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V. M. Sineglazov, Dr.Sci.(Eng), Prof., A. A. Komapov
(National Aviation University, Ukraine)

Hybrid Approach for Forest Fire Search

A new approach of forest fire search based on satellites and unmanned aerial vehicles data processing is proposed. For processing video images, it is supposed to use convolutional neural networks.

More than 40,000 hectares of forest fund territories are annually covered by forest fires in the Ukraine. Forest fires occur mainly as a result of careless handling of fire. The share of fires of natural origin in comparison with fires caused by anthropogenic activities is small. So it is very important to detect forest fires in time. Detecting a fire at an early stage before it turns into a catastrophic event is critical to neutralizing fires and saving lives and property. Due to the rapid spread of fire, it is important to detect it at the stage of the first manifestations of fire.

Use of satellites and UAVs for information collection.

Satellite systems, fixed remote cameras, and manned aircraft are common technologies for remote fire monitoring, but these technologies have a number of limitations in terms of cost, temporal, and spatial resolution. Although the coverage of the territory when using the satellite monitoring system is quite large, the accuracy and timeliness of detecting a fire or its previous state only by processing data from satellites is currently insufficient. On the other hand, the use of unmanned aerial vehicles (UAVs) for monitoring purposes requires a fairly large number of them due to a small viewing area, although with a higher resolution than conventional weather satellites.

The joint use of data from satellites and UAVs will allow, on the one hand, to obtain an approximate reference to a more or less localized problem area of the territory where to direct the UAV, which will allow positioning and identify the problem at the required level of accuracy.

One of the problems in solving applied problems based on satellite data is that most of them have a low spatial resolution. For example, in [1], the authors used satellite products with a spatial resolution of 250 m to 1 km to detect smoke in a forest fire using a backpropagation neural network. The use of low spatial resolution data is due to the fact that they make it possible to estimate the spread of smoke during a fire due to their frequent updating and large coverage of the surveyed area once. However, due to the low spatial resolution, it is difficult to detect active fires and their spread.

Analysis of available methods to increase the resolution of images / images.

The problem of increasing the spatial resolution of an image (super-resolution) arises in many applied areas, both image processing and video [2]. Spatial resolution is characterized by the density of pixels in the image and is measured in pixels per unit area [2]. Image spatial upscaling techniques can use multiple low spatial resolution images to create a single high resolution image, or operate solely on a single low spatial resolution input image.

With the beginning of the development of methods and models of deep learning for solving various applied problems, the problem of increasing the spatial discrimination of an image began to be solved also using deep learning methods. The most suitable methods today are those based on the idea of using Generative Adversarial Networks (GANs) to increase image resolution. These networks consist of two neural networks, a generator and a discriminator, and are trained without a teacher. The idea of the model is as follows, one neural network (generator) generates an image of the highest difference, while the other neural network (discriminator) will try to guess whether this image is genuine or generated by the network. Model training ends when the first network has learned to generate "real" high-resolution images that the other network cannot distinguish from real ones. This approach was proposed in [3] under the name Super Resolution Generative Adversarial Networks (SRGAN).

Detecting a fire early, before it becomes a disaster, is critical to preventing catastrophic fires and saving lives and property.

Several methods of visual fire detection are known. Color model movement, spatial and temporal characteristics are mainly used because fire has very specific characteristics compared to another object. Nearly all of the proposed methods follow a similar detection pipeline, i.e. first find moving pixels using background subtraction and then apply a color model to find areas of fire color. These areas are further analyzed spatially and temporally to detect irregular and flickering fire characteristics. Since motion is the dominant feature, these methods only work with fixed cameras, i.e. in surveillance scenarios. To obtain reliable results, it is advisable to use deep neural networks (convolutional) to extract significant features from the data and train discriminatory classifiers to detect fires. Since fire is a non-rigid object with dynamic shapes, most approaches use motion and color features [4], [5] or spatiotemporal features [6], while background subtraction is widely used to improve accuracy and reliability [7]. In addition, most of the work involves fire detection in the observation scenario, i.e. the camera is installed in a fixed location to detect flames and/or smoke, which is unacceptable when using a UAV. Therefore, in this work, we consider the structural-parametric synthesis of hybrid convolution neural networks for the analysis of dynamic visual scenes, for example, when the camera is mounted on a UAV, which, in turn, makes background subtraction and motion analysis difficult.

The proposed approach is to perform the following steps.

1) Obtaining moving pixels and areas [7], [8].

2) Extraction of possible areas of flame and/or smoke using a color model, such as HIS, which is used in [7], [8].

3) Further analysis of candidate regions, e.g. foreground area analysis [8], dynamic fire behavior analysis [5], [9].

Results.

The NASA Space Apps Challenge dataset with and without fire photographs was chosen to build, train, and validate the convolutional neural network and the Grad-CAM algorithm.

In general, the sample included:

- 700 images of fires, some of which contain heavy smoke;
- 200 images of nature without fires.

Conclusion.

The problem of detecting forest fires is considered. The necessity of detecting fires using satellite information and information received from the UAV from infrared sensors and a video camera is shown. The results of information processing with the help of the YOLO neural network detector are presented.

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