Generating Model to Predict the Spread of Volcanic Fallout Ash Spreadby using Image-to-Image Translation of Weather Map

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Abstract

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1 Introduction

The volcanic eruption is one of the most severe natural disasters which occasionally happens. However, compares to the other disasters which can be predicted, like typhoons and storms, predicting exact time and scale of volcanic eruption considers as a very difficult tasks which might never be accurate, according to Einarsson (as cited in 3, para 7 & 30). Though there exist various ways that volcanic eruption causing countless casualties and massive economical loss, according to Yun Yun (12, p. 274), the fallout ash, focus of this research, considers as one of the most significant by-products making deadly effects. Including the respiratory damage of lives, threatening the safety and reliability of air transportation, and collapse of structures caused by sedimentation of the ash, the fallout ash causing various impairments on wide range of areas (12, p. 274-275).

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To mitigate the hazardous effects caused by the fallout ash, it is important to properly predict the direction of ash spread and evacuate or alert citizens reside through the path of the ash dispersion. Historically, by using Eulerian or Lagrangian approach Bonadonna et al. (2, p. 3-4), the scientists are tried to make Volcanic Ash and Dispersion/Tracking Model (VATDM). These models usually focus on the predicting the pathway of fallout ash dispersion and the amount of deposited ash while accepting limited variables (12, p. 276).

However, these models' predictability might be limited due to computing performance (10, p. 745-746). In order to make faster prediction, the fellow scholars conducted researches on making lighter and faster prediction model (Searcy et al. (8)), standardizing the eruption parameters which requried for running the model (Webley and Mastin (11, p. 7)), and figuring out the way to store and retrieve different kinds of data (satelite and prediction from mathematical model) more efficiently (Sorokin et al. (9)). Though the advance of the models' and predict utilizations' efficiency has been improved with the effort of numerous scholars, still the needs of the calculation process lasts, which yet limiting the ability of prediction with respect to the computing power.

In this research, we are going to suggest a faster way to get the prediction on the pathway and area that might be affected by volcanic fallout ash: Image-to-Image Translation. By utilizing the state-of-the-arts deep neural network, our goal includes verifying whether conditional GAN based deep neural network is able to extract the relationship between flow of air (represented by weather maps) and the spread of fallout ash.

2 Methods

Data Collection To achieve our goal, making generator which predict the possible area of ash spread with respect to the given pair of weather maps, we first need to collect input and output data pairs. In order to collect these, for the input image, we will download those from "Meteorological Data Open Portal" operated by Korea Meteorological Administration (KMA) (MDO). To get the output data that will be paired with the weather maps, we will go through the traditional procedure with either FALL3D, or Puff-UAF model.

The simulation parameters except for the weather data – plume height, number of particles to be predicted, and the mountain that has been erupted) will be set manually. To represent various eruption cases, for each mountain to be used as sample, we will run the simulation with the constants representing Volcanic Explosivity Index (VEI) 3 (Moderate-Large Eruption), VEI 5 (Very Large Eruption), and VEI 7 (Massive Explosive Eruption) (6, p. 1232). The remaining, but the most important, parameter for the simulation model, weather prediction data, will be obtained by the same location where we found the weather maps: download prediction made by RDAPS(regional data assimilation and prediction system) (MDO). These datasets are extremely huge: one day of weather data takes 1.32 GigaBytes, and we are thinking of getting at least 5 years of data for both training and testing sets. We need to find a reliable storage to save all the weather data, weather maps, and output images.

Model structure Starting from conditional GAN, which has been shown to have better performance on generating indistinguishable images compare to the "real" images Isola et al. (4), we are going to choose proper loss function which have the best result on predicting the relationship between elements dicpicted on the weather maps to the spread of the ash. For the convolutions, we will use U-Net architecture proposed by Ronneberget et al. Ronneberger et al. (7), as the architecture has been achieved a promising result on several different imaging tasks (4, 5).

Model Analysis and Experiments While we mauver over various loss functions, we are going to make various models utilizing different loss functions and compare those with quantitative score. As indicated on the previous paper Isola et al. (4), it is difficult to say there exist one best representation on the quality of translated images. Therefore, we need to set a realiable measurements before we analyze models using different loss function.

Once we decide the model structure, we need to verify the amount of sufficient size of training datasets so that it can translate the weather map image to simulation result flawlessly. In order to do this tasks, we need to train model with different amount of inputs. As Korean Peninsula experiencing four distinctive seasons, while we picking up the training set randomly, we would better ensure that we picks a combination of data which represent the dynamic climate of Korea. After we fit the model with different number of training datasets, we will investingate how well each model draw the result.

3 Timeline

The first thing we should do is to get the input. As there is no opened API to get the weather maps and data from KMA, but they provide an interactive website to download the data, it might take some time to get all data manually. Moreover, the calculation time for that simulation was not ignorable, according to previous experiment (takes approximately one hour to get one output with the laptop having Intel's i5-3320M CPU). Considering the factor that we have access to better computing power than the previous test, we are expecting to finish data collection within two months after project initiated.

The next step is to train the generator with given input-output pair. To fit conditional GAN based model and to verify the result with various test cases, we are expecting to take two additional months here. For the last one month of this research, we will write a report and posters.

4 Conclusion and Future Direction

We are expected to have faster way to predict possible pathway and area of volcanic fallout ash spread by using simpler and lighter input, weather maps, compare to the weather dataset predicted by RDAPS. Not only reduce the computing time to predict the spread, the model aims to reproduce as same result as possible compares to the original training result.

Because of the weather maps' style is different with the agencies that produce the map (NOAA's way of making the map and KMA's way of making the map is different), our model was not focused to produce an output from the maps that has been publicized by different agencies. Moreover, because of the limitation of dataset, we are only able to train and test on the area near Korean Peninsula; the models could not be verified on the different regional settings.

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