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Runway visual range prediction using Convolutional Neural Network with Weather information

SungKwan Ku¹, Seungsu Kim², Seokmin Hong^{3*}

¹ Department of Aviation industrial and System Engineering, Hanseo University

² Institute for Intelligent Systems and Robotics (ISIR), Sorbonne University

³ Department of Unmanned Aircraft Systems, Hanseo University

honsm@hanseo.ac.kr

Abstract

The runway visual range is one of the important factors that decide the possibility of taking offs and landings of the airplane at local airports. The runway visual range is affected by weather conditions like fog, wind, etc. The pilots and aviation related workers check a local weather forecast such as runway visual range for safe flight.

However there are several local airfields at which no other forecasting functions are provided due to realistic problems like the deterioration, breakdown, expensive purchasing cost of the measurement equipment. To this end, this study proposes a prediction model of runway visual range for a local airport by applying convolutional neural network that has been most commonly used for image/video recognition, image classification, natural language processing and so on to the prediction of runway visual range.

For constituting the prediction model, we use the previous time series data of wind speed, humidity, temperature and runway visibility. This paper shows the usefulness of the proposed prediction model of runway visual range by comparing with the measured data..

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

1. Introduction

The aircraft safety is affected by weather factors like icing, thunder storm, mountain waves, turbulence, microburst, wind shear, visibility, etc [1]. The pilots should be aware of a local weather forecast for safe flight. In particular, among various information in the weather forecast, Runway visual range of a local weather forecast is used as an important factor on a pilot's decision on whether taking off and landing on the runway or not. However there are several regional airfields that does not provide the weather forecast. For safe flight, this study proposes a runway visual range prediction method for a local airport that does not provide the weather forecast.

This study utilizes the convolutional neural network (CNN) to propose a runway visual range prediction model. The CNN makes a learning model with a nonlinear relationship between inputs and outputs for predicting runway visual range. To this end, we generates a learning model which makes use of the previously measured time series data of wind speed, humidity, temperature and runway visual range as input values and validate the usefulness of proposed model of runway visual range with the weather data of a specific airfield.

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Corresponding Author: *honsm@hanseo.ac.kr*

Tel: +82-41-671-6287

Author's affiliation

Department of Unmanned Aircraft Systems, Hanseo University, 236-49, Gomseom-ro, Taean-gun, Chungcheongnam-do, 32158, Korea

2. Runway visual range and convolutional neural network

2.1 Runway visual range

Runway visual range is an important factor of weather conditions for taking off and landing an aircraft compared to visibility near airfields. Runway visual range is a measure of the sight distance between landing/taking-off aircraft and ground objects in the runway, and expresses the extent to which the runway and runway centerline are identified in bad weather conditions like fog.

In the Incheon International Airport in Korea, low visibility below minimum visibility threshold for landing occurs from February to June. The fog due to night radiant cooling and the fog from the sea occur for this period. The fog is the main weather cause below the minimum visibility threshold of runway visual range affecting taking off and landing at each airport or airfield [2]. In particular, the Incheon International Airport that is placed near the coast is affected by sea fog.

2.2 Convolutional neural network

The convolution neural network was introduced in the 1990 [3]. The convolution neural network is a neural network that imitated the principle that the visual cortex of brain handles and recognizes the image. However, it was not rarely used because it is inadequate to process complex images. In 2012, it came to take a dramatic spotlight [4]. So far, it is the most widely used neural network in the field of the computer vision.

A CNN constitutes an input layer, an output layer and multiple hidden layers. The hidden layers of a CNN are organized with convolutional layers, pooling layers, fully connected layers. The convolution layer utilizes a filter matrix over the array of input values and applies convolution operation to obtain a convolved feature map. The pooling layer plays a role of reducing the spatial size of the representation

3. Implementation on the CNN model and experiment

3.1 CNN model

In this paper, we present a runway visual range prediction model using CNN. The prediction model is consisted of three convolutional layers and two fully connected neural network layers as seen in Figure 1. In order to avoid over-fitting, we add averaging pooling and drop-out layers. Three hours of past weather information (wind speed, temperature, humidity and runway visibility) are fed into the network. The prediction model forecasts for one hour ahead runway visual range.

The weather data measured from 01 April 2016 to 30 July 2016 at the Taean airport of Hanseo university are used to make the prediction model. Among the given four months of measured weather information, 80% of them, that is, the weather data from 01 April 2016 to 06 July 2016 are used for training, and the rest from 07 July 2016 to 30 July 2016 is used for validation. All weather data in this paper is normalized. The network is implemented using Keras API based on Tensorflow, and it is trained using Adam optimizer. Quadro M2200 GPU is used for training. 20 epochs of training were performed. Figure 2 shows the training and testing errors by epoch. As seen in Figure 2, the testing and training errors are saturated from 7 epochs.

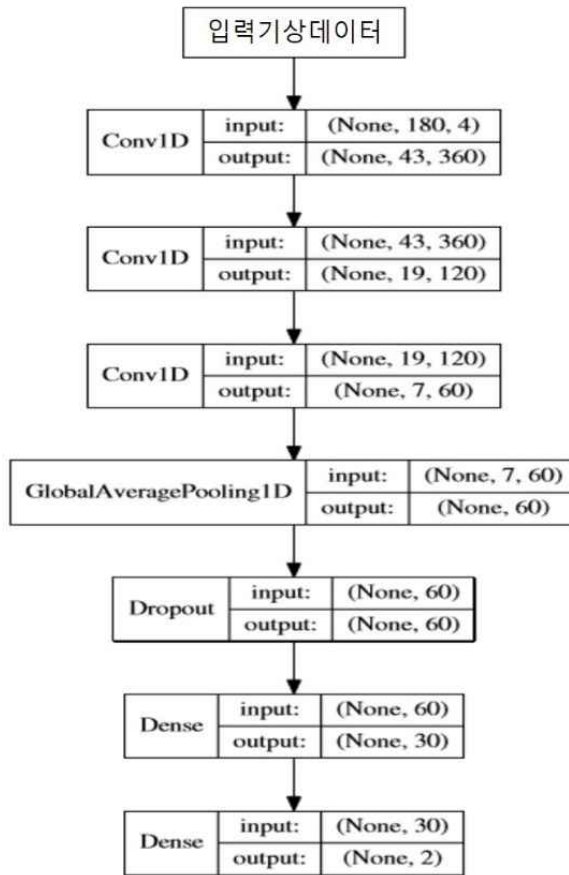


Figure 1. CNN model design for runway visual range forecast

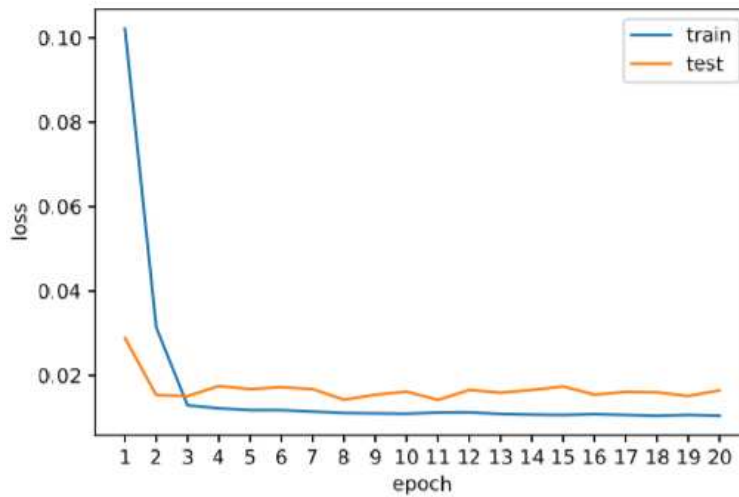


Figure 2. Training and testing errors by epoch

The final absolute mean error for the testing data is 1.5% ($1.43 \pm 6.22\%$ and $1.64 \pm 7.20\%$ errors for 1/2 hour and 1 hour ahead forecast respectively).

3.2 Experiment

In the section, the weather data measured for 24 days from 07 July 2016 to 30 July 2016 at the Taean airport of Hanseo university are used to validate the prediction model. Figure 3 showed the actual (green line) and estimated (red line) runway visual range.

As seen in Figure 3, the estimated runway visual range could predict the runway visual range after 1 hour. The RMSE (root mean square error) is 0.0739.

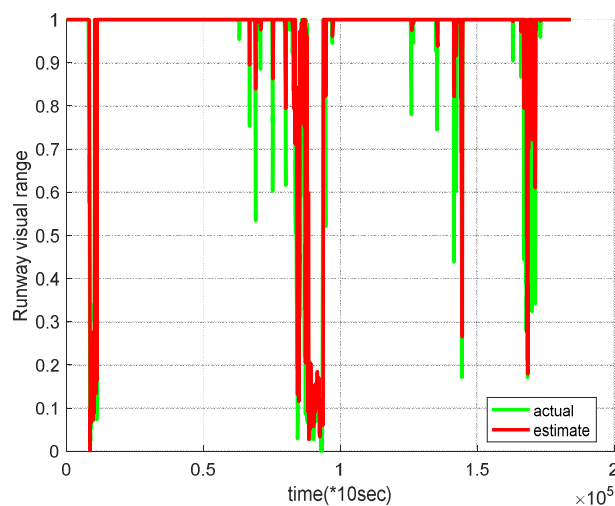


Figure 3 Runway visual range forecast (1 hour ahead) for 1 month

Figure 4 is magnified from 7000 tick to 12000 tick of Figure 3. As seen in Figure 3, the estimated runway visual range is predicted properly with comparison of the actual runway visual range.

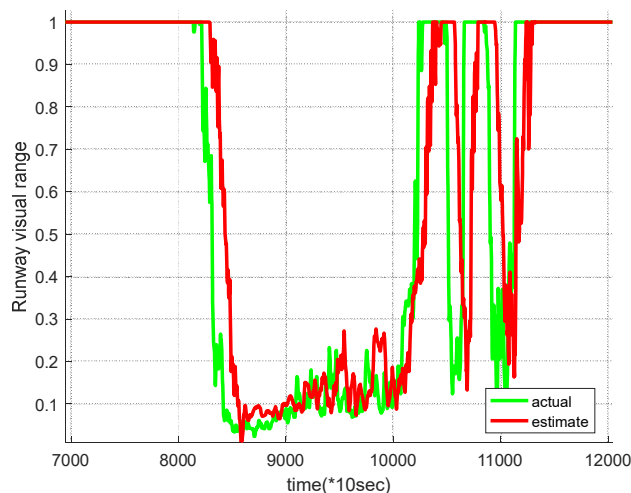


Figure 4 runway visual range magnified from 7000 tick to 12000 tick of Figure 3

4. Conclusion

This paper proposed a prediction model for runway visual range using convolutional neural network. We developed and simulated a CNN prediction model for forecasting the runway visual range after 1 hour by using

wind speed, temperature, and humidity and runway visual range. We used the measured weather information on three month for constituting the prediction model. To validate the proposed model, the runway visual range of 24 days were predicted. The prediction model could forecast the runway visual range with RMSE of 0.0739. This predicted result showed a high similarity to measured runway visual range after 1 hour. However, the prediction model has several parts to be improved like tracking the peaks. In the near future, we will do research to improve the accuracy of the model.

Acknowledgement

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