UAV Surveying for Environmental Studies

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SUMMARY

Unmanned aerial vehicles (UAVs) have become a proven environmental monitoring technology and can fill the gap between conventional field surveying and satellite remote sensing for data collection. Especially it plays an increasingly important role in acquiring data for smart and precision agriculture, transportation and natural disaster management such as flooding to support emergency-response planning during the event and assessing damage in spatial and temporal measurements. UAVs can acquire high-resolution imagery or video with flexibility in the frequency and time of data acquisition to map and monitor flooding. In addition, their versatility, adaptability, and flexibility make them an essential tool for flood study. In contrast, their short flight endurance and small-scale coverage remain areas of weakness for their wide-scale implementation in remote sensing. The presentation discusses integrating deep learning and geospatial methods to map floods using UAV imagery and ground survey data. The method was implemented and tested using UAV data acquired over the city of Princeville, North Carolina during Hurricane Matthew and Hurricane Florence. This approach achieved 98% accuracy in mapping inundation areas and demonstrated that UAVs could be effectively used for accurate and timely flood mapping.

1. INTRODUCTION: APPLICATION OF UAV FOR ENVIRONMENTAL STUDIES

Our environment faces several problems, including agricultural (shortage of food and energy, weeds, and crop disease) and flooding globally. Unfortunately, many of these have worsened with time, resulting in a severe environmental crisis (Li et al., 2019). Therefore, it is becoming increasingly essential to raise awareness of these problems and take action to reduce their negative impact. Collecting information about the environment is a key step during each study in the field of environment. However, obtaining this information is frequently difficult because of the timing, cost, and inaccessibility of a particular area for the field survey. Recently, UAVs have emerged as power technologies, allowing researchers to obtain spatial data products suitable for rapid mapping and analysis of environmental processes. Unlike satellite and other data acquisition technologies, they can deliver high temporal and spatial resolution imagery of specific landscape features for accurate and rapid assessment. UAVs can be flown with different sensors that can be configured to detect a variety of potential data requirements, especially for areas with complex urban landscapes and inaccessible regions due to hazardous environments. Additionally, UAVs have lower costs with frequent revisit operations that are affordable and beneficial for monitoring and inspecting infrastructures damaged by flooding. However, their short flight endurance, low payload capacity, and small-scale area coverage are the drawbacks of using them for wide-scale implementation in flood mapping.

For example, UAVs have been used in precision agriculture which involves the use of remote sensing techniques and other technologies for data collection and assessment with a minimum of human assistance. In addition, remote sensing UAV systems have been applied in the agricultural industries in capacities such as weed mapping, monitoring and estimation of vegetation yield, irrigation management, crop spraying, and monitoring of vegetation health and detection of diseases (Tsouros et al. 2019; Hashemi-Beni and Gebrehiwot 2020, Dorbu et al., 2021; Hashemi-Beni et al., 2022). The system was used by Allred et al. (2018) to identify drainage pipes on farms to ensure control of the amount of water on a field. Crop production and plant health status can be determined by the use of a LiDAR sensor mounted on a UAV. The images retrieved from LiDAR were used for the textural analysis of total plant volume and soil surface estimation for some specific crops (Christiansen et al., 2017). Determination of water stress and health status of pomegranate crops in Greece was achieved through the use of UAV to capture thermal and multispectral information from the study field (Katsigiannis et al. 2016).

UAVs are used in transportation for traffic monitoring, traffic safety, and highway infrastructure management (Outay et al., 2020). UAVs' use in road safety includes overall surveillance of road networks, gathering data for a quick and detailed traffic incident, and risk assessment. Risk assessment is performed at risk-prone locations to mitigate possible accidents. It is depicted by the thorough analysis of vehicle trajectories and maneuvers pulled from UAV-based video analysis (Mehmood et al., 2018; Zhang et al., 2013; Gu et al., 2019). On the other hand, the adoption of UAVs for taking detailed and quick data where there was a traffic incident is the other fast-growing research area (Ardestani et al., 2016, Raj et al., 2017; Pérez et al., 2019; Škorput et al., 2020). This research focuses on generating a UAV-based scene diagram mapping, 3D reconstruction of the accident scene, and enhancing UAV image processing. The traffic monitoring domain also adopts UAVs mainly through automated extraction of traffic parameters expressing the traffic flow state (speed, count, flow, and density of vehicles). Various tools and algorithms have been developed that help estimate traffic parameters from video footage captured from UAVs (Braut et al., 2012; Wang et al., 2014; Zhang et al., 2019; Ahmed et al., 2020). In addition, UAVs have been widely used in two main areas of infrastructure management, i.e., bridge inspection and monitoring and pavement distress recognition (Otero et al., 2015; Gillins et al., 2016; Seo et al., 2018). Multi-rotor UAVs are used to detect and inspect defects, cracks, and signs of distress in pavement and bridges, delivering promising results through easing the task and bringing economic advantages.

In flood hazard mapping and monitoring applications, UAVs have been used mainly to acquire accurate and up-to-date spatial information on the flooding environment and monitor the situation with high precision and high sampling frequency (Hashemi-Beni et al., 2018; Karamuz et al., 2020). In addition, the fast development of UAV technology creates the opportunity for quantitative estimation of hydraulic data such as flood extent areas(Feng et al., 2015; Gebrehiwot et al., 2019), vegetation flood detection (Hashemi-Beni and Gebrehiwot, 2021), and water level estimation (Gebrehiwot and Hashemi-Beni, 2021; Wu et al., 2020). UAV Synthetic Aperture Radar L-band data can be utilized to map floodwater extent under dense vegetation ((Wang et al., 2022).

Accurate flood mapping a vital to get meaningful information to support effective emergency response, planning, and mitigation. It also helps to manage floods effectively and prevent loss of human life and property (Wang et al., 2019). Over the past decades, several computational approaches have been developed for mapping floods using remote sensing data using high-resolution data, including UAV imagery. In recent years machine-learning algorithms, such as support vector machines (Rahmati et al., 2020), artificial neural networks (Falah et al., 2019), and random forests (Wang et al., 2019), have been successfully applied for flood detection and mapping tasks and showed promising results. Moreover, these algorithms are advantageous in data-scarce areas. However, they are highly dependent on feature engineering, one of the time-consuming processes in machine learning. The drawbacks of conventional machine learning algorithms for big data analysis have recently been overcome by using deep learning, which can automatically extract image features directly from the input data. One of the most popular deep-learning approaches commonly applied to imagery is the convolutional neural network (CNN). It has been used for flood extent mapping and has shown great potential (Gebrehiwot et al., 2019; Gebrehiwot et al., 2020; Hashemi-Beni et al., 2021; Gebrehiwot et al., 2021).

This presentation discusses integrating deep learning such as DeepLabV3+ and geospatial methods for flood mapping using UAV imagery and ground survey data.

2. METHODOLOGY

2.1 Deep Learning Model Architecture

Our approach in This study fine-tunes a pre-trained deep learning model called DeepLabV3+ (Figure 1). This model is an encoder-decoder network created by the Google research group (Chen et al., 2018) and includes atrous convolutions to overcome fully convolutional neural networks (FCNs) (Long et al., 2015) issues related to the excessive downsampling due to consecutive pooling operations in the model. Furthermore, DeepLabV3+ has spatial pyramid pooling and encoder-decoder structure which helps encode multiscale object information through multiple atrous convolutions with different rates. As a result, the encoder and decoder structures can more accurately capture an object's boundary with this information.

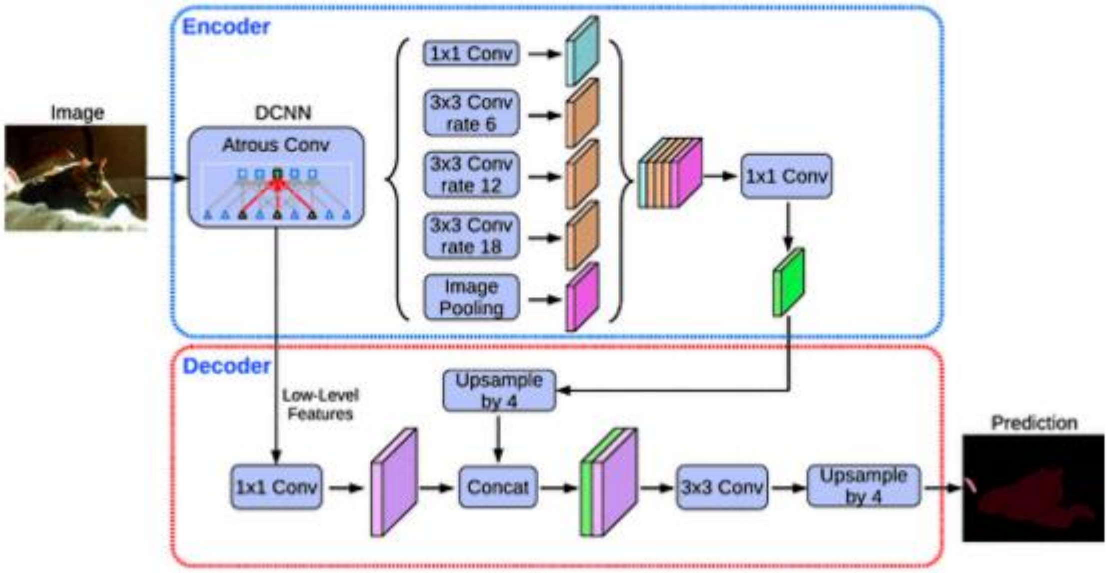


Figure 1. DeepLabV3+ architecture (Chen et al., 2018)

Instead of ResNet101, this model uses Xception as the backbone of the encoder. The input image is down-sampled by a factor of 16. It also uses 1 × 1 convolutions applied before concatenating to reduce the number of channels of low-level features.

2.2 Study Areas and Data

A flood-prone area was selected for the research as a study area: Princeville, NC, USA. This town is located along the Tar River in Edgecombe County in North Carolina (Figure 2). According to the United States Census Bureau, Princeville has a total area of 6.4 km2. Over the past years, Princeville has gained national attention because of its history of flooding and storm flooding due to hurricanes. For example, Hurricane Matthew hit North Carlina and devastated the town of Princeville; flooding left 80% of the city underwater. In addition, Princeville's location along the Tar River makes it particularly vulnerable to severe damage associated with floods. During Hurricane Matthew, North Carolina Emergency Management collected UAV imagery over Princeville using a Trimble UX5 fixed-wing UAV for flood assessment purposes. Each image has three bands (RGB) with 2.6 cm spatial resolution and 10,816 m^2 land coverage.

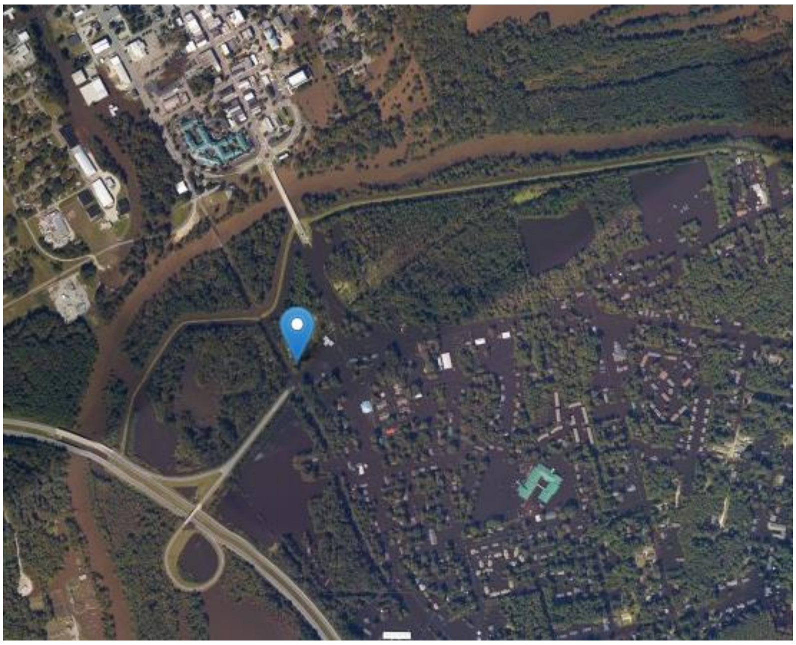


Figure 2. Study area. Princeville during Hurricane Mathew (Source: NOAA)

2.3 Data Processing

The study follows the following procedures to create a flood map using UAV imagery using deep learning.

2.3.1 Data preparation

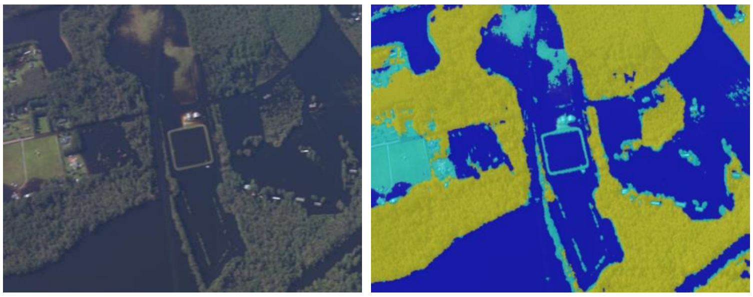
The study used 150 UAV images labeled by Gebrehiwot et al. (2019) for training the model. These images were annotated into three classes: (1) flood, (2) non-flood, and (3) vegetation. The study also used the median frequency balancing technique to deal with the class imbalance problem that exists in the annotated dataset. This technique works by assigning the weight to each class in the loss function by the ratio of the median of the class frequencies calculated on the entire training set divided by the class frequency. Finally, georeferencing is done using eight Ground Control Points (GCPs) in our study area. Note that increasing the number of GCPs can improve the accuracy of the final outputs.

2.3.2 Training and testing

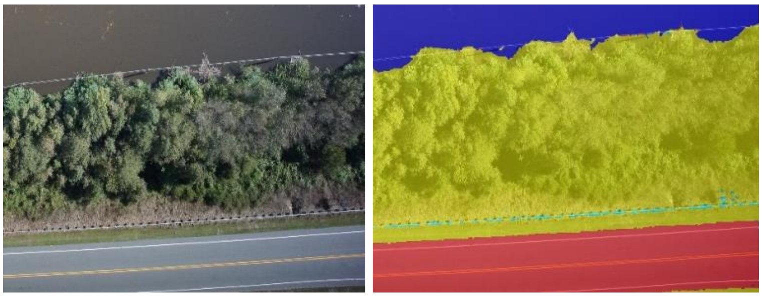
In this stage, first, we modified the pre-trained model's classification layers and replaced them with three classes of output layers for flood detection purposes. Then, to train DepLabV3+, the 10-fold cross-validation approach is used to avoid overfitting and improve the accuracy of the results. For that, the study partitioned the training data (150 images) randomly into 10 equal subsets, called folds. The nine folds were used as a training set at each run, and the remaining one-fold was used as a validation set to measure the segmentation errors. The above procedures were repeated ten times, using a different fold as the testing set each time. Finally, the average error from all ten folds is used to estimate the segmentation errors. The classification layer is trained from scratch during this stage, while others were initialized from the DepLabV3+ model and updated by the back-propagation rule.

3. RESULTS

This section presents the qualitative and quantitative results obtained by the network. Sample classification results of DeepLabV3+ are shown in Figure 3. The overall accuracy and kappa index achieved based on our approach are about 96.5%% and 0.92, respectively. Furthermore, the model achieved 98.9% in detecting the flooded area from the UAV imagery. As we have seen from the results, DeepLabV3+ effectively detects floods from the input data. In this study, Python. MATLAB and ArcGIS were used for data processing.



(a1) (a2)



(a1) (a2)

Figure 3. Sample classification results. (a1-a2) Test images; (b1-b2) Results

4. CONCLUSIONS

technology is a powerful data collection platform to quickly deliver high-resolution imagery for damage assessment and effective emergency response activities. This study investigated integrated deep learning with a geospatial approach to detect and map floods using high-resolution UAV imagery. For that, the DeepLabV3+ model is modified and trained to extract floods. The results showed that DeepLabV3+ is very suitable in flood mapping with an overall accuracy of 96.2% and a Kappa index of 0.92. Overall, the results showed that deep earning could be effectively used to ma floods using a high-resolution UAV dataset.

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