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Forest Fire Detection based on Color Spaces Combination

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Abstract

Manual surveillance of inaccessible areas covered in trees and foliage is a difficult, labor-expensive and challenging task. On the other hand, early discovery of forest fires signs is essential in the preservation of the environment, therefore, the need for fast and efficient methods is very important. The characteristic color of the forest fire can be classified with the specific image processing techniques, especially during the late spring and summer when the color of the fire is easily distinguished from the color of trees and foliage, or generally flora. In this paper, a new method for the detection of forest fires is proposed. The method combines several predetermined and fuzzy criteria for image segmentation. A hybrid technique consists of a combination of different components of different color spaces.

Keywords: Forest Fire Detection, Unsupervised method, Image Processing, Color Space, Classification

I. Introduction

Fires are a global phenomenon and a long-standing problem that affects the entire ecosystem on Earth. Wildfires have always been a part of nature playing a key role in shaping the ecosystem. In controlled conditions, the wildfires are considered as agents of renewal and change, but if left uncontrolled they can be deadly and leave a long-lasting impact on the landscape. The cause of the fires is a very complex problem to tackle, but in the vast majority of cases, it is the human intervention that ignites the fires. One might think that the extreme weather conditions that we have experienced on Earth in recent years are the main culprit for the increase in the global fires, but they are not the main causes of wildfires. Instead, once the fire is ignited, they can evoke uncontrollable spread of the fires causing the enormous destruction and the loss of human lives and assets.

In 2019, huge fires have been recorded in Brazil, Bolivia, the Democratic Republic of the Congo, Siberia, Alaska, Greenland, and Indonesia just to name a few. Globally, fires released about 4.7 gigatonnes of carbon dioxide in one year, which is about average for global fires over the past 17 years. This problem should be considered as a global problem with effects on a local population, as well as surrounding regions and countries. The fire haze can cross borders and oceans, and cause significant health concerns as well as international tensions. The secondary effects of wildfires in humans include an increased risk of respiratory illness and heart attacks. This is why fire prevention is the key to tackling wildfires.

Manual surveillance of forests implies the employment of mechanical devices or humans to monitor vast and mostly inaccessible forest areas. This task is considered very challenging, difficult, dangerous to humans and requires many costly resources. According to [1], wildfires burnt over 1.2M Ha of natural land in the EU and killed 127 people (firefighters and civilians) in 2017. This is why automated fire detection systems are desirable. They can make the early detection of forest fire achievable, and play a crucial role in minimizing the destruction of forests that are vital for human survival, such as the Amazon rain forest. Automated systems usually employ various remote sensors to provide enough data for the effective forest survey and management. The current approaches include ground-based systems, (un)manned aerial vehicle-based systems and satellite-based systems [2]. Every system uses a different set of sensors, methods, and algorithms to carry out the basic functions, and has a different set of features. Some of these systems are systematically reviewed in [3]. In recent years, unmanned aerial vehicles are becoming an increasingly viable option, due to their availability and low-cost. Essential parts of these systems are computer vision-based methods which allow very fast detection of abnormalities in the monitored areas.

Still images can provide more information about an area than many other sensors, e.g. ultraviolet and infrared sensors. They are very popular because they do not bring any complexity during the execution nor require much maintenance [4][5], and their inexpensiveness is a bonus. Image segmentation is considered as the first and the most

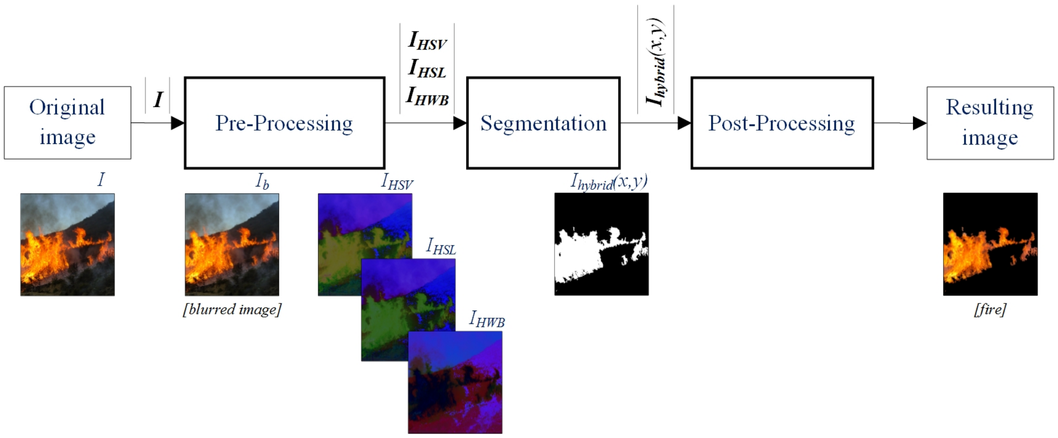

Fig. 1. The block diagram of newly proposed method for Forest Fire Detection.

important step in the computer vision methods. In recent years, it has gained a lot of attention due to the growing popularity of the computer vision. Image segmentation of wildfire images is not a trivial task since many factors can affect the appearance of the fire in images. Throughout its life, the fire can change the appearance in terms of color and luminosity. The dynamic changes of smoke and background also play a significant factors, which determine the success ratio of the method. In current literature, the most fire segmentation methods use some color criteria or a combination of different color spaces. Every color space has different properties described in the literature. The modeling efficiency of a method depends on the choice of the color space, or on the choice of components from multiple color spaces.

In this paper, we present a new method for image segmentation and detection based on the fire-color information. The current research methods are the best-described in [6]. These methods use one of the following color spaces RGB, YCbCr, HSI, YUV or CIELab, or some combination of their components. We combine components from the three very different color spaces HSV, HSL and HWB and define a new criteria for the image segmentation. Since some components are identical in chosen color spaces (component H), and the others require mostly basic linear transformations, the method executes fast and is a potentially viable option for the implementation in hardware. We tested our method on a new Corsican Fire Dataset (CFDS) described in [7]. The resulting F1 score indicates that the method is competitive with the current research and can be used on the majority of images in the chosen dataset with certain limitations.

The paper is organized as follows: related work on fire detection using still image processing is briefly reviewed in Section II. In Section III, we described a new method for fire segmentation and detection. Implementation and experimental results are presented in Section IV, and in Section V we conclude the paper with some remarks.

II. Related Work

Image content understanding and analysis have been studied for many years by many researchers. Existing extensive research on the fire detection can be categorized in many categories. Some works are based on the analysis of the video content [8][9][10], and the others are based only on the analysis of still images [11][12]. Lately, supervised methods have become very popular and they usually require some learning steps from the existing dataset [13]. These methods can provide valuable results on a given dataset but can be unusable for any other dataset due to overfitting problem. Unsupervised methods usually try to exploit only the data available in the 2D image, such as color or spatial information. Some methods make use of various visual signatures, such as color, motion or geometry of the fire regions. The latest comprehensive survey of the existing fire detection algorithms is provided in [6]. The algorithms use different color spaces, such as RGB [8][9][10][14][13], YCbCr [11][15], YUV [16][17], HSI [12], HSV [18] or the combination of different color spaces [19][20].

III. Our method

Fig. 1. shows the proposed method for forest fire detection.

III-A. Pre-Processing

First, the image I_{RGB} is loaded and blurred with 7×7 filter, and the resulting image I_b is created. The image I_b is then converted from RGB to HSV, HSL and HWB color space to create I_{HSV}, I_{HSL} and I_{HWB} images. The components of the resulting image are separated and the average of S, W and B channels of the entire image are calculated.

III-B. The New Criteria for Segmentation

The image is then segmented by the new criteria shown in the Eq (1).

$$
\begin{aligned}
C = (S > 35)\wedge \\
((H \geq 330 \wedge H \leq 65)\wedge \\
((L > 70)\vee \\
(B < B_{avg} \wedge W < W_{avg})\vee \\
(W > W_{avg} \wedge S > S_{avg}))\vee \\
(W \geq 98 \wedge B \leq 2))
\end{aligned} \tag{1}
$$

The criteria consists of 6 decision rules. The rationale behind the selection of these criteria is described below.

1) **Saturation** condition ($S > 35$). It consists of a single limitation of the saturation channel, where the values greater than 35% are chosen. This ensures that saturated and brighter colors are selected, e.g. the forest fire flame. This condition is in conjunction with the **Color** condition and all other limitations that are in relation to the **Color** condition to ensure more saturated red, orange and yellow colors are selected.
2) **Color** condition ($H \geq 330 \wedge H \leq 65$). This condition relates to the limitation of H component that is the uniform component for all chosen color spaces: HSV, HSL, and HWB. The values of the component are limited to values between $0° \rightarrow 65°$ and $330° \rightarrow 360°$. These values represent red, orange and yellow hue of the color which are relevant for forest fire detection.
3) **Lightness** condition ($L > 70$). It consists of a single limitation to the lightness of the color, where the values greater than 70% are chosen. This condition is not in the connection with the next condition (**Blackness-Whiteness**) because it ensures that the colors on the edges of the forest-fire flame center are selected.
4) **Blackness-Whiteness** condition ($B < B_{avg} \wedge W < W_{avg}$). The blackness of a pixel must be less than the average blackness of the image. The whiteness of a pixel must be less than the average whiteness of the image. These two conditions together ensure the edges of the fire are selected.
5) **Whiteness-Saturation** condition ($W > W_{avg} \wedge S > S_{avg}$). It consists of limitation of the pixel whiteness, where its value must be greater than the average whiteness of the image, and the pixel saturation must be greater than the average saturation of the image. This limitation is in a disjunctive relation to the **Lightness** and **Blackness-Whiteness** condition, and this ensures that the pixels near the center of the fire are selected.
6) **Color-Irrelevant** condition ($W \geq 98 \wedge B \leq 2$). Whiteness of the pixel should be greater or equal to 98% and the blackness of the pixel is to be less than 2%. This condition is in a disjunctive relation to the **Color** and all conditions in relation to it, while also in a conjunctive relation to the **Saturation** condition to ensure the center of the flame is selected.

The criteria are tested on every pixel in the image and the new resulting image I_{hybird} is created. The values of pixels in the resulting image can have one of two values: $\{0\}$ or $\{255\}$ as denoted in Eq (2). These two sets represent a set of fire pixels $\{255\}$, colored as white, and a set of non-fire pixels $\{0\}$, colored as black.

$$
I_{hybird}(x, y) = \begin{cases} 255 & \text{if } C \text{ is true} \\ 0 & \text{otherwise} \end{cases} \tag{2}
$$

III-C. Post-Processing

The resulting image at this stage can have many small regions not necessarily representing fire pixels. Hence, we analyze connected components to identify small white blobs in the image, and then remove blobs with minimum size less than 150. This number is empirically chosen and it works very well on the chosen dataset.

In the last step, the method generates appropriate masks as shown in Fig. 2 and Fig. 3.

IV. Implementation and Results

IV-A. Implementation

Our method has been implemented in Python v3.6 with OpenCV v3.3. The image processing was performed on Intel i7 1.7GHz CPU with 8GB of RAM.

IV-B. Dataset

The method was tested on the subset of the fire segmentation images from the Corsican Fire DataSet[1] (CFDS), described in [7]. It consists of 2,000 images from different parts of the world. We tested our method on the 500 fire images recommended by the dataset authors. The selected images have heterogeneous color and texture of fires, similar environments, light conditions, and vegetation. The image resolution ranges from 183×242 to 4000×3000. Every image is annotated with the respect to twelve different parameters in regard to the fire and the environmental conditions. These parameters are essential for providing a good analysis of any forest fire detection algorithm. For every image in the dataset, the ground truth (GT) image is provided. The images are the result of the manual segmentation by an expert.

IV-C. Results

The two metrics are used for the analysis of the results of the presented method: the accuracy (Eq. 4) and F1 score or F-measure (Eq. 4). The latter metric was introduced by the information retrieval community and corresponds to the harmonic mean of precision and recall [21].

$$
Accuracy = \frac{TP + TN}{TP + TN + 1 + FP + FN} \tag{3}
$$

$$
F_1 = \frac{2 \cdot TP}{2 \cdot TP + FP + FN} \tag{4}
$$

[1]The dataset is available upon a request at http://cfdb.univ-corse.fr/.

The selected results of the method are presented in Fig. 2 and Fig. 3. Results considered as good results (F1 score is greater than 0.9) are displayed in Fig. 2, and not so good results (F1 score is less than 0.1) are displayed in Fig. 3.

In terms of performance, the best results are recorded for the images in two groups: (1) when the flame is in the dark-green or similar colored surrounding, and the image is captured with the camera that can capture the high amounts of the natural contrast (assuming that the image is not edited in post-production), and (2) when the flame is in the dark surrounding (e.g. in the dark). In real-life situations, these conditions are not constant.

Some images are more suitable for the analysis than others. Some undesirable situations are for example when the smoke of the fire is between the camera and the fire itself. This lowers the average saturation of the image that in return makes the part of the criteria for saturation more tolerant, which affects results. Next, if the low-quality camera is used and the image does not have a very well defined texture this will significantly affect the accuracy of the results. This is due to the part of the criteria that smooths out transitions similar to the *effect of blurring*, which in the combination with a blurry image can blur the fire to the extent of losing its characteristic contrast to the background. If a special near infra-red camera is used (the chosen dataset has such images, but they are not considered in this study), the fire in images appear in some tone of blue color. These images are not suitable for our method. If the camera with the low contrast is used, then some objects that naturally do not have a large amount of contrast will be similar to the flame, hence the results will be compromised. If an image has a large amount of smoke that also reflects the red-yellow-orange hue of the flame, the algorithm marks a large area of the smoke as the fire. This is the result of the smoke covering a large area of the image, which in return lowers the average saturation of the image. In the end, this will result in high false-positive pixels in the image. This is the case for most images in Fig. 3.

The performance of the method is obtained with two metrics: Accuracy and F-score. Both metrics were designed to compare the resulting image with the ground truth image, but F-Score is considered more reliable. The proposed method was tested on the 500 images from the Corsican Fire dataset. The average accuracy is 0.93, while the F1 score of 0.79 was measured on the given dataset. The F1 score for 26% images is greater of equal to 0.9, for 64% (or 319 images) is more than 0.8, and only 9% of images have an F1 score of less than 0.5.

V. Conclusion

In this paper, a new unsupervised forest fire detection method is proposed. From the results, some conclusions can be made regarding the optimal conditions in terms of the acquisition camera, the surroundings, and the terrain. The camera that can provide high spectra of colors with high contrast and representation of saturation of color is needed. The best results are obtained for images where the presence of fire is more than 40% of the whole image. In such a case, the F1-score is usually more than 0.9. The method is not suitable for images created with any type of IR camera, as this kind of camera does not represent colors in the way perceived by the human eye. The surroundings and the terrain being photographed should be ideally the forest, with not a lot of dry grass and brightly colored stones and boulders, as these objects can deteriorate the results. Clouds should be avoided for the same reason. The terrain with sand and gravel of orange, red or yellow color should be avoided as the results might not be reliable and the algorithm can be prone to false-positive results. If this kind of terrain takes more than 80% of the image, the algorithm is prone to false-negative results too.

The results are optimal in the forest surroundings. The fire in the image with this surrounding can be present as little as less than 15% and it will still be detected. If the fire is brighter than the detection capabilities are even better. The images with dominant red and yellow colors are better suitable for this algorithm. The results shown in Fig. 3. are predominately (56%) saturated with orange color, the percentage of the fire pixels which are superimposed with smoke is more than 50% in average, and the brightness of the environment is more than 40% on average.

We can conclude that the method is suitable for certain types of forest fires and surrounding conditions. The results indicate that the method detects fire with reasonable accuracy and it is suitable for image segmentation.

The future work will focus on the application of additional image processing techniques for improving the overall results, the parallel implementation [22] or designing the accelerator for real-time application [23][24][25].

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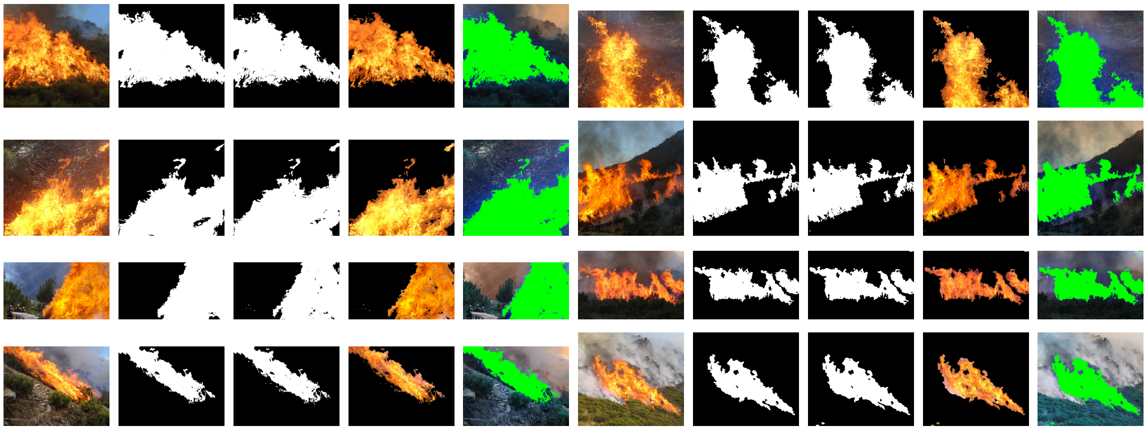

Fig. 2. Detection capabilities of our method showing the best results: (1) the original image, (2) the ground truth image, (3) the resulting segmentation mask, (4) the region selected as fire, and (5) the region not selected as fire (displayed in green for better clarity). **Best viewed in color**.

Fig. 3. Detection capabilities of our method showing the not good results: (1) the original image, (2) the ground truth, (3) the resulting segmentation mask, (4) the region selected as fire, and (5) the region not selected as fire (displayed in green for better clarity). **Best viewed in color**.

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