Early Forest Fire Detection Using Drones and Artificial Intelligence

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Abstract – **Forest and urban fires have been and still are serious problem for many countries in the world. Currently, there are many different solutions to fight forest fires. These solutions mainly aim to mitigate the damage caused by the fires, using methods for their early detection. In this paper, we discuss a new approach for fire detection and control, in which modern technologies are used. In particular, we propose a platform that uses Unmanned Aerial Vehicles (UAVs), which constantly patrol over potentially threatened by fire areas. The UAVs also utilize the benefits from Artificial Intelligence (AI) and are equipped with on-board processing capabilities. This allows them to use computer vision methods for recognition and detection of smoke or fire, based on the still images or the video input from the drone cameras. Several different scenarios for the possible use of the UAVs for forest fire detection are presented and analyse in the paper, including a solution with the use of a combination between a fixed and rotary-wing drones.**

Keywords – early forest fire detection platform, drones, UAVs, artificial intelligence, computer vision

I. Introduction

The most up to date information on the current fire season in Europe and in the Mediterranean area is provided by the European Forest Fire Information System EFFIS [1]. Each year this institution provides annual report on the forest fires in Europe, the Middle East and North Africa. According to the latest report, which they provided for 2017 [2], the dramatic effects of wildfires have caused damages of over 1.2 million hectares burnt natural lands in the EU and killed 127 people, including fire fighters and civilians. Over 25% of the total burnt area was in the Natura 2000 network, which destroyed much on the efforts of the EU countries to preserve key natural habitats and to save the biodiversity of Europe for the future generations. The same report says that these fires caused estimated losses of around 10 billion euros.

Despite these large numbers, EFFIS informs also that the report is showing a decrease in the number of fires, compared to the number of fires, which occurred annually during the last decade. This decrease can be explained with the more severe actions and sanctions to the people that caused the wildfires and with the introduction of more advanced technical solutions for early detection of fires. Obviously, the fight against fires can mitigate the damages, but the numbers, which represent the burnt area and the human lives, are still huge. This reason presents the necessity to constantly develop, implement and upgrade the solutions and systems for fire detection.

The most important factors in the fight against forest fires include the earliest possible detection of the fire event, the proper categorization of the fire and fast response from the firefighting departments.

The aim of the proposed platform is not only to use modern technologies, but also to improve the above-mentioned factors by reducing the fire detection time, by minimizing the false alarms and by issuing of timely responses and notifications to the fire services in case of real forest fires.

In the paper, we discuss the proposed platform for early forest fire detection, which involves two types of UAVs – a fixed-wing drone and a rotary-wing drone. Both UAVs will be equipped with cameras, which will be optical, thermal or both. The fixed-wing drone will constantly patrol the monitored area and will observe the territory below. Since this drone will fly at medium altitude (350 m to 5500 m), it might report false alarms because of the altitude or the lack of clear visibility. If the fixed-wing UAV detects a fire, it will trigger an alarm, which will activate the rotary-wing drone. The rotary-wing drone will then closely inspect the area, where the fire is suspected to have occurred, by using the GPS coordinates provided by the patrol drone. The role of the second drone is to either confirm or reject the alarm bases on its close observation of the area and will then go back to its base station. It will not permanently monitor the targeted area. The reason to use a second drone is to reduce the number of false-positive alarms as the rotary-wing drone will fly at much lower altitude (10 m to 350 m) compared to fixed-wing UAV and will have better and more detailed visibility of the area. If the fire is confirmed, another alarm will be triggered by the rotary-wing drone and the ground level teams and the fire protection departments will be informed.

The platform is completely automated since both drones have on-board computers and processing capabilities. They can detect fires based on the data captured by their thermal cameras and they can process this data without the need for centralized computing engine. In addition and to further improve the platform, we have planned to implement artificial intelligence by allowing the drones to make fire predictions based on computer vision techniques. In order to implement this artificial intelligence solution we will rely on and use neural networks.

The neural networks are currently a very hot topic in the computing systems, because of their ability to "learn" how to perform tasks by considering examples, without being programmed or instructed to follow specific rules. The neural networks are inspired by the biological neural networks that constitute human brains.

II. Conceptual Model of a Platform for Early Forest Fire Detection

This section describes the conceptual model of a platform for early forest fire detection that is going to be implemented under an international project entitled "Forest Monitoring System for Early Fire Detection and Assessment in the Balkan-Med Area" SFEDA. The project was designed with the intention to create a transnational cooperation among the countries in the Balkan-Mediterranean Area and more specifically between Bulgaria, Greece and Cyprus. The goal of the project is to achieve the proof of the effectiveness of the technology and the implementation of a system for early detection and prevention of wildfires targeting a positive environmental impact and climate change resiliency. The purpose of the project is to apply and demonstrate three differently implemented platforms for wildfire detection in three forests in the different countries (Bulgaria, Greece and Cyprus) and by sharing experiences and expertise to promote and strengthen the cooperation of the cross-border partners and improve the infrastructure for fire surveillance. All of the three developed platforms will be part of one system under the name THEASIS. The focus of this paper is to investigated the possibilities and development stages of the platform for early forest fire detection, which is going to be implemented by the University of Ruse on the territory of National Park "Rusenski Lom" near Ruse, Bulgaria.

A. Model of the platform for early forest fire detection

Fire detection systems for outdoor environment could be implemented by using specialized cameras, which are able to capture multispectral images. The biggest challenge that arises in these setups is where to place the camera(s) in order to have the best view on the observed territory. Since these systems have their limitations, since they provide stationary point of view, we have decided to investigate a new approach. The platform that is proposed in this paper will use unmanned aerial vehicles, which are going to patrol above the desired territory and will constantly observe for fire-related events. The drones will be equipped with specialized optical and thermal cameras and will be able to capture video or still images. In addition, the drones will also have constant bidirectional connection to the base station and they will be able to provide a feedback about their observations (Fig. 1).

Figure 1. The main part of the platform for early forest fire detection with use of fixed wing and rotatry wing UAVs

The platform will consists of two types of UAVs, which will fly at different altitudes as shown in Fig. 1. The terrain of National Park Rusenski Lom involves a steep canyon along the river covered by very dense forest vegetation. The altitude variates from the ground level (0 meters) at reverbed to 150-170 meters at the highest points of the canyon. This makes the location very difficult for observation. To provide an overall overview of the park and to observe the difficult terrain we have decided to use a fixed-wing UAV with vertical take-off and landing. The drone will fly at medium altitude and will provide long-term observations of the forest area of the national park. The fixed-wing UAV will patrol, following a specific pattern, above the forest area and if it detects increased temperature levels by its thermal camera sensor it will immediately raise an alarm and will send the GPS coordinates of the area to its base station.

In order to reduce the false alarms we are planning to use second drone that will confirm the detection of the fire. For that purpose, smaller drone with rotary wings will be used. It will fly to the location of the potential forest fire by using the GPS coordinates provided by the fixed-wing drone and it will provide close inspection. To have a better view of the observed territory the rotary-wing drone will fly at lower altitude in the range from 10 meters to 350 m.

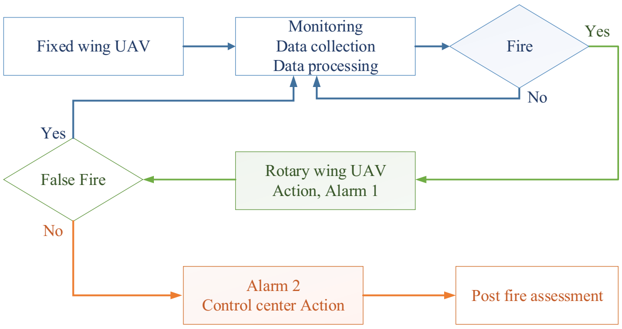

Figure 2. Flowchart of the operating principle of the early forest fire detection platform

The flowchart of the operating principle is provided in Fig. 2. As it can be noticed, the system implements three stages for fire detection. The first stage (coloured in blue) presents the role of fixed-wing UAV. To have a wide-angle view this drone will fly at an altitude from 350 meters up to 5500 meters. If a fire is detected, the rotary wing drone starts its operation (green colour) by inspecting the suspected area from low altitude. Its role is to confirm the fire. If the fire is real then the drone informs the ground level firefighting services (orange colour) and continues its function to assist ground level services. The second drone can be used also for post fire assessment. Since both drones are going to be equipped with specialized multispectral cameras, a thorough analysis could be made. Images captured by multispectral cameras can be processed and used for generating the NDVI (normalized difference vegetation index) maps of the terrain. NDVI is a simple graphical indicator that can be used for fire damage assessments.

B. Planned equipment

During the last decades, unmanned aerial vehicles have been widely used in different areas – military, agriculture, photography, fire service and many others. These aircrafts are mainly classified into two types - fixed-wing UAVs and rotary-wing UAVs with both types having their advantages and disadvantages. Since the developed platform is going to use both types of UAVs, it will also take advantage of their benefits. The fixed-wing UAVs have several advantages, such as higher cruising speed and higher flight altitude, high flight efficiency, long endurance and range. Rotary-wing UAVs on the other hand are more flexible, since they can take-off and landing vertically no matter of the type of environment. Nowadays there are hybrid drones that combine the benefits of both.

After making a thorough analysis, we have decided to use ALTi Transition-F vertical take-off and landing (VTOL) fixed-wing UAV [11], which together with its ground control station are shown in Figure 3. The ALTi Transition-F is class leading VTOL fixed-wing unmanned aircraft, developed as an ultra-compact, efficient and affordable system with the ability to take-off and land vertically almost anywhere with endurance of up to 12 hours and unmatched real world performance, according to its manufacturer [11]. The dimensions of the aircraft are 3000 mm wingspan, 2300 mm length and 525 mm height and its maximum take-off weight is 16 kg. The main wings are removable, which significantly reduces the size and allows for rapid deployment, transport and storage. Depending on the payload, the endurance of the UAV varies, for example with 2.8 kg payload the endurance time is about 10 hours. The high endurance is due to the enhanced aerodynamic design with ultra-lightweight carbon fuselage.

Figure 3. ALTi Transition VTOL aircraft and its ground station [11]

The telemetry and control links between the drone and its ground station are completed using two channels for data communication. One of the channels is duplex for simultaneous bidirectional control and data transfer, while the other is used as radio channel for high definition real time video streaming. The second channel is set to work in simplex mode for downstream video transfer. That video is going to be used for analysis of the observed area.

- Zoom: x20 + x2 digital (total x40);
- HFOV: 60° WFOV – 3° WFOV – 1.5° DFOV;
- Thermal Resolution: 640x480;
- Pitch FOR: -45° to + 135°;
- Roll FOR: -180° to + 180°;
- Weight: 250 grams
- Dimensions: Diameter = 64 mm, Height=94 mm.

Figure 4. The NightHawk 2 camera and its parameters [12]

The high altitude drone will be equipped with NightHawk 2 EO/IR camera with 20x zoom and thermal resolution of 640x480 as shown in Fig.4. This camera is able to capture different temperature levels, and once the UAV detects increased or abnormal temperature levels it will immediately raise an alarm and will send the GPS coordinates of the problematic area to its base station. The camera weighs only 250 grams, which will not cause significant downgrade in the drone performance and will not reduce its endurance.

Since the drone will fly at higher altitude, the view distance from the camera to the ground surface could be significant and this could lead the reporting of many false alarms. In order to minimize their number a second drone with rotary-wings will be used. The use of a rotary-wing UAV will provide the possibility for close inspection. It will be equipped with higher quality camera and it fly at lower altitude for better visibility. To confirm the detection of the fire we have planned to use as rotary-wing UAV the DJI Matrice 210 RTK drone, which is shown in Fig. 5. The advantage of the Matrice 200 series of drones it the fact that they are IP 43 certified, which means that they can withstand humidity and can fly in foggy or rainy conditions.

Figure 5. DJI Matrice 210 RTK with dual gimbal [13]

The reason to choose this drone is its dual downward gimbal, which allows it to carry two cameras. The drone can be equipped with one IR and one standard/zoom camera. We are planning to use the Zenmuse X4S 4K optical camera, which comes with a 20-megapixel 1-inch sensor, with maximum ISO of 12800 and increased dynamic range. The second camera on the drone will be Zenmuse XT2 thermal camera, which integrates a high-resolution FLIR thermal sensor and a 4K visual camera with good stabilization and processing technology for quick transformation of aerial data into powerful insights.

As further improvement of the platform, we have planned to implement artificial intelligence by allowing the drones to make fire predictions based on computer vision techniques. In order to implement image recognition a computing engine is required. Another benefit of the drones is the fact that they can be equipped with high performance on-board computers, which enables their developers to transform these aerial platforms into truly intelligent flying robots that can perform complex computing tasks and advanced on-board image processing. Example of one such high-performance embedded computer, specially designed for the DJI series of drones is the DJI Manifold [14]. The Manifold has the processing power of a graphics card for PCs and supports DirectX 11 and Open GL 4.4. It also supports NVDIA CUDA, which allows it to be used for processing in many AI applications, including for computer vision and deep learning. This means that the developed aerial platform will perform on-board image recognition and could raise an alarm if it detects smoke or fire in the images, which it captures and processes. This will lead to decreased fire detection and reporting times.

C. *Development stages*

There are three main development stages for bringing the platform for early forest detection in action. They include the planning, the designing and the building of the system. In the implementation process, most of the project team will be involved with distributed tasks. The planning stage involves meetings of the team, discussions and building of a conceptual model, as well as defining the specifications of the equipment that is going to be purchased. The designing stage involves prebuilding tasks, which include clarification of the conceptual model, purchasing of the equipment and additional discussion and talks. The last and most difficult stage from the development process is the actual building of the system. This stage involves actions that are separated in two main tasks: preparation of the system components and laboratory testing of components. These actions must be implemented before the actual use of the system. The preparation of the system components involves tasks as components testing, assembling of the components, camera testing, DSP module testing, GPS module tests and also troubleshooting of the system, while the laboratory testing involves practical tests of the UAVs and their components and laboratory testing of the fire detection system.

In addition, the system could be improved by implementing computer vision (CV) techniques [3, 4, 5 and 6]. For this purpose, we have used artificial intelligence concepts for training a neural network to recognize smoke in images taken from the drone. Before providing more details about our CV implementation, we have included some basic information about artificial intelligence, neural networks, deep learning and the connection between them. Smoke detection using images can be defined as binary classification problem, in which we have as input an image, which has to be classified as containing smoke or not. If it is classified as image, which contains smoke, the reported output value is one. Otherwise, the output value is zero.

III. Artificial Intelligence, Neural Networks and Deep Learning

Artificial intelligence has become extremely popular in the recent years as it has the ability to perform tasks, which are inherent to a human mind. Artificial intelligence, sometime referred to as machine intelligence, is implemented by using neural networks.

The neural networks are specialized computer models, which can be trained to perform different tasks. They are used for classification of images, speech recognition, translation of texts and more complex tasks, like control of autonomous vehicles, etc. There are several types of neural networks, but the most widely used for image detection and computer vision are the convolutional neural networks [7, 8]. They consists of input layer, hidden layers and output layer of interconnected neurons, as shown in Fig.6. Depending on the number of hidden layers, we have machine learning methods (with just one hidden layer) and deep learning methods (with more than one hidden layers), in terms of methods for training the neural networks. For example, Fig. 6 presents a deep neural network, since it has two hidden layers.

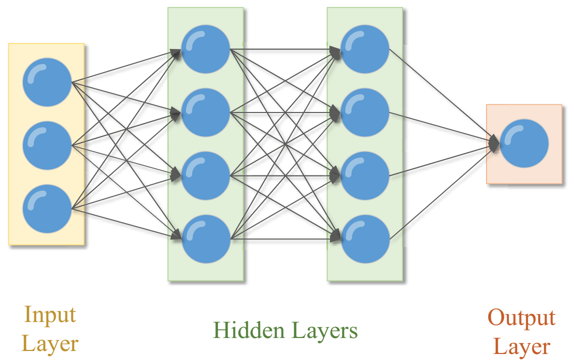

Figure 6. Example of neural network with two hidden layer

Input neurons represent the data, which is going to be used for training. For example, if an input is an image the input neurons might represents the values for each pixel. Neurons hidden in the middle layers usually perform mathematical computations. The links between neurons are parameterized with weights, which dictate the importance of the input value.

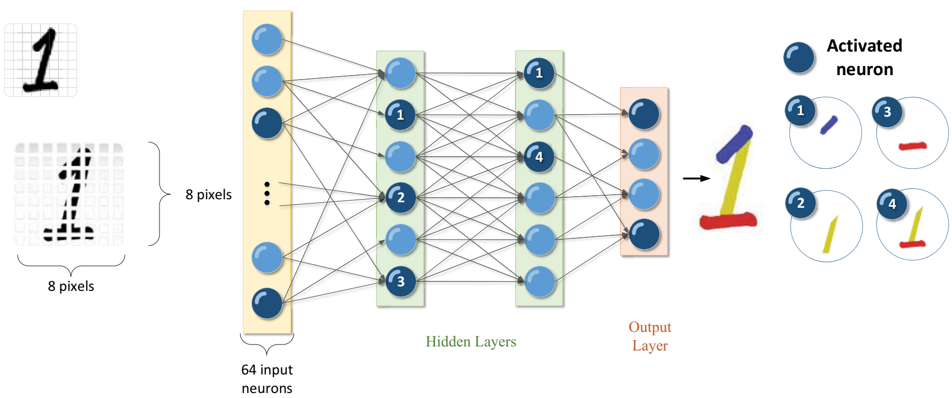

Figure 7. Image detection principle performed by neural network model

All of the weight are randomly set, but during the learning process, they can change in order to fine-tune the loss function. Each neuron in the network has activation function, which is extremely important for the final result.

The image detection principle is shown on Fig.7. This example reveals how neural network can recognize a digit from a given image with resolution of eight pixels by eight pixels (the low resolution is given for simplicity). All of the image pixels are passed to the model as input neurons. Depending on the weights assigned to the links, different sets of hidden layers might be activated. The uniqueness of the activated neuron defines the output. Before performing such complex tasks, each neural network must be trained. The training can be describes as a process of finding the weights of the links between the neurons, where the loss function is minimized. The training could be supervised and unsupervised.

Machine learning systems learn how to combine inputs to produce useful predictions on never-before-seen data. In the supervised learning approach, the machine learning algorithms construct models by examining many examples and attempting to find a model that minimizes the loss. The loss is defined as the difference between the actual value and the predicted output. The loss function is minimized by changing the values of the weight of the links between the neurons. Supervised learning can be used on both structured and unstructured data. Simple machine learning algorithms work well with structured data, but when it comes to unstructured data, their performance tends to be low. This is where neural networks have proven to be so effective and useful. They perform exceptionally well on unstructured data. Structured data is well defined input that has meaningful values, while the unstructured data refers to things like audio and images, where the goal is to recognize what is in the image or what the text is (like object detection). Here the features might be the pixel values in an image and it is not clear what each pixel of the image represents by itself in the image and therefore this falls under the unstructured data.

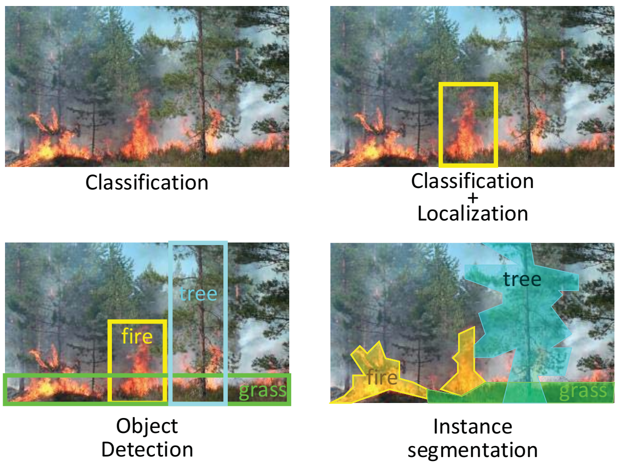

Figure 8. Comparison between image classification, object-detection and instance segmentation

Based on the discussion from above, the system for early forest fire detection can be categorized as binary classification problem. The image classification models classify images into a single category, usually corresponding to the most salient object. In the forest, the most salient object could be a tree, a river, a bush or even the forest itself. For this reason, the image classification as a particular solution could not be effective. Assigning a label with image classification models can become tricky and uncertain. Object detection models are therefore more appropriate to identify multiple relevant objects in a single image or in our case just one the smoke. There is one more advantage of object detection and that is the ability to localize the object in the image. Comparison between image classification, object detection and instance segmentation is provided in Fig.8.

IV. Building of a Computer Vision Neural Network for Detection of Smoke in Images

In order to improve the platform and to implement the smoke detection functionality from still images it is first necessary to train a network to learn how to recognize the smoke. There are several steps to do that. To utilize the object detection algorithms we first need to define the input data. The input data, also known as dataset is a set of images, in which smoke is present, marked and labelled. The dataset must be separated in two parts – for training and for testing. This is the main requirement to avoid the so-called overfitting. Sometimes after training, neural networks are performing very well with the training data (or very similar images) and not so well on new images. This is called overfitting the model and it is illustrated in Fig. 9. Actually, there are two things to do with the data. The first one is to estimate the parameters for the machine learning methods and the second one is to evaluate how well the machine learning methods work. A bad approach would be to use all of the data to estimate the parameters (i.e. train the algorithm) because then there would not be any data left for testing the method and in that case, the model might become overfitted. Reusing the same data for both training and testing is also not a good idea, because in order to evaluate the model it is needed to know how the method will work on data, which was not used for its training. A good separation of the dataset is about 75% of the images for training and 25% for testing.

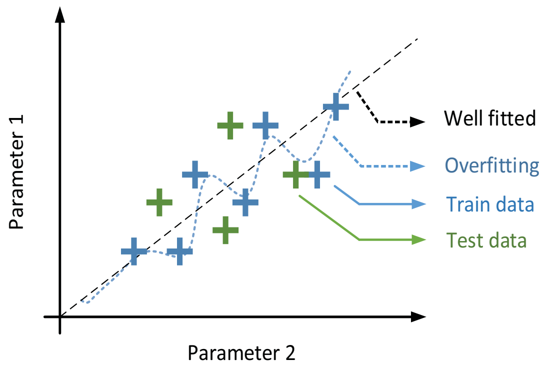

Figure 9. Fine-tuning against overfitting of the model

Fig. 9 reveals the fine-tuning against the overfitting of the model. Assuming that the blue crosses are training data, if the model is trained only on that data, it might become overfitted, meaning that if new data is passed to the model (green crosses) there will be a high loss function.

After collecting many images for the dataset, it is necessary to annotate them all. Annotation includes specification of the object coordinates and a corresponding label. For the smoke detection model, we have collected about 300 images, which include smoke. For their labelling, we have used the LabelImg tool [10], which is a graphical image annotation tool written in Python and uses Qt for its graphical interface. After the labelling of the images, we have used a ready script to convert the XML files to a .csv and then to create the TFRecords. The TFRecord input data is needed because we have used Tensorflow [9] as a training platform. We have separated the input data to be 80% (240 images) for training and 20% (60 images) for testing.

After the creation of the required input files for the Tensorflow Object-Detection API, the model can be trained. For the training, an object-detection training pipeline is needed. Training an object detector from scratch can take days, even when using multiple GPUs. To speed up the training we can take an object detector trained on a different dataset and reuse some of its parameters to initialize the new model. For that purpose, we have downloaded a model named ssd_mobilenet_v1_coco [15]. The model comes with preconfigured pipeline configurations. It is only necessary to adjust the *num_classes* to one (because we only have one class - smoke) and to set the path for the model checkpoints, the training and test data files as well as the label map. In terms of other configuration parameters, like learning rate, batch size and others the default settings would probably be ok.

Training can be done either locally or on the cloud. GPU processing unit with at least 2GB memory is acceptable for local computing. We have started training on a computer with 4GB GPU. At every 10,000 steps of the training, the process is saved as a checkpoint. It is recommended to evaluate the checkpoints from time to time in order to avoid overfitting the model.

After finishing with the training, the model has to be exported to a single file (Tensorflow graph proto), so it can be used for inference. If more images are used for the input dataset, the model could become more accurate, but in that case, there is a tradeoff between the model speed and the model accuracy that one must consider.

V. CONCLUSIONS

The system for early forest fire detection is still in its development stage. We are still waiting for some equipment to be purchased, but we have planned and discussed the actual implementation. We have performed a thorough research and some simulation experiments and we believe that we follow the right way to achieve the goal. We also believe that we apply adequate approach that is also up-to-date. We think that the system could enhance the available platforms for fire detection and we hope that such improvement could significantly reduce the damages caused by untimely or late fire detection.

ACKNOWLEDGMENTS

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