SMOKE AND FOG CLASSIFICATION IN FOREST MONITORING USING HIGH SPATIAL RESOLUTION IMAGES

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ABSTRACT

Forest fires cause major damage to human habitats and forest ecosystems. Early detection may prevent serious consequences of fast fire spread. Although there are many smoke detection algorithms employed by various optical remote sensing systems, there is still a major misdetection of images containing fog. Fog exhibits similar visual characteristics to smoke. Furthermore, when monitoring dense forests many smoke detection algorithms would fail in robust recognition due to fog covering the trees at dawn. There have been more or less successful attempts to separate smoke from a fog in optical imagery however, these algorithms are strongly connected to a specific application area or use a semi-automatic approach. This work aims to propose a novel smoke and fog separation algorithm based on color space model calculation followed by rule-based shape analysis. In addition, the internal properties of the smoke candidate areas are examined for linear attenuation towards higher energy wavelength. Those areas are then investigated for internal shape properties such as convex hull and eccentricity. Several tests conducted on various high-resolution aerial images suggest that the system is effective in differentiating smoke and fog and thus considered to be robust in early fire detection in forest areas.

Keywords: smoke, fog, detection, image, rule-based

INTRODUCTION

Wildfires have a severe impact on local and global ecosystems and may affect infrastructure, wildlife, and human health [1], [2]. Therefore, early and robust forest fire detection is becoming increasingly important. Different data sources have been used in smoke detection applications. These include satellite imagery with low spatial resolution, aerial photos with moderate to high spatial resolution, and other imagery acquired by UAVs (unmanned automated vehicles) or drones [3]. The latter is an economical and fast way to monitor forests and significantly decreases the risks associated with the safety of the pilot. Unlike satellite imagery, aerial and drone photos are not challenged by cloud cover and their spatial resolution ranges from submeter to centimeter-level, however, due to the processing time, the limitation is in the number of spectral bands. Visual Red, Green, and Blue bands together with Near-Infrared bands are commonly used to store information by UAVs [4]. A large number of algorithms for smoke detection are tested on all available data sources although with varying success [3]. Early detection of forest fire requires accurate detection of smoke since it rises above the three crowns and indicates fully developed fire. The authors in [5] use a color space approach to segment smoke plums from the UAV acquired data. The suggested algorithm accurately detects smoke from thousands of video frames taken from one

specific forest fire location. However, the generality level in this approach is low since the fire occurs over one limited time interval and does not vary in chromatic characteristics. Color, texture, and shape properties of smoke are commonly applicable and work either as an independent method [6] or in combination with deep learning (DL) techniques [7], [8]. Additionally, motion analysis was implemented in robust fire detection methods [9] which require video data. It is hard to achieve a general performance for smoke descriptors derived from image pixel values, thus there are always false positive or false negative responses in these algorithms. Moreover, in cases where satellite imagery is used, the process of smoke detection relies on a wider spectral resolution where a particular band combination delineates the presence of smoke [10]. This puts a higher demand on the spectral resolution of the imagery, which is hard to achieve for UAVs. In this work, we focus on the imagery taken by UAVs which is sparse in spectral resolution but allows for high temporal and spatial resolution. There was a successful attempt to deploy a robust approach for early forest fire detection using visible band data of high spatial resolution [11]. Color and texture features were inputs for Artificial Neural Network which successfully recognized smoke and fire objects in RGB images. It was observed that the algorithm enabled separation between dense smoke and clouds, however, no observations were described regarding fog over forests at dawn.

The task of smoke detection over forest-covered areas using only visible bands is even more challenging since it is hard to separate smoke from fog due to its very similar visual appearances. In cases when the fog is dense and covers partial areas under the field of view, it is impossible to visually distinguish the differences. The traditional approach with color and texture descriptors is not robust enough and is usually prone to errors when tested on arbitrary images [6, 7], thus other descriptors based on the physical properties of smoke and fog should be investigated. In [12] the authors bring into work the atmospheric scattering model to calculate coefficient vectors according to the equation of light reflection. The features are then set into a Support Vector Machine (SVM) to determine the similarity with the objects. It is a computationally heavy approach and depends upon the correct preparation of the features. However, there is a difference between smoke and fog in their scattering properties and it has not been extensively addressed in earlier research for this application. In this work, the optical differences between smoke and fog are considered and the assumption is that the smoke attenuates light linearly towards a higher energy wavelength. On the contrary, fog will show a non-linear light reflection behavior towards the red spectral interval. This hypothesis has its source in [13] where the different attenuation properties of fog and smoke were proven in a laboratory environment. A simple and fast feature and rule based approach is suggested to classify smoke and avoid smoke alarms in case of fog presence in forest land cover.

MATERIALS & METHODS

There are no open databases with UAV-based imagery focused on forest fire detection. For this study, only visible channel data is necessary thus the dataset was gained through internet search using sites such as Shutterstock, Unsplash, and forest fire news reports. The resolution of the downloaded images varies from 3600 × 5400 pixels to 300 × 230 pixels. The information about the place is not relevant for the study, we kept the images containing dense or moderate forest as a background, which is covered by white to gray smoke or fog of varying densities. Black smoke is excluded from the study

because it usually originates from the burned man-made features, which are usually not present in the forest. White smoke usually indicates that the fire has just started. Gray smoke, on the other hand, usually designates that the fire is slowing down. Some of the forest fire dataset images contained fire flames but the classification focuses only on the presence of smoke. The total data set includes 100 images, where 50 images contain fog. The remaining 50 are images of smoke. An example of the data is in Figure 1.

a) b)

Figure 1. a) Foggy forest, b) Smoke over the forest

The proposed method classifies smoke and fog in forest environments. Prior to the workflow, an assumption on light attenuation properties of fog and smoke is done. Regions with fog and smoke are cropped out and investigated on the relationship of the representing values between Red, Green, and Blue bands. Fog is expected to show no linear behavior in attenuation, meaning that there is no correlation between Red, Green, and Blue channels. As opposed to fog, smoke supposes to show linear attenuation towards the red channel. In this process, the data is confirmed as containing smoke or fog. These assumptions are later used in the evaluation of the results. The images that do not answer to the defined conditions of linear or non-linear attenuation were marked for validation.

Since smoke and fog share similar or almost the same visible color information, the next step is to accurately extract all candidate features for smoke or fog based on the fact that these features are in different shades of gray and thus are not eligible for color variation investigation. The input is the RGB image, which is transformed to grayscale by two methods as in equations 1 and 2.

$$G_1 = \big((0.2989 * R) + (0.5870 * G) + (0.1140 * B)\big) \quad (1)$$

$$G_2 = (R + G + B)/3 \quad (2)$$

Where R, G, and B are the red, green, and blue portions of the image. G_1 is more detailed in gray levels and G_2 keeps only the most frequently appearing values in local regions. To enhance the contrast between the objects and keep only the features that may represent fog or smoke, an approach of local contrast enhancement is suggested according to equation 3.

$$F = G_1(G_1 - G_2)^2 \quad (3)$$

After this operation, the features in *F* will be subjected to a very high threshold value so that only the enhanced values corresponding to an interval from light gray to white are accumulated. The difference image between G_1 and G_2 is also evaluated to a high threshold and then both results are combined through a logical operator AND.

To this end, a binary image that has candidates for smoke or fog is calculated. Since the smoke of fog occupies a larger area, a rule regarding the size of a blob is created and applied. Only the biggest blob is left for further processing. As a next calculation step, a set of shape descriptors is applied to the smoke/fog blob. Three shape rules are coded into the algorithm. The first one relies on the assumption that the candidate blob fills at least 25% of the image. The second one is the relationship between the actual area of the blob and its convex hull. This descriptor implies that the irregular shape of smoke passes through while the smoother fog shape fails this condition. The third one is the eccentricity of the ellipse, which is the ratio of the distance between the foci of the ellipse and its major axis length. The value is between 0 and 1. An ellipse whose eccentricity is 0 is a circle, while an ellipse whose eccentricity is 1 is a line. The whole process is illustrated in Figure 2.

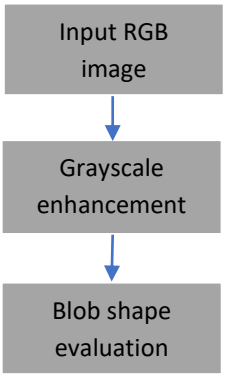

Figure 2. Workflow

To reveal the effectiveness of a grayscale processing step the example image of RGB, the difference G_1 - G_2, and *F*, are shown in Figure 3.

a) b) c)

Figure 3. a) Forest smoke RGB image, b) Grayscale difference G_1 - G_2, c) Feature image *F* as in equation 3

RESULTS

Totally 100 images that comprise forest fire and fog are processed with the suggested algorithm. Classification of smoke is done. Datasets of forest fire and fog went through the algorithm with the output of delineated smoke area and an alert on smoke presence.

In case of fog image the no smoke alert is activated. Two functions within the method are described and used, the first one to extract the candidate features and the second one to compare the features with the shape descriptors. The mean processing time of each image is 0.006 s. Some examples of input, and the final output are in Figure 4.

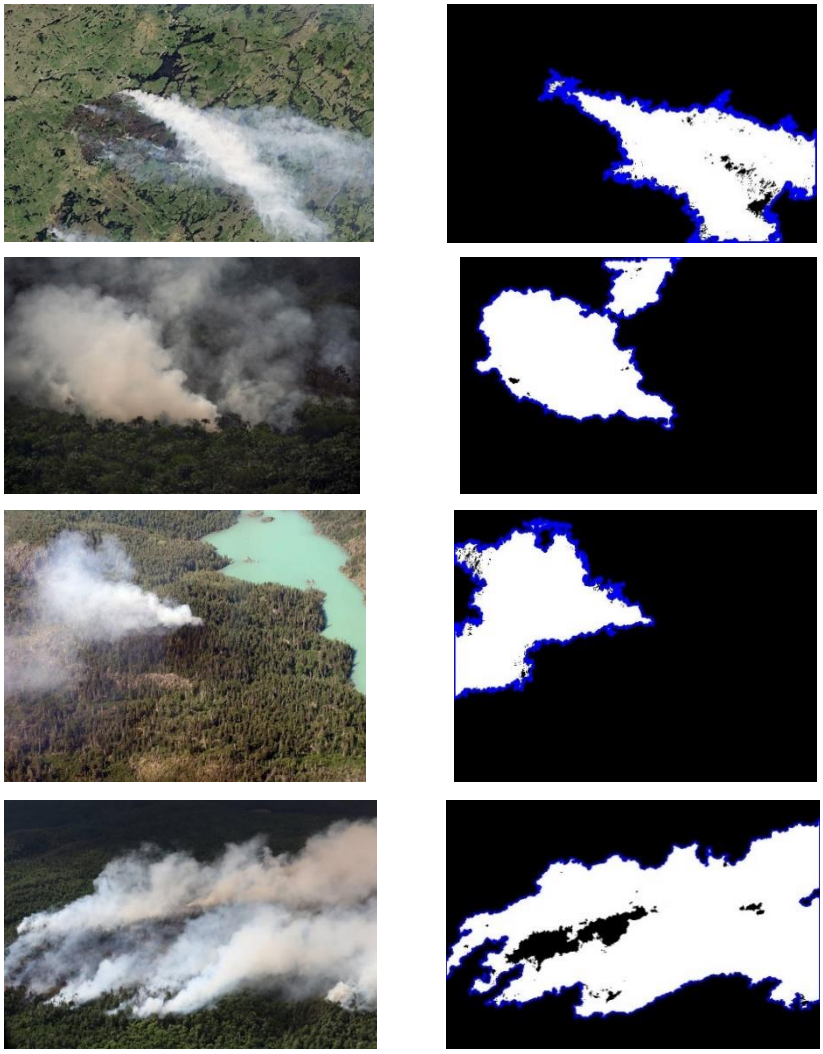

Figure 4. Results of smoke classification

The results are evaluated by counting TP (True Positive), FN (False Negative), and FP (False Positive). FP comes across when fog is identified as smoke. FN is observed when smoke is present but not found by the algorithm. Table 1 displays the counteract between these measurements.

Table 1. Precision of the results

Dataset	Number of images	TP	FN	FP	Accuracy
Smoke data	50	45	5	0	90%
Fog data	50	46	0	4	92%

There is no reason to perform the Precision/Recall analysis since the data is prepared so that in each image there is either smoke or fog. Instead, we calculate the percentage of the successful alerts in smoke imagery and the percentage of no smoke found alerts in fog images. The remaining images that result in a FN or FP are sorted out and evaluated as how well they follow the linear pattern of intensities decreases towards the red channel. Additionally, the order of dominance of color channels is investigated. This evaluation is present in Table 2.

Table2. Parametric evaluation of the FP and FN images

Image	Linear attenuation	Order of attenuation of the channels	Area/Convex Hull
Smoke_1	No	RGB	0.8344
Smoke_2	No	GBR	0.8040
Smoke_3	No	RGB	0.8027
Smoke_4	Yes	BGR	0.8637
Smoke_5	Yes	BGR	0.8533
Fog_1	No	GRB	0.7578
Fog_2	Yes	RGB	0.7365
Fog_3	No	BGR	0.7090
Fog_4	No	RBG	0.7738

It can be seen in Table 2 that two of the smoke images are following the linear attenuation of the intensities while one of the fog images shows the linear characteristics of smoke attenuation.

CONCLUSION

The proposed method for smoke and fog classification has shown a successful outcome on the set of images containing either smoke or fog. The results are evaluated against such parameters as linearity of intensities attenuation and solidity of the shape. According to the results, a general shape eccentricity is higher than 0.7 for the fog objects and less than 0.7 for smoke blobs. As for the solidity parameter, it was found that it is higher for the fog areas and lower for the smoke objects. Although smoke can be of diverse shapes depending on the propagation time and wind power, it generally billows up and thus forms a cone like shape. Even in cases of low wind, the shape if smoke in forest fires is similar to a cone. This observed quality may be a reason to the comparatively low value of eccentricity of the extracted smoke blob. The fog pattern on the other hand, looks as if it lingers in sheets over the forest. Extraction of such shape results in a large, smooth oval blob. This yields a high value of eccentricity and a high value of the ratio of the area to its convex hull. Knowing this, it is easy to assume that the classification of smoke and fog may be clearly defined and performed. However, in this work, we used publicly available imagery with only visible red, green and blue bands. No further pre-processing was carried out, but the imagery contained the original spatial resolution as well as possible enhancement introduced by the data creators. The

latter may lead to a possible failure in smoke identification. In earlier work on smoke and fog delineation, there are traditional image processing approaches described, where there are combinations of various color space processing and SIFT [6], which is both computationally heavy and not precise in fuzzy conditions such as smoke. Here, the original RGB image is transformed to grayscale and subjected to a very robust calculation of possible smoke areas. Only two descriptors of shape are used which makes computational time very efficient. In cases where the algorithm failed, the solidity shape parameter could not be satisfied. By visual examination of the four false positive fog images, it could be noticed that the density of the fog is exceptionally low, thus, the extracted candidates show a shape similar to smoke. The same poor behavior in fog imagery occurs when fog is partially under the tree crowns and thus the extracted blobs may be of the same shape as smoke.

An attempt to incorporate a smoke behavior described in [13] is done. According to the theory, smoke should exhibit linear attenuation of intensity profile towards higher energy wavelength and fog should do the opposite, with no linear attenuation. Although a major part of the smoke imagery follows this pattern, we could not connect failure in smoke detection and this property. The reason for that may be the unknown processing of the data as well as the limitation in spectral resolution.

The suggested algorithm for smoke and fog classification is simple, time efficient and robust. The detection rate is 90% for the smoke data set and 92% for the fog dataset. The algorithm works only on images that contain either smoke or fog. For future development, a valuable component would be a dataset with a higher number of spectral bands that are unprocessed with any enhancement techniques. This would enable a proper test of the linear behavior of smoke in digital imagery.

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