according to increase in the neural network. The network structure was expanded from a single-layer neural network to a more complicated deep neural network to address these problems.

However, the problems such as excessive learning and the vanishing and explosion of gradients, which indicate the characteristics of data, arose from the deep structure. The problems of deep neural network were improved by using the back-propagation of errors method proposed by P. Werbos in 1975, the nonlinear activation function, and the proper weight initializations by G. Hinton in 2006[3][4][5].

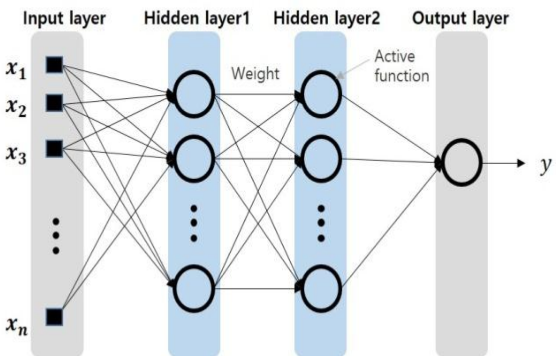

Figure 1: The structure of deep neural network

In general, a neural network with two or more hidden layers is referred to as deep neural network. We implemented learning by constructing a neural network structure with two hidden layers as shown in Fig 1. A round circle represents a node in Fig 1. Each node contains an active function such as sigmoid function or rectified linear unit (ReLU) function. The arrows connecting the nodes of each layer represent the flow of the signal, and the data of the previous node is multiplied by the weight and transferred to the next node. The input data multiplied by the received weight is summed up, and the weighted sum is used to generate an output value through the active function. Each weight is updated through learning to minimize an error between the output value and the actual measured value.

Runway visual range

Runway visual range is a measure of the sight distance of moving aircraft and ground objects near the runway, and indicates the extent to which the runway and runway centerline are identified in bad weather conditions such as fog. Runway visual range is a more precise measure of weather conditions for aircraft taking off and landing compared to visibility near airfields.

In the case of runway visibility at Incheon International Airport in Korea, low visibility below minimum visibility threshold for landing occur mainly from February to June. The fog caused by night radiant cooling and the fog coming from the sea mainly occur during this period, and the main cause of the weather below the minimum visibility threshold of visual range affecting taking off and landing at each airport or airfield is fog[6]. In particular, the airports such as Incheon International Airport that are located in the coastal area are affected by sea fog.

DEVELOPMENT OF A DEEP NEURAL NETWORK ESTIMATION MODEL

Model Implementation and Development

The deep neural network of this study is constructed as shown in Fig 2. The measured weather data used as input to the neural network were the past measured data of wind speed, temperature, humidity, and runway visibility (RVR).

The visual range estimation model proposed in this study applies the relative degree of fog that directly affects visual range. Although the cause of the fog varies depending on the type of fog, temperature, humidity and wind speed affecting the dissipation of fog were used as the main input data. The visual range values measured were also used as the input values for the time series correction of the estimated values by existing input values.

In addition, we included the past weather information for a certain period as well as the current weather information at the measurement point as input to estimate visibility. For this, we used wind speed, temperature, humidity and visibility data as input ranging from the past data to the current data. As mentioned previously, 4*m pieces of data (m Ticks × 4 pieces of weather formation) were entered as shown in Fig 2. In Fig 2, subscript n means the current weather data, and subscript n-m means the weather data measured m ticks ago.

As shown in Fig 2, the model consists of 4 layers; the input layer with 80 nodes, the hidden layer 1 with 20 nodes, the hidden layer 2 with 10 nodes, and the output layer with 1 node.

As for this configuration, we used a procedure that identified relatively simple structures to complex structures and identified the characteristics of empirical data in order to find the structure with an appropriate condition for the development of the model. We used the sigmoid function as an active function and updated the weights with the error back propagation method using the stochastic gradient descent (SGD).

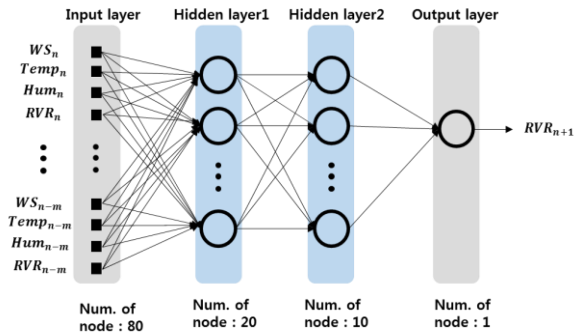

Figure 2: DNN based RVR estimation model

Simulation

This study carried out repeated simulations while changing the relevant variables to derive an appropriate learning iteration and rate. We selected 200 and 0.001 as the appropriate learning iteration and rate, respectively. This study used the initial input values that were initialized through the random function.

In order to confirm and verify the developed model, we trained deep neural network by using one day data in that period. For the trained model, model calibration was conducted so that the measured data and estimated data by the model were visually compared to ensure similarity or consistency.

Fig 3 shows those values after the calibration. In the figure, the solid line represents the actual measured values and the dotted line represents the estimated values by the model.

Fig 4 shows a 1: 1 comparison of the measured values and estimated values by the model in Fig 3. If the data dots are on a straight line with slope 1, it means that the measured values and estimated values by the model are equal. The more they are on the line, the higher the similarity is. The quantitative value for this can be confirmed by the difference between the straight line and the data dots. The correlation coefficient (R^2) of the data was 0.9981, and the root mean square error (RMSE) value was 31.3123, indicating that data similarity was high.

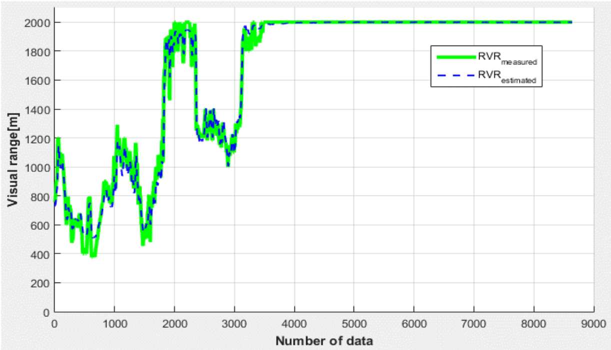

Figure 3: Measurement and estimation result of runway visual range using the DNN of 1day

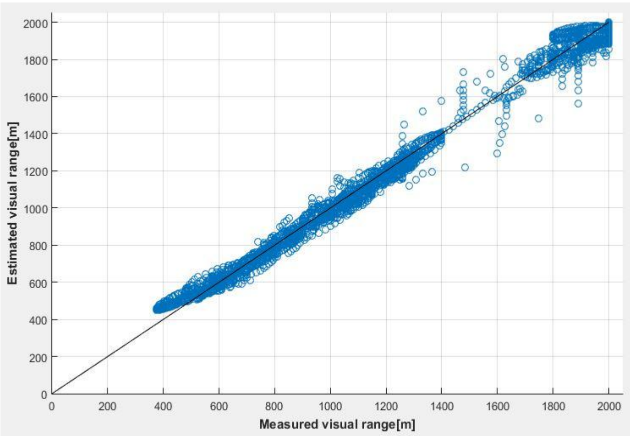

Figure 4: Measurement versus estimation result of runway visual range using the DNN of 1 day

CONCLUSIONS

This study proposed an estimation model for runway visual range using deep neural network. We constructed and simulated a deep neural network to estimate runway visual range using data such as wind speed, temperature, and humidity that could affect visibility.

After learning with one day data, we developed the estimation model with the correlation coefficient (R^2) of 0.9981 and the RMSE of 31.3213 via a calibration by comparing the estimated values with the measured values. This is high accuracy result. Furthermore, it is necessary to conduct additional studies and do research on efficient decision algorithms by using other methodologies to improve the accuracy of the model.

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