ADVANCES IN FOREST FIRE RESEARCH

2022

Edited by

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AI-driven Real-time Forecast of Wildfire Development in Hong Kong

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Keywords

Fire Perimeters; Wildfire Forecast; TCNN; Smart Firefighting

Abstract

Climate changes have already altered the wildfire regime and increased the wildfire frequency and severity in Hong Kong. Hong Kong is a typical wildland-urban interface, where small high-population urban areas are surrounded by 70% wildland. Statistics show that the burning areas in over 80 % of accidents are less than 1,000 m2, and the burning time cannot last for 24 hours in Hong Kong. To improve the wildfire response and reduce the life and property loss in fires, a real-time fire forecast is required to achieve the most accurate and real-time fire forecast. This study firstly introduced the development of the wildfire spread models and then reviewed the AI-based model emphatically in the wildfire simulation and prediction. The blank parts in the short time series wildfire prediction aroused the attention of authors. Thus, an AI-based method was proposed to predict the wildfire front in real time. This study currently aims to establish the virtual wildfire scenario database in Hong Kong and realizes the AI-driven wildfire prediction model for suppressing fire spreading.

1. Introduction

Wildfire has been a long-existent phenomenon on Earth. It is an important natural process to consume the fuel accumulation in the wildland. The wildfire happens even without human behaviors interfering. However, with the expansion of human living space, urban cities are gradually occupying the wildlands where human behaviors have a great effect on wildfire, increasing the frequency of wildfires. Simultaneously, wildfire can negatively influence the residents who live in the wildland-urban interface (WUI) (Manzello, 2020). The wildfire is a global natural disaster that is concerned by many countries and regions (Fig. 1). Hong Kong is such a typical city full of wildland-urban interfaces (WUIs), as 70% of its land is covered by woodland, Shrubland, and wetland (Civil Engineering and Development Department Hong Kong, 2014; Warren-Rhodes & Koenig, 2001).Thus, Hong Kong cities are constantly threatened by wildfires. There have been more than 1,000 times wildfire accidents reported per year over the last 10 years, according to the data provided by Fire Service Department in Hong Kong (Hong Kong Fire Services Department - Access to Information, 2021). Thus, it is crucial to control the wildfire in time to prevent the hazard from causing huge damage to the city.

(a) California WUI wildfire in 2018 (b) Australia WUI wildfire in 2019 (c) Hong Kong WUI wildfire in 2019

Figure 1- Global wildfire accidents in (a) the USA, (b)Australia, and (c) Hong Kong, China.

After the occurrence of wildfire, grasping the spreading trends is always one of the most effective strategies in controlling the fire. Therefore, Scholars have been devoted to developing the wildfire spreading prediction tools in the last decades (Fig. 2). Overall, the trends are evolving from statistics-based models to physical-based models. The data acquired from the computation tools are no longer the static burning probability. Instead, the information turns into the intuitive spreading perimeter to guide the fire scientists to locate the flame front based on mathematical physic-based models.

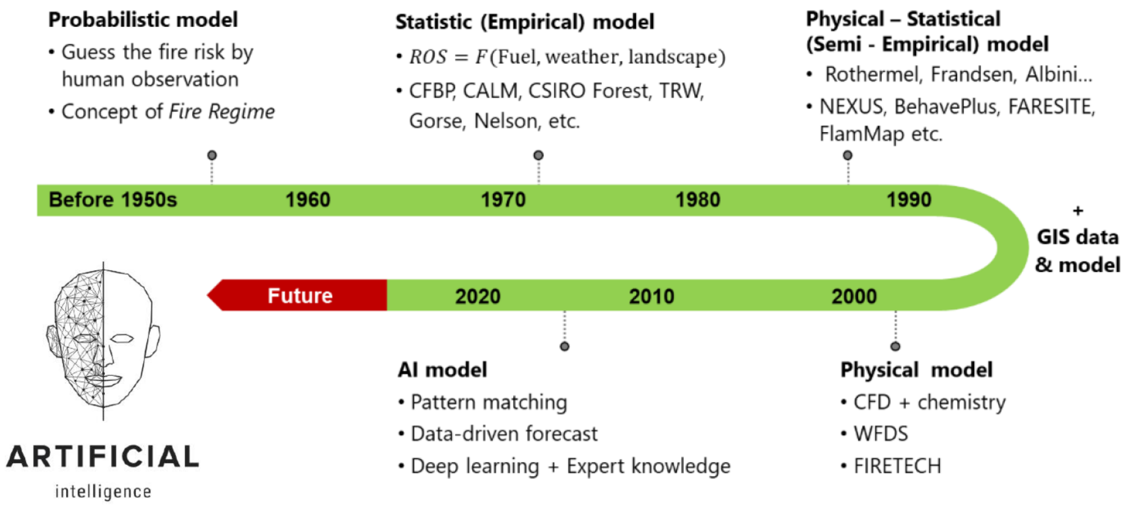


Figure 2- Computational tools for wildfires over the last several decades.

At first, the wildfire spreading models were merely based on static possibility until the empirical models were come up with to transform the likelihood into the statistic question before the 1990s. The turning point was that, according to the empirical models, Finney (1998) developed the FARSITE software to simulate the fire propagation, which was subversive work at that time to make the wildfire visualized in 1998. It combined the GIS data with the statistic data, rendering the prediction convincing. Since the 2000s, a number of numerical methods came out, such as HIGRAD/FIRETEC and Fire Dynamics Simulator (FDS). These numerical methods pay attention to the physical laws of combustion, which make the simulation exquisite but consume a huge amount of time and computation costs.

Gladly, the AI models were proposed to change the way researchers dealt with wildfire spreading. The physical-based computation can be switched into a data-driven matchup in the database. The AI-based models largely decrease the computation time and make real-time prediction possible. In 2019, Hodges (Hodges & Lattimer, 2019) firstly combined FARSITE software with AI algorithms. In his work, he successfully converted the physical-based numerical method into a phenomenological model, which cut the running time when ensuring the prediction accuracy. His job reflected the long-time series wildland fire and the output results were a fire spreading figure in 6 hours. His successful applications in California pave the way for the AI-based wildfire prediction globally.

However, according to the statistics, the burning areas in over 80 % of accidents are less than 1,000 m^2 and the burning time cannot last for 24 hours in Hong Kong. Nevertheless, the short time series real-time wildland fire spreading prediction and local database is blank. There is no current guidance for firefighters, warning them of the wildfire spreading trends. Therefore, it is urgent to make up this field of study in Hong Kong to reduce the danger of wildfire. The real-time wildfire prediction is the basis for the Hong Kong wildland digital twin, which can interact with the firefighters to ensure the city safety.

2. Dataset

FARSITE is widely used by the U.S. Forest Service as an effective tool for simulating the growth of natural fires in wilderness areas (Srivas et al., 2016). It requires an input set that contains different parameters before running the spreading prediction. Due to the lack of real-scenario wildfire data, all the wildfire scenarios are numerical generated by the software FARSITE. It is worth noting that the AI-based algorithm cannot distinguish the difference between numerical simulation results and real-scenario wildfire data, so the model cannot result in huge biases. It is feasible to validate the model in the temporary simulation data. The next action is to replace the original simulation data with real-scenario wildfire data step by step.

FASITE is a mainstream software used by American wildfire researchers. The related input database can be acquired from the Interagency Fuel Treatment Decision Support System (IFTDSS) website. However, it lacks the geography information in Asia. Therefore, it is important to pre-process the local geography parameters to make use of this software in Hong Kong. In this study, the Hong Kong Sunshine Island is chosen as the study area where it is an isolated island in Hong Kong with few species of vegetations. The pixel resolution is 5 m × 5 m, which is much finer than usual 30 m × 30 m.

At the early stage, the software FARSITE is used to add up the dataset. The parameters to be inputted into the software include five compulsory geography information, such as elevation, slope, aspect, fuel model, and canopy cover (Fig. 3). Three optional parameters are stand height, canopy base height, and canopy bulk density respectively to reflect the crown fire. These are the basic information for the wildfire simulation starting. After obtaining all the data, the ignition boundary should be decided. As for the ignition boundary, the ignition locations will start as a point, following the development of a short-time series wildfire. Then the fuel moisture, the temperature, the wind speed, the wind direction, the relative humidity, and cloud cover percentage are required to input, starting the wildfire spreading in the regulated burning periods.

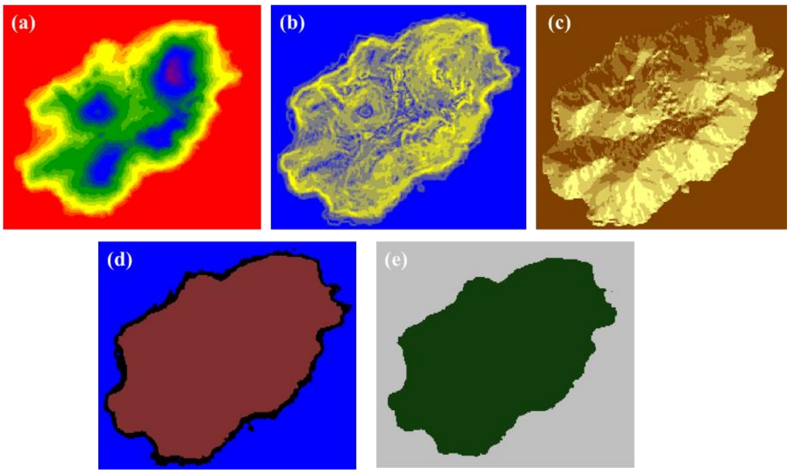


Figure 3- Geography information, (a) elevation, (b) slope, (c) aspect, (d) fuel model, and (e) canopy cover.

To ensure that the dataset has enough data and convincing results, the temperature, the wind speed, the wind direction, the relative humidity, and the cloud cover percentage are seen as five variances to control the simulation results. Because the research area is given and confirmed, while the five parameters in the geography model do not need to change. Likewise, the fuel moisture data is also calculated based on the automatic generation by the software. Once the ignition location is confirmed, the wildfire spreading will get into calculation according to the parameters which is set beforehand.

3. Methodology

3.1. Forward model for spreading simulation

The Rothermel and Albini spread models (Albini, 1985; Rothermel, 1972) were used to calculate the wildfire surface spread rate. In the model, $\boldsymbol{V_{s,\ peak}}$ is calculated according to the following equations:

$$V_{s,peak} = \frac{Q''\zeta}{\rho\epsilon Q_{ig}}(1 + \phi_s + \phi_w) \tag{1}$$

where Q'' is the heat release rate per unit area, ρ is the fuel density, Q_{ig} is the heat of pre-ignition, ζ is the propagating flux ratio (percentage of heat released which pre-ignites fuel), ϵ is the effective heating number (percentage of fuel which is involved in ignition), ϕ_w is the wind coefficient, and ϕ_s is the slope coefficient (Hodges & Lattimer, 2019).

It is widely recognized that the Rothermel and Albini spread models can be applied to predict the wildfire spread perimeter in the peak spreading direction. Therefore, the combined model will be the basis of the spreading model to build the wildfire scenario dataset.

3.2. Forward model for AI-based prediction

The total flow chart of this paper is proposed in Fig. 4. The core of this study is to turn the mathematical spread model into an AI-based algorithm model. The huge difference is that the wildfire front prediction is no longer based on the physical laws proposed by the previous researchers. Instead, the model will find the inner connection among the input parameters to describe the wildfire fronts.

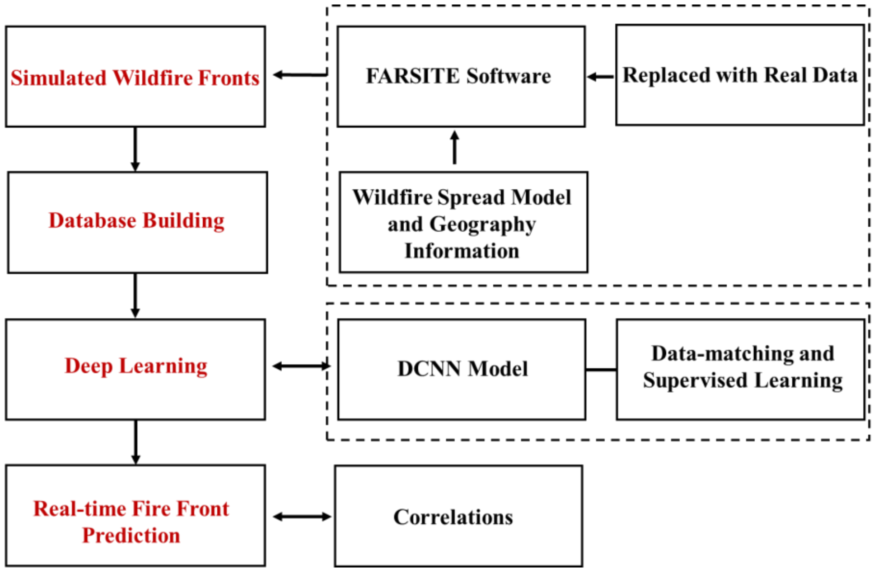


Figure 4- Flow Chart for the AI-based prediction

In order to reasonably find the connection of spreading trends in geo-information, this paper will use Deep Convolutional Neural Network (DCNN) as the basis to build the above-mentioned AI algorithm. The DCNN method (Krizhevsky et al., 2012)consists of many neural network layers. Two different types of layers, convolutional and pooling, are typically alternated. The depth of each filter increases from left to right in the network. The last stage is typically made of one or more fully connected layers (Fig. 5):

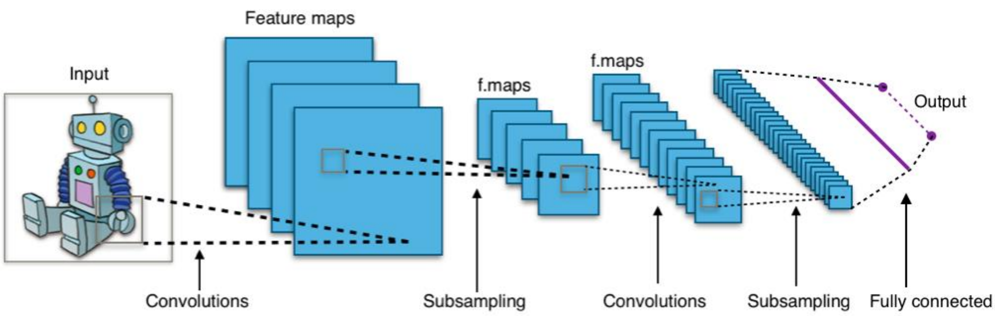


Figure 5- DCNN visualization (Deep Convolutional Neural Network — DCNN | Deep Learning with Keras, n.d.).

The local features of small sub-regions in the images which contain geography information are extracted by neurons, and then the information of these features can be fused into the subsequent processing stage to detect more advanced features such as the probability of fire or spreading trends. Compared with the visual tasks (target detection, classification, segmentation, and motion tracking) in computer vision that involve images with only three color channels as input, the input involved in this paper is more complicated: in addition to basic geographic information, it needs to be added the factors affecting combustion, such as elevation, slope, fuel model, etc. Therefore, the use of mature computer vision DCNN is higher computational cost and poorly robust. For this reason, we have proposed two feasible improvement methods.

First, use a smaller but sparse perception field. In the first layer of DCNN, each convolution kernel is used to connect sub-regions of the picture, and the size of the sub-region is called windows or perceptual field. Traditional visual tasks use overlapping windows to ensure that the convolution kernel can obtain global information. Compared with the computer vision dataset which includes Strenuous sway and changes, the merge of input images has three characteristics: fixed; the field affected by wildfire is limited; the information density of the unified field is large. Therefore, smaller windows can only use the information needed for DCNN learning to associate high-level features. The sparse perception field is to trade off the accuracy and computational cost. As the perception field becomes sparser, the number of convolution kernels that need to be learned will be less, and the weight parameters that need to be updated can usually be reduced exponentially. Although it will bring a loss of accuracy, it is worthwhile for spreading trends tasks that do not require pixel-level accuracy.

Second, partial pooling is performed. The pooling layer in DCNN is used to filter the repetitive and redundant information brought by the convolutional layer. In the images, the information density of the same area under different channels is different. If the same pooling strategy is used for all channels, some of the information in the high-density channel will be lost, while the information of the low-density channel will be retained. Therefore, the DCNN performs small-size pooling on high-density channels (Elevation, Slope, Aspect, Fuel Model, and canopy cover), and large-size pooling on low-density channels (temperature, relative humidity, wind speed, wind direction, and cloud cover).

Besides, the model can be correlated with the updated parameters to realize the data assimilation to some extent. It gets rid of the traditional frameworks that the data cannot be changed during the simulation. In summary, it can be a good reference in the wildfire front prediction in the short-time series wildfire, combined with traditional spread model and geography information using a deep learning method.

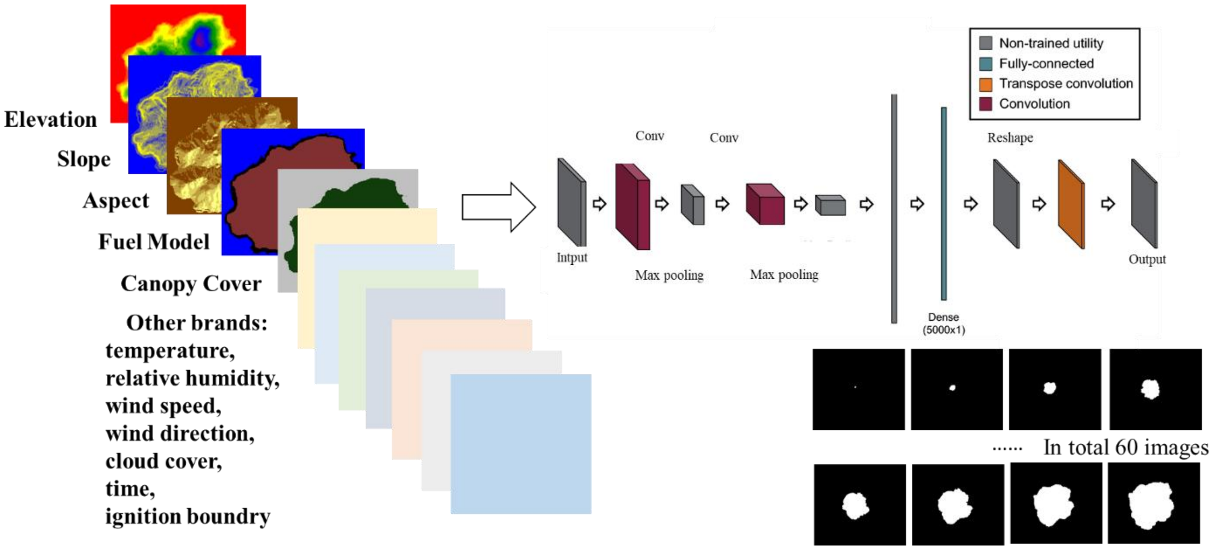
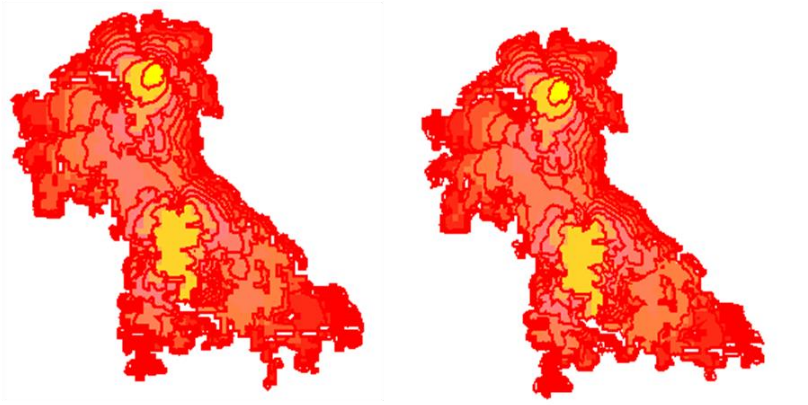


Figure 6- DCNN training model in the paper.

The input images (Tiff format) were 225 × 199 pixels with 12 brands, while 60 output images represent the location of wildfire front with the time step of 5 minutes in five hours (Fig. 6). Six hidden layers are included in the network, including two convolutional, two max pooling, one fully connected classification, and one transpose convolutional layer, which is referred to as Hodges (Hodges & Lattimer, 2019).

The layers in the model made full use of used leaky rectified linear unit (ReLU). The hidden layers in the model are to calculate the pixel possibility whether they need to be colored based on the dataset. In total, the DCNN model works depending on the convolutional layers to form the colored pixel instead of forming the wildfire front according to the traditional spread model.



(a) FARSITE simulation (b) DCNN-based Prediction

Figure 7- Wildfire perimeters in (a) FARSITE simulation, and (b) proposed DCNN-based prediction.

4. Conclusion

This paper firstly introduced the development of the wildfire spread models and then reviewed emphatically the AI-based model in the wildfire simulation and prediction. The blank parts in the short-time series wildfire prediction aroused the attention of authors. Thus, a new AI-based method was proposed to predict the wildfire front in a short time response. This study currently aims to establish the virtual wildfire scenario database in Hong Kong, and realizes the AI-driven wildfire prediction model for suppressing fire spreading. The more detailed analysis and applications of this algorithm will be conducted in the future journal paper.

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