

Disaster Monitoring using Unmanned Aerial Vehicles and Deep Learning

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Abstract: Monitoring and identification of disasters are crucial for mitigating their effects on the environment and on human population, and can be facilitated by the use of unmanned aerial vehicles (UAV), equipped with camera sensors which can produce frequent aerial photos of the areas of interest. A modern, promising technique for recognition of events based on aerial photos is deep learning. In this paper, we present the state of the art work related to the use of deep learning techniques for disaster monitoring and identification. Moreover, we demonstrate the potential of this technique in identifying disasters automatically, with high accuracy, by means of a relatively simple deep learning model. Based on a small dataset of 544 images (containing images of disasters such as fires, earthquakes, collapsed buildings, tsunami and flooding, as well as “non-disaster” scenes), our preliminary results show an accuracy of 91% achieved, indicating that deep learning, combined with UAV equipped with camera sensors, have the potential to predict disasters with high accuracy in the near future.

Keywords: Deep Learning, Disaster Monitoring, Unmanned Aerial Vehicles, Drones, Image Processing.

1. Introduction

Climate change and global warming lead to an increase of hydro-meteorological disasters around the world. According to the International Disaster Database (EM-DAT) (Centre for Research on the Epidemiology of Disasters, 2017), there is a large increase of natural and/or technological disasters in the last two decades, and this increase is expected to continue.

Although preparedness and prevention of disasters are processes far more important than dealing with them after happening, some are inevitable and cannot be easily predicted. Monitoring of possible disasters and fast identification of their occurrence are crucial for mitigating their effects on the physical environment or to humans. Fast alerting and immediate response are important aspects for dealing effectively with them.

Disaster monitoring can be facilitated by the use of unmanned aerial vehicles (UAV) such as drones, which are becoming more and more popular, having various benefits such as small size, low cost of operation, exposure to dangerous environments and high probability of mission success without the risk of loss of aircrew resource. These and other benefits are explained in related work, either independently (Petrides, Kolios, Kyrkou, Theocharides, & Panayiotou, 2017), (Zhang & Kovacs, 2012), or in relation to other remote sensing techniques such as airplanes and satellites (Matese, et al., 2015). UAV have demonstrated

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to compete with traditional acquisition platforms (i.e. satellite and aircraft) due to low operational costs, high operational flexibility and high spatial resolution of imagery.

UAV have been successfully used in scenarios of detecting earthquake-triggered roof-holes (Li, et al., 2015), oil spills and flooding (Luo, Nightingale, Asemota, & Grecos, 2015), victims (Andriluka, et al., 2010) etc. Drones are usually equipped with camera sensors, which could be optical cameras operating over the visible light spectrum, infrared to operate in low light conditions (by detecting emitted heat) or hyperspectral ones, considering particular spectra for events of interest. Images collected by the sensors can then be processed locally by an on-board computer system or sent to control centers for remote processing. In both cases of local and remote processing, *automatic* identification of events of interest (i.e. potential disasters) are important for sensing the disaster while it is happening, taking immediate life-saving actions, either by governmental organizations or the citizens themselves (Kamilaris & Pitsillides, 2014).

A modern, promising technique for image recognition is deep learning or convolutional neural networks (CNN) (LeCun, Bengio, & Hinton, 2015). Deep learning allows computational models composed of multiple processing layers to learn representations of data with multiple abstraction levels. Krizhevsky et al. demonstrated the potential of CNN in the ImageNet large scale visual recognition challenge (ILSVRC) in 2012 (Krizhevsky, Sutskever, & Hinton, 2012). Deep learning seems to have better performance in image recognition tasks (Liu & Wu, 2016), in comparison to common techniques used for analyzing images such as scalable vector machines (SVM) and artificial neural networks (ANN) (Saxena & Armstrong, 2014).

Thus, drones equipped with camera sensors using deep learning models to identify various (possibly disastrous) events constitute a recent practice with high potential (Zeggada, Melgani, & Bazi, 2017), as the identification is fast (i.e. in seconds after the model has learned the problem), flexible (i.e. many events can be identified in once) and scalable (i.e. learning process is continuous and adaptable).

2. Related Work

Related work involves disaster detection by using deep learning techniques. Table 1 lists the relevant efforts, together with their level of accuracy in respect to events' identification. From Table 1, the research efforts in #1 and #2 use aerial photos from UAV.

As Table 1 indicates, deep learning is a recent technique as all the efforts listed have been published in 2016-2017, while accuracy is relatively high (72-99%).

In this paper, our contribution is two-fold:

- Presentation of the (still limited) work in this research field,
- Demonstration of the potential of deep learning and UAV for disaster monitoring based on a small dataset we have created (see Section 3), which contains various events of interest.

In the following section, we describe our methodology to develop this dataset, as well as the analysis performed and preliminary findings.

No.	Disaster	Image source	Accuracy
1.	Fire (Kim, Lee, Park, Lee, & Lee, 2016)	Aerial photos	Human-like judgement
2.	Avalanche (Bejiga, Zeggada, Nouffidj, & Melgani, 2017)	Aerial photos	72-97%
3.	Car accidents and fire (Kang & Choo, 2016)	CCTV cameras	96-99%
4.	Landslides (Liu & Wu, 2016)	Optical remote sensing	96%
5.	Landslides and flood (Amit, Shiraishi, Inoshita, & Aoki, 2016)	Optical remote sensing	80-90%

Tab. 1. Related work.

3. Methodology and Analysis

As a deep learning model, we used the VGG architecture (Simonyan & Zisserman, 2014), pre-trained with the ImageNet² image dataset (Krizhevsky, Sutskever, & Hinton, 2012). VGG constitutes one of many successful” architectures, which researchers may use to start building their models instead of starting from scratch. Other popular ones include AlexNet (Krizhevsky, Sutskever, & Hinton, 2012), GoogleNet (Szegedy, et al., 2015) and Inception-ResNet (Szegedy, Ioffe, Vanhoucke, & Alemi, 2017). Each architecture has different advantages and scenarios where it is more appropriate to be used (Canziani, Paszke, & Culurciello, 2016). We selected VGG as it is easy to use, being automatically integrated to the TensorFlow open-source software library for machine intelligence as a Python class (TensorFlow, 2017). Our aim was to “wire” the VGG architecture (i.e. the pre-trained convolutional layers) with a dense layer, trained with a dataset of aerial photos containing various natural disasters. As such dataset is not publicly available (to our knowledge), we decided to develop our own, by searching Google Images for relevant images, using the following keywords:

[Disaster | Landscape] + "aerial view" + "drone"

² ImageNet Image Database. <http://www.image-net.org/>

where [Disaster] could be *earthquake, hurricanes, flood* and *fire*. We selected only images originating from aerial views, most likely captured by UAV³. We decided to map together images from earthquakes and hurricanes showing collapsed buildings, as well as images from hurricanes, earthquakes or tsunami showing flood. For fire, we selected images showing active flames or smoke. Finally, we selected normal images of various [Landscapes] showing aerial views of *cities, villages, forests* and *rivers*, to examine if and how the deep learning model can actually predict disastrous events. The different groups of images are listed in Table 2.

No.	Image Group	No. of Images	Relevant Possible Disaster
1.	Buildings collapsed	101	Earthquakes and hurricanes
2.	Flames or smoke	111	Fire
3.	Flood	125	Earthquakes, hurricanes and tsunami
4.	Forests and rivers	104	No Disaster
5.	Cities, villages and urban landscapes	103	No Disaster

Tab. 2. Description of our disaster dataset.

Based on this dataset, we trained our deep learning architecture to classify automatically aerial photos according to the image group (i.e. disaster category or landscape) where they belonged. We used 82% (444 images) of our dataset as training data and 18% (100 images) as testing data, dividing our dataset randomly in training and testing. We note that the combination 80-20 (i.e. for splitting training and testing data) showed the best results in our experiments (we also tried 70-30, 75-25, 85-15 and 90-10 with 3-6% less accuracy). Besides, it is the combination highly preferred in the literature too.

The training procedure required 20 minutes on a Linux machine (Intel Core i7, 8 MB RAM), while the testing procedure needed less than 5 minutes for all the 100 images used for testing. Our overall accuracy was 91% and the confusion matrix of the predictions vs. the actual classifications is depicted in Figure 1.

³ We read through some webpages (i.e. 10%) of the automatically identified images, to find out more if they were really taken from drones. The large majority was indeed captured by UAV.

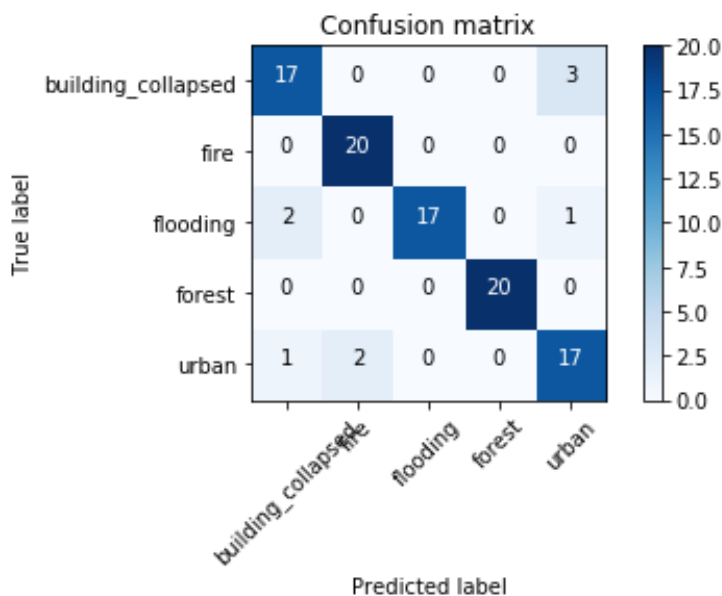


Fig. 1. Confusion matrix of the deep learning architecture based on the disasters dataset.

It seems that the deep learning architecture managed to learn the problem relatively correctly, although it confused flooding events with urban landscapes that involved lakes and rivers or collapsed buildings (3% of the 9% total error) as well as buildings collapsed with urban landscapes (4% of the 9% total error). Except from the relatively high accuracy, there are some other important advantages of using deep learning in image processing. Previously, traditional approaches for image classification tasks had been based on hand-engineered features, whose performance affected heavily the overall results. Feature engineering (FE) is a complex, time-consuming process which needs to be altered whenever the problem or the dataset changes. Thus, FE constitutes an expensive effort that depends on experts' knowledge and does not generalize well (Amara, Bouaziz, & Algergawy, 2017). On the other hand, deep learning does not require FE, locating the important features itself through training. It generalizes well (Pan & Yang, 2010) and it is quite robust even under challenging conditions such as illumination, complex background, different resolution, size and orientation of the images (Amara, Bouaziz, & Algergawy, 2017). Its main disadvantages are that it takes (sometimes much) longer time to train, and it requires the preparation and pre-labeling of a dataset containing at least some hundreds of images. However, after it does learn the problem under consideration, its testing time efficiency is much faster than other methods like SVM or KNN, even when considering hyperspectral cameras/images (Chen, Lin, Zhao, Wang, & Gu, 2014).

4. Conclusion

In this paper, we have presented the state of the art work related to the use of deep learning techniques for disaster monitoring and identification, based on aerial photos captured by UAV. We have also created a small dataset of 544 images, creating a deep learning model based on VGG, in order to show the potential of this technique in identifying disasters automatically and with high accuracy. Based on our small dataset, accuracy has been 91%. However, the authors expect that a larger dataset would effectively reduce the error (possibly reaching more than 95% accuracy) and that these preliminary results indicate that the CNN architecture used (and deep learning in general) has the potential to predict disasters with high accuracy in the near future. Challenges in the use of UAV for disaster monitoring still exist, such as their limited computational capability, low energy resources and regulation issues for flight allowance, which hinder real-time data processing, area coverage and flexible use. Nevertheless, the opportunities combining UAV with deep learning techniques are large, as deep learning can provide high-accuracy event identification in real-time without requiring much processing capacity.

Finally, UAV with deep learning could enable better disaster modelling, especially when combined with geo-tagging of the events identified and geospatial applications. This would facilitate the integration of relevant actors (i.e. action forces/authorities, citizens/volunteers, other stakeholders) in disaster management activities with regard to communication, coordination and collaboration.

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