Deep Learning Drone Flying Height Prediction for Efficient Fine Dust Concentration Measurement

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Abstract

Fine dust concentration has been collected so far by fine dust concentration monitoring towers at fixed heights. However fine dust concentration level varies significantly with heights. It is possible for people to get informed of wrong dust concentration information. Drone equipped with a fine dust sensor can fly up and down to sense fine dust concentration. Drone can solve the wrong fine dust concentration information problem. But we face too much energy consumption problem of drone and possibly delayed information because drone should fly from ground up to top. To solve this problem, we propose to cut drone flying height by predicting the height, using deep learning methods, at which maximum fine dust concentration can be sensed. Experimental results show that the proposed methods save 58.28% of flying distance.

Keywords: Fine dust concentration, drone, deep learning, RNN, CNN, prediction of maximum flying height.

1. Introduction

Healthcare problem caused by air pollution has been a big issue among people these days. The concentration of fine dust is very harmful for human being's health. Fine dust is one of main causes of air pollution problem. To avoid the threat of fine dust, the Korean government has installed fine dust sensing stations in the country. However, the location of the installed stations didn't consider the height. Unlike other air pollutants, the concentration of fine dust is strongly affected by air flow, temperature, and other weather conditions [1]. Because air flows move fine dust, fine dust has different levels of concentration at different heights in the same place.

Table 1. Different levels of fine dust concentration by height [2].

	PM_{10}(µg/m³)		$PM_{2.5}$(µg/m³)		$PM_{1.0}$(µg/m³)	
Rooftop	40.7	30.9	24.3	18.1	20.0	15.0
Ground	48.9	34.7	29.9	19.7	25.2	16.0
Difference	+8.2 (20.2%)	+3.8 (12.3%)	+5.6 (23.0%)	+1.6 (8.9%)	+5.2 (26.2%)	+1.0 (6.7%)

* PM_n: Particulate matter n micrometers or less in diameter.

As given in Table 1, fine dust shows different concentration levels between high rooftop and ground. This illustrates that the fine dust station installed on the rooftop does not give true fine dust concentration information for real life. Table 2 shows 224 of 264 fine dust sensing stations are installed at over 10m height above ground in South Korea.

Table 2. Number of fine dust sensing stations by height in South Korea [3][4].

	5m	**10m**	**15m**	**20m**
Numbers	9	31	203	21

Because of height limitation of the installed stations, it is impossible to measure the worst (maximum) concentration level of fine dust in real time. To solve

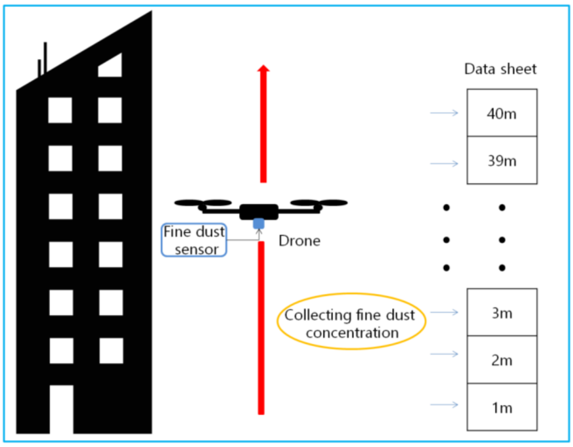

Figure 1. Measuring fine dust concentration by height.

this serious problem, we propose to use drones for measuring fine dust. Drone has demonstrated a possibility to measure air quality including fine dust, pressure, wind, relative humidity, ozone, and other gases [5][6][7]. In Fig. 1, a drone is equipped with a fine dust sensor. Thus, the drone flies up and down in order to measure fine dust concentration at different heights. The drone can measure the level of fine dust concentration at allowed heights. The drone will send the maximum (highest) level of fine dust concentration and its corresponding height (m) as well as level of concentration-height matching data. We can be informed of more realistic and true fine dust concentration information in real time. In addition, if we are informed of both maximum level of concentration and its corresponding height, it will be helpful for the people who live in the city with buildings and apartments.

But we face one practical problem in carrying out fine dust concentration measurement at different heights by drones. A drone cannot fly up to the maximum allowable height every minute. It will consume too much energy of drone and may not give us real time fine dust concentration information. Thus, we need to cut flying height of drone. If we can predict the height point of maximum fine dust concentration level, we can stop drone flying-up at the predicted height. A machine learning approach, reinforcement learning, has proven to control drone in 2017 and 2018 [8][9]. In our research, we implemented deep learning approaches such as deep neural network (DNN) and recurrent neural network (RNN) to predict height point of maximum fine dust concentration level. We compared predicted height points to actual height points for verification of our proposed work. Experiment results have shown a practical possibility of our proposed work. In experiment the proposed DNN model has shown 80.3% of accuracy and the proposed RNN model, 84.5%, respectively and the DNN has saved 57.31% of flying distance while the RNN, 58.28%, respectively.

2. Prediction of Maximum Fine Dust Concentration and Flying Height

To obtain maximum flying heights of drone, fine dust concentration data at different heights were collected. The actual data were collected (measured) by drone, ranging from ground to 40m in height for 14hours. Collection was made every 10 cm whenever the drone flied up.

From the collected actual data, a normal distribution model of fine dust concentration levels at each height increment of 10 cm, was derived. Thus, we obtained a total of 400 different normal distributions. The actual data were used to train the DNN and RNN models. The one-year past (historical) fine dust concentration data were obtained from [10][11]: average fine dust concentration per hour, average temperature per hour, average wind speed per hour, average ground fine dust concentration per hour, and average humidity per hour were used as the input to generate training and test data sets.

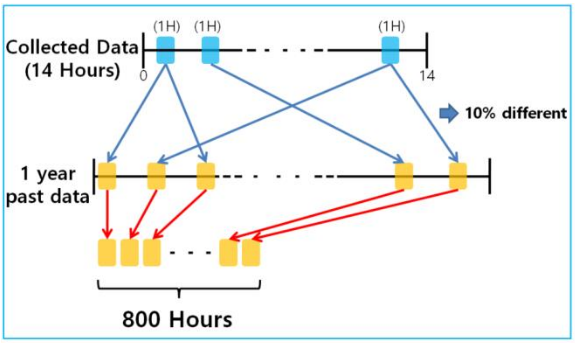

Figure 2. 800 hours sample data generation.

As shown in Fig. 2**,** a sample data of 800 hours was selected in one-year past data. The sample data are within range of 10% centered from the collected actual data. The range of 10% is measured by avg. fine dust concentration/hour, temperature/hour, wind speed/hour, and humidity/hour, respectively. The past data were applied to the actual fine dust concentration data by the following formula:

$$G_m = (Actual_m / Past) * Average_{past}$$

G_m: Normalized data for training and testing
m: flying heights in meters ranging from 1 (ground) to 40 (top).
$Actual_m$: Collected actual data at m height (every 5 minutes)
$Past$: Past data at the same time as the actual data
$Average_{past}$: One-year averaged data of past for a specific hour.

The normalized data were used as the mean value of the standard normal distribution. Thus, we can generate the realistic fine dust concentration data $\boldsymbol{x}$ by the following Z formula:

$$\boldsymbol{x} = Z \times \sigma + G_m$$

* σ: Standard deviation

We generated 10,000 data sets for training while 1,000 data sets for testing accuracy from the above standard normal distribution.

Table 3. Input & output data type for training DNN and RNN models (PM_{10}).

	Data Type					
Input	Ground PM_{10} Concentration	Ground Temp.	Avg. PM_{10} per Hour	Avg Temperature	Avg Wind Speed	Avg Humidity
Output (Target)	Height of Maximum Concentration					

* *Ground PM_{10} Concentration*: Measured on the ground by drone in real time (current time)
* *Ground Temperature*: Measured on the ground by drone in real time
* *Ave. PM_{10} per hour*: Averaged fine dust concentration per hour from historical data which the meteorological administration provides
* *Ave.Temperature (per hour)*: Averaged temperature per hour from historical data which the meteorological administration provides
* *Avg.Wind Speed (per hour)*: Averaged wind speed per hour from historical data which the meteorological administration provides
* *Avg.Humidity (per hour)*: Averaged humidity per hour from historical data which the meteorological administration provides

Our deep learning models, DNN and RNN will be trained using the above data sets. The proposed DNN and RNN models will predict the height at maximum fine dust concentration level. The proposed DNN model has 6 input nodes and 1 input node given in Table 3 and has 6 hidden layers. The proposed RNN model has 7 sequence lengths and 1 hidden size (Output). No hidden layer was used, and LSTM (Long Short-Term Memory models) was applied for cells.

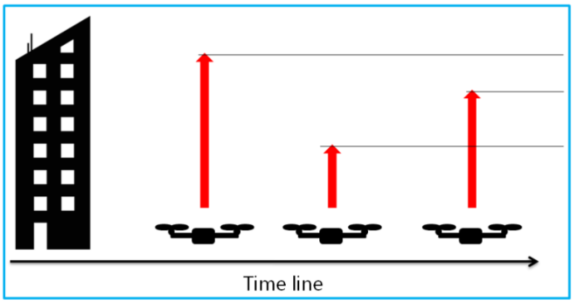

Figure 3. Target height of drone.

The height points of maximum fine dust concentration the drone will be predicted by DNN and RNN, respectively, as shown in Fig. 3. In order to predict the height point, input data will be entered in DNN and RNN models, respectively. By predicting the height point in advance, the drone does not need to fly up to the allowable top point, 40m to find the maximum (highest) fine dust concentration level. Fig. 4 shows the flowchart of the proposed fine dust concentration measurement processes by drone. The detailed algorithm steps are as following:

Step 1. When the system is operated, input data of data sets, which were recalled from database (DB), will be entered in two different deep learning prediction models, DNN, RNN. The input data will be 'Ground fine dust concentration,' 'Ground temperature,' 'Average fine dust concentration,' 'Average temperature,' 'Wind speed,' and 'Humidity'.

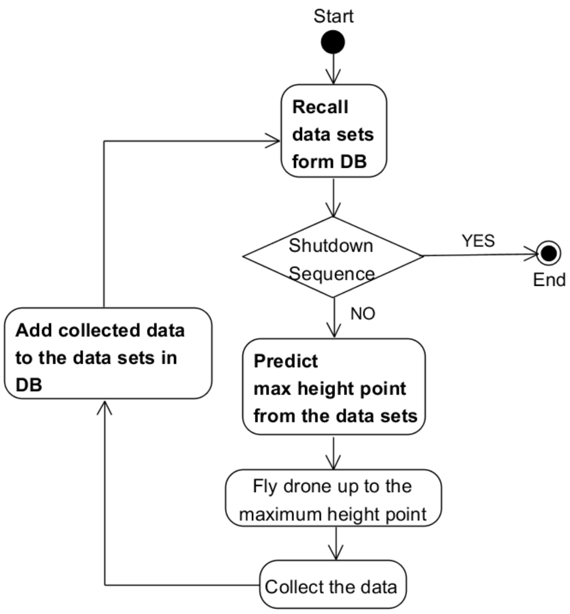

Figure 4. Flowchart for the prediction of highest point of fine dust concentration.

Step 2. The shutdown sequence will be checked to stop the system or not.
Step 3. The height point of maximum fine dust concentration level is predicted by DNN and RNN, respectively.
Step 4. Drone receives the maximum height point and will fly up to the point.
Step 5. When drone flies, it will collect fine dust concentration data. The collected data are 'Average fine dust concentration of every 10cm of height', and 'Average temperature of every 10cm of height'.
Step 6. The collected data will be added to the data sets in DB.

3. Simulation Results

The actual data and generated data were used for training DNN and RNN models, respectively. Fig. 5 shows accuracy of prediction of DNN and RNN by comparing the original data. The accuracy of DNN prediction is 72.67% on average while the one

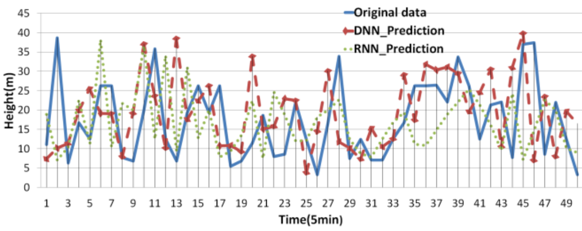

Figure 5. Comparison of actual and predicted data by DNN and RNN.

of RNN prediction has 80.61% accuracy on average. The prediction accuracy results mean that the proposed approach can be practically applied. The gap between predicted heights (10cm) is too narrow and so we consider error of ± 40cm. Accuracy is calculated by:

Predicted max height / Actual max height

Table 4. Cost-saving and accuracy for 10-hour flight.

	Flying Distance(m)	**Accuracy (%)**	**Saving (%)**
5-min cycle	4,800m	-	-
DNN	2,366.4m	72.67%	50.7%
RNN	1,886.7m	80.61%	60.69%

In Table 4, according to the predicted height by DNN, the drone flew 2,366.4m out of 4,800m and by RNN, it flew 1,886.7m out of 4,800m for 10 hours of flight. Both used 5-min flying cycle of measurement. DNN max concentration height point prediction shows 50.7% saving of full flying distance, 4,800m while RNN max concentration height point prediction saves more flying distance by60.69%.

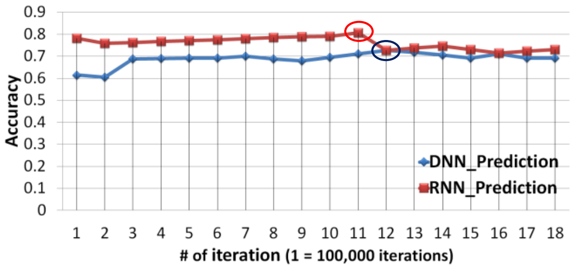

Figure 6. Prediction accuracy vs. training time.

Fig. 6 illustrates the prediction accuracy depending on training time (the number of iterations). The DNN prediction model provides the best accuracy, 72.67% at 12-time training point (12X100,000 = 1200,000 iterations) while the RNN prediction model shows the best one, 80.61% at 11-time training point.

4. Conclusion

In this paper we propose the deep learning prediction methods of drone flying height at which maximum fine dust concentration can be sensed. Our experimental results show that the proposed DNN and RNN prediction models can be practically applied to save energy of drone and to provide real time fine dust concentration information. It is necessary for us to obtain more real actual data with drone flight to increase reliability of experiment in the future. We will do more research on optimal measurement cycle time to have the best prediction accuracy in the future.

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