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Due to global climate change, industrialization, urbanization, population growth, and the other outstanding features of new century, intensive forest fires have become a whole-planetary problem. They grow year by year, so forest fire response operations become challenging and expensive.

Traditionally, these operations continue to be based on visual observations and decision-maker’s estimations. However, smoke and flame substantially distort observations, while high temperature does not allow to approach the fire closely. That is why, inaccurate and incomplete observations cannot be a reliable basis for planning response operations.

It is known that the efficiency of response operations depends mainly on the availability and usability of real-time forest fire monitoring tools and technologies such as unmanned vehicles, remote sensing, image processing.

Decision-maker always requires a clear picture of the ongoing processes in order to understand a direction and a rate of fire spreading. At the same time, existing implementations of real-time forest fire monitoring systems offer a result in the form of a flat two-dimensional image of a burning area on a map [2].

Thus, the topic of our interest is a study of the ways of 3D reconstruction of the forest fire process during its real-time monitoring, which can provide decision-maker with a clear model of the fire front spreading to make in-time decisions on the fire response.

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The aim of this work is to develop a method of 3D reconstruction of the fire front based on uncertain observations captured by remote sensing from UAVs within the forest fire monitoring system. We propose to use multiple cameras simultaneously to capture the scene and recognize its geometry. We assume that multi-directional views of the process can be used to estimate volumetric nature of the fire front as well as the fire processes.

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# Remote Sensing and Image Processing in Forest-Fire Monitoring System

## **Observable attributes of the forest fire and sensors**

**The main attributes of the forest fire are heat, smoke, and flame**, including such its manifestations as light, flicker, and motion [19]. All of them are observable by **optical and infrared cameras**.

Modern electro-optical cameras have a high enough resolution and wide field of view, but the quality of their images depends heavily on lighting conditions.

The broadband thermal infrared camera measures energy release within the combustion reaction but it has a limited dynamic range. Images captured by infrared (IR) camera are usually affected by such interferences as saturation, reflected sunlight, energy radiated from non-fire sources.

Thus, both optical and infrared cameras have their drawbacks and can provide imprecise, uncertain, or ambiguous information in captured images because of interferences and distortions. Turbulence and vibrations of UAV distort captured images additionally.

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## Remote Sensing

## Fig.1.

## Monitoring UAVs capture images flying towards the fire and hovering around it. Obviously, such UAVs should perform onboard only stabilization, geo-localization, and geo-rectification of images (Fig. 1). Their sensors capture and transmit images to the ground control station. The digital elevation model represents cartographic dataset describing terrain surface, so the captured images are transformed to a stream of geo-mapped frames where each frame is complemented with the coordinates of the upper left corner of the frame and scale value. This makes it possible to merge images taken from different positions of observation.

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## Image processing

## Fig.2

It is assumed that that fire spreads in three-dimensional space  above the terrain discretized by a grid  of isometric cubic cells 

There are three channels to process image from each UAV at the ground center: one for image frames captured by infrared camera and two separate channels providing flame and smoke recognition based on the image frames captured by optical cameras (Fig. 2). In the infrared channel, image pixels represent a heat radiation by colors ranged from black to white, so the image analysis is performed in three stages: image mapping, image averaging, and gray color evaluation. Burning areas are always represented as white areas within the image, while non-burning areas are black. Clearly, a plenty of pixels is greyed due to uncertainty of observations. As the result of the image analysis, each cell  is associated with a certain “degree of grayness”  ranged in the interval  and based on the average brightness  of this cell.

In the optical channels, the process of image analysis is performed in such sequential stages as mapping, transformation (only in optical camera channels), averaging, filtering, generalization, and conversion of images.

As the result of image processing, each cell  is associated with certain degrees of grayness” , flame (), and smoke () recognized within this cell and normalized in the range [0, 1].

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# Method of 3D Fire Front Reconstruction

# Fig.3

To obtain the volumetric fire front representation, we must reconstruct it from uncertain observations based on the results of the image analysis. However, such reconstruction is quite challenging because of fire spreading. Fig. 3 shows the forest fire observed by UAVs’ sensors from two distinct viewpoints. It’s impossible to directly observe the combustion process covered by smoke. Therefore, the viewpoints for observation are often selected at the opposite sidesf the fire front. Nevertheless, a significant part of the combustion process remains hidden due to presence of hidden areas and occlusions in the observed scene such as shown in Fig. 3. Furthermore, fire fronts can cover a sufficiently deep area that is poorly visible from two opposite viewpoints.

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# Method of 3D Fire Front Reconstruction

## Scene geometry

Fig.4

The forest fire scene is represented in Fig. 4. A configuration of viewpoints can be defined as a set of poses (Pose A, B, C in Fig. 4). The pose is a description representing the UAV location and the sensor orientation within three-dimensional space.

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# Method of 3D Fire Front Reconstruction

## Spatial Representation

## Fig.5

The grid of cells  used in the image processing at the ground center is not suitable for the information presentation during the process reconstruction because of the spreading of the fire front.

We create a new 3D structure to reconstruct fire front based on a grid of voxels, which are considered as certain cubic volumes of equal size.

Voxels are a bit like cells that discretize a space in a grid , nonetheless, they are organized in a completely different way.

Each voxel is considered as a node in a certain tree-like structure called octree. Each node of the octree can be recursively divided into 8 sub-nodes, each of which is also a voxel but has a smaller size.

Such recursive process can be both top-down and bottom-up. Initially, we can start from the voxel that covers the overall forest fire area and subdivide it recursively down to the minimum voxel size reachable with respect to the sensor resolution.

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# Method of 3D Fire Front Reconstruction

## Scene Representation

Within the scene, each voxel belongs to a specific class , which describes the type of its inner content within the considered reconstruction scene:

1. Unmarked (). It is a type of voxels that have not been seen by sensors. Initially, the reconstruction scene is represented by a 3D vector filled by unmarked voxels.
2. Empty (). It is a type of voxels that lie between the sensor position and sensed “surface” of the fire process represented by flame and smoke.
3. Flame (). These voxels represent a remotely sensored “surface” of the fire corresponding to a burning kernel of the fire process.
4. Smoke (). This type of voxels represents the areas within the scene shrouded in smoke, which prevents sensoring the inner voxels.
5. Uncertain (). It is a type of voxels that can not be precisely assessed as “burning”, i.e. voxels that are possibly involved in the combustion process due to the uncertain observation but there is no certainty about it.
6. Burnt (). Such voxels represent the areas that are already burnt and, therefore, cannot be involved in the combustion processes.
7. Fuel (). This type of voxels corresponds to the vegetation areas that do not participate in combustion processes but can be ignited due to readiness of the fuel. It should be noted that voxels, which do not contain flammable vegetation, belong to the “empty” class instead of the “fuel” class.

Occluded (). These voxels represent the areas occluded by other voxels that prevent perception of the fire front depth.

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# Method of 3D Fire Front Reconstruction

## Classification of voxels

## Fig 6

3D convolutional neural network (3D-CNN) can be used to classify voxels within the reconstructed scene.

It is a special kind of CNNs using the 3D volumes in the kernels instead of 2D maps.

We propose to use VoxNet [22] architecture (Fig. 6).

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# Method of 3D Fire Front Reconstruction

## Soft Rough Fire Front Model

The model of the fire front can be represented using soft sets of cells [23]. Considering a set of voxel classes  and a 3D vector of voxels , we can define a *soft set of voxels* over  as a pair  where  is a mapping of  into the set of all subsets of the set . This set can be defined as , where each  is an -element of the soft set (a set of voxels of a class  at the reconstruction moment ). Using the voxels of a class , we can define a lower approximation containing the cells, which definitely belong to the -element of the soft set , while using the voxels of classes and , we can define an upper approximation containing the cells, which possibly belong to the - and - elements of the soft set, . As the result, both lower and upper approximations constitute a soft rough set of voxels  that represent a 3D fire front model at the reconstruction time. Other voxels belong to the negative area of the rough set . The boundary area of the fire process is a subset of the set of voxels, which belong to the upper approximation, but don’t belong to the lower approximation, .

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# Implementation

# Fig.7

The proposed method of 3D reconstruction of the forest fire front has been implemented using Visual C++, OctoMap framework, ConvNet and Fast Artificial Neural Network (FANN) libraries. The software prototype has been tested, the reconstruction rate has been evaluated during the simulation. The initial weights of neural networks have been randomly generated. The simulation results show that the method can achieve an accuracy of reconstruction up to 98% (Fig. 7), which shows the rate of correctly classified voxels (true positive) from the prepared test set.

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Conclusion

1) The proposed in the paper method of 3D reconstruction of the forest fire front is based on uncertain observations captured by remote sensing from UAVs within the forest fire monitoring system.

2) We suggest to use multiple cameras simultaneously to capture the scene and recognize its geometry including depth.

3) Multi-directional observation allows us to perceive and represent a volumetric nature of the fire front as well as the dynamics of the fire processes.

4) The novelty of our approach lies in the use of soft rough set to represent forest fire model within the discretized hierarchical model of the terrain as well as in the use of 3D convolutional neural network to classify voxels within the reconstructed scene.

5) The developed method provides sufficient performance and good visual representation to fulfill the requirements of fire response operations