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 the exact time and scale of volcanic eruption considers as a very difficult task 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 economic loss, according to Yun (12, p.274), the fallout ash, the 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 the collapse of structures caused by sedimentation of the ash, the fallout ash causing various impairments in a 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 who reside through the path of the ash dispersion. Historically, by using the Eulerian or the Lagrangian approach, according to Bonadonna et al. (2, p.3-4), scientists are tried to make Volcanic Ash and Dispersion/Tracking Model (VATDM). These models usually focus on 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). To make a faster prediction, the fellow scholars conducted researches on making a lighter and faster prediction model (Searcy et al. (8)), standardizing the eruption parameters required for running the model (Webley and Mastin (11, p.7)), and figuring out the way to store and retrieve different kinds of data (satellite and prediction from the 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 last, which yet limiting the ability of prediction 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 Generative Adversarial Network (GAN) based deep neural network can extract the relationship between the flow of air (represented by weather maps) and the spread of fallout ash.

2 Methods

Data Collection To achieve our goal, making a generator which predicts the possible area of ash spread for the given pair of weather maps, we first need to collect input and output data pairs. To collect these, for the input image, we will download those from the "Meteorological Data Open Portal" operated by the Korea Meteorological Administration (KMA) (from MDO). To get the output data that will be paired with the weather maps, we will go through the traditional procedure with either the FALL3D or the 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 the sample, we will simulate 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) (from 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 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 has the best result on predicting the relationship between elements depicted on the weather maps to the spread of the ash. For the convolutions, we will use the U-Net architecture proposed by 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 the quantitative metric. As indicated in the previous paper (Isola et al. (4)), it is difficult to say there exists one best representation of the quality of translated images. Therefore, we need to set reliable measurements before we analyze models using different loss functions.

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 images to simulation results flawlessly. To do these tasks, we need to train models with different amounts of inputs. As the Korean Peninsula experiencing four distinctive seasons, while we picking up the training set randomly, we would better ensure that we pick a combination of data that represents the dynamic climate of Korea. After we fit the model with a different number of training datasets, we will investigate how well each model draws the result.

3 Timeline

The first thing we should do is to get the input. As there is no available 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 a previous experiment (it 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 the project initiated.

The next step is to train the generator with a given input-output pair. To fit the 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 month of this research, we will write a report and posters.

4 Conclusion and Future Direction

We are expected to have a 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, but the model aims to reproduce as the 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 (National Oceanic and Atmospheric Administration (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 have been publicized by different agencies. Moreover, because of the limitation of the dataset, we are only able to train and test on the area near the Korean Peninsula; the models could not be verified on the different regional settings.

References

[MDO] Meteorological data open portal. Online Databse; Korea Meteorological Administration (KMA); `https://data.kma.go.kr/`.

[2] Bonadonna, C., Folch, A., Loughlin, S., and Puempel, H. (2012). Future developments in modelling and monitoring of volcanic ash clouds: outcomes from the first iavcei-wmo workshop on ash dispersal forecast and civil aviation. *Bulletin of Volcanology*, 74(1):1–10.

[3] Fountain, H. (2015). Pressure, and mystery, on the rise. Online; The New York Times; `https://www.nytimes.com/2015/01/06/science/predicting-what-a-volcano-may-`

`or-may-not-do-is-as-tricky-as-it-is-crucial-as-iceland-well-knows.html` (last accessed on 02/12/17).

[4] Isola, P., Zhu, J.-Y., Zhou, T., and Efros, A. A. (2016). Image-to-image translation with conditional adversarial networks.

[5] James, S., Wohlhart, P., Kalakrishnan, M., Kalashnikov, D., Irpan, A., Ibarz, J., Levine, S., Hadsell, R., and Bousmalis, K. (2018). Sim-to-real via sim-to-sim: Data-efficient robotic grasping via randomized-to-canonical adaptation networks.

[6] Newhall, C. G. and Self, S. (1982). The volcanic explosivity index (vei) an estimate of explosive magnitude for historical volcanism. *Journal of Geophysical Research: Oceans*, 87(C2):1231–1238.

[7] Ronneberger, O., Fischer, P., and Brox, T. (2015). U-net: Convolutional networks for biomedical image segmentation.

[8] Searcy, C., Dean, K., and Stringer, W. (1998). Puff: A high-resolution volcanic ash tracking model. *Journal of Volcanology and Geothermal Research*, 80(1):1 – 16.

[9] Sorokin, A., Girina, O., Korolev, S., Romanova, I., V.Yu, E., S., M., A., V., and I., B. (2016). The system of computer modeling of ash cloud propagation from kamchatka volcanoes. *2016 6th International Workshop on Computer Science and Engineering (WCSE 2016)*, II:730–733.

[10] Tanaka, H. L. and Yamamoto, K. (2002). Numerical simulation of volcanic plume dispersal from Usu volcano in Japan on 31 March 2000 using PUFF model. *Earth, Planets, and Space*, 54:743–752.

[11] Webley, P. and Mastin, L. (2009). Improved prediction and tracking of volcanic ash clouds. *Journal of Volcanology and Geothermal Research*, 186(1):1 – 9. Improved Prediction and Tracking of Volcanic Ash Clouds.

[12] Yun, S.-H. (2013). Conceptual design for the dispersal and deposition modelling of fallout ash from mt. baekdu volcano. *The Journal of the Petrological Society of Korea*, 22:273–289. (Written in Korean).