Finding the Shape of Noise: Smoke Recognition in Images

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Abstract:

This paper proposes a novel method utilizing Gaussian blur to identify and mark regions of smoke in an image. The method exploits a characteristic of smoke by applying a Gaussian blur and analyzing change in pixel intensity variance. The primary image processing technique is as follows. Two copies of the image are made for comparison. Then, two different Gaussian kernels are convolved with a respective image and the change in variance is measured by the Fisher Discriminant Ratio. Finally, a thresholding process classifies the image's pixel into smoke and non-smoke classes. Smoke tends to decrease the intensity value of pixels and the edges of objects. To this degree, a Gaussian blur has the same effect as smoke. Therefore the change in variance when the Gaussian blur is applied is a key characteristic to identify smoke.

Introduction:

Wildfire detection is of utmost importance in today's climate. In the United States alone, around 17 million acres of land have been destroyed due to wildfires in the last two years [1]. There are several surveillance systems for wildfire detection. Satellite imaging has a resolution of >1km. However, the wildfire would need to be several kilometers in berth to be detected and weather conditions such as clouds can also reduce visibility [2]. The second option are ground camera networks. These cameras are already employed to detect fire. The stationary camera is mounted to a ground tower and streams real-time images and a fire-detection algorithm detects the presence of fire in the image. However, for long-range point of view, the fire may not be visible, and smoke would be the only feature attributed to the presence of a fire [3]. A third option, similar to ground cameras, is to use UAVs with a camera mounted. The UAV method is the most promising since it can maneuver to any location and detect details a ground tower surveillance system would not be able to. A significant problem of UAV surveillance is the battery lifetime due to the camera's constant power-draw[4][5]. Therefore, it would be helpful if the camera did not need to supply a constant stream of images. This paper proposes using the local statistics of an image to cluster regions where smoke is likely detected. Thereby extracting more information per image, rather than relying on more images.

Relevant Work:

The current fire and smoke detection algorithms in use are based on color, spatial, and temporal features [6], [7], [8]. On the image processing-dependent work, Toulouse et al provides a comparative analysis of all the rule-based fire thresholding algorithms in literature. Toulouse conducts a comparative analysis of the pixel classification rules throughout literature and proposes a new rule-based feature extraction and training with an SVM classifier. The rules are chosen by majority-voting, then for each pixel the voted rules are applied, and the pixel feature is input to an SVM. The performance benchmarks were not provided.

As far supervised learning methods go, the convolutional neural network method used in smoke and fire recognition demonstrates higher accuracy than traditional image processing techniques [9][10]. Sun et al applied a CNN on a diverse and complex dataset of wildfires images. The data varied in parameters such as time of day, background complexity, and field of view. Sun et al conducted kernel principal component analysis on the dataset for dimension reduction where the number of principal components was 256. Then the CNN was trained on a random seeded dataset. The test accuracy was reported to be 94.1% [10]. However, according to Wang, a CNN will generalize poorly because any non-fire or non-smoke feature will also be learned during training. This is due to the nature of the data, which usually contains a complex background. Wang introduces a preprocessing segmentation of suspected flame area using color features, and then training the CNN with the preprocessed data. The final CNN model has an accuracy of 88% [9].

In the cited work, it is apparent that the smoke and fire detection algorithms use some form of a preprocessing technique to improve on the state-of-the-art [Toulouse], [Wang], [Toreyin]. In this proposal, a similar operation is applied. However, the preprocessing of the image takes a step further than the rule-based thresholding employed by current efforts. A key characteristic of smoke is the lowering pixel intensity value [7]. This characteristic is exploited by observing the change variance of pixel intensity values when a comparative Gaussian filter is applied. If smoke is present, then the resultant convolution will not affect the region of smoke nearly as much as another region with edges or high frequency information. The variance of pixel intensity is more homogenous in a region where smoke is present. Regions containing high frequency information or edges will blur upon the convolution or edge information may be lost entirely. To track the changes in variance of pixel intensity, the Fischer Discriminant Ratio (FDR) is chosen as the appropriate metric. The FDR relates the within-class and between-class variance by calculating the respective scatter matrices. This ratio is especially relevant to the comparison of variance between a pixel intensity matrix. Two copies of the image are made. One copy will serve as the ground truth (image GT), while the other copy will be modified to compare against (image V).

Both images are split into a grid of equal sized square blocks. Both copies undergo a Gaussian convolution, however image V's Gaussian variance parameter must be significantly higher than image GT's variance parameter in order to achieve the desired change in variance effect. The Fischer Discriminant Ratio (FDR) between the corresponding blocks of image V and image GT is calculated and stored into an array.

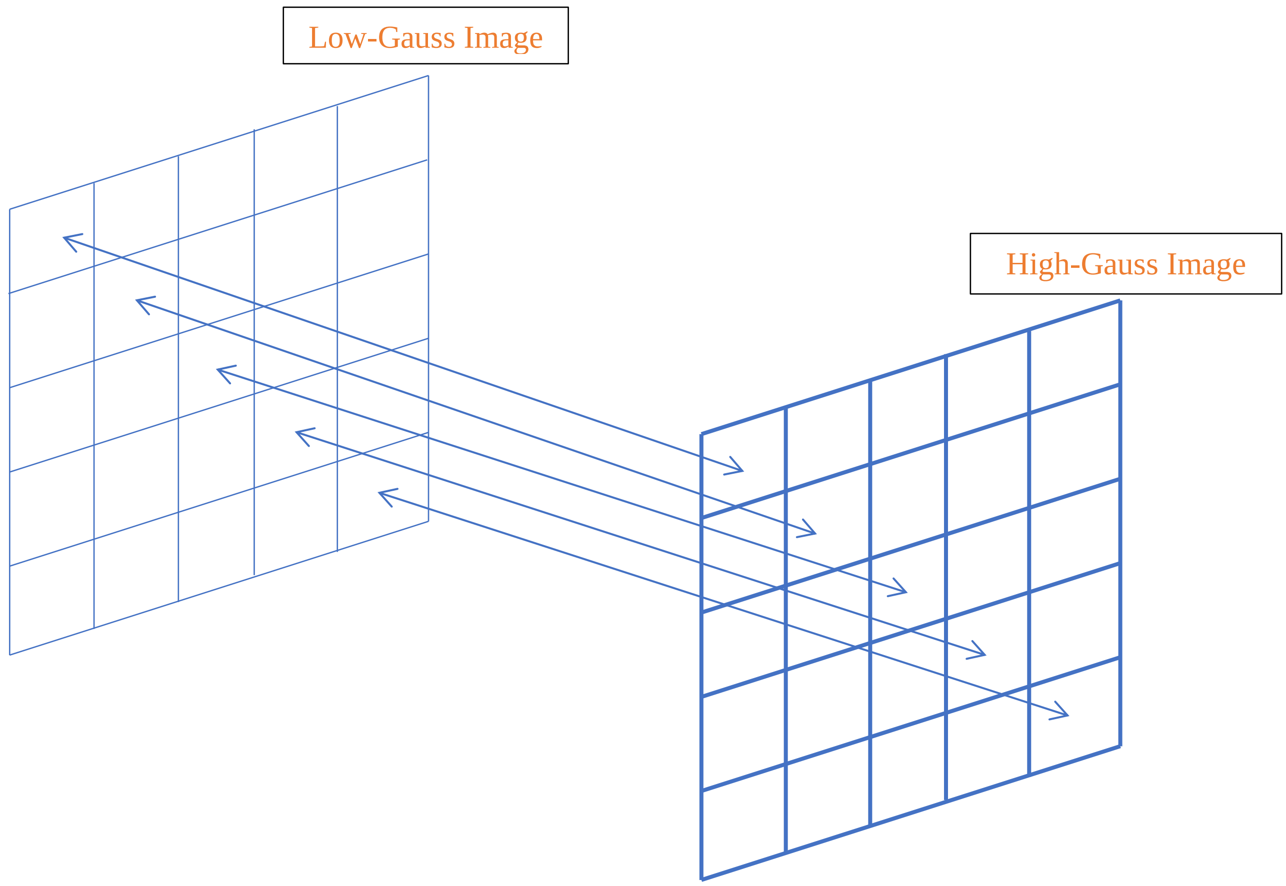

Figure 1. Two copies of an image are compared to each other. The blocks of the Low Gauss Image are compared to the spatially corresponding blocks of the High Gauss Image. The FDR is calculated between the spatial-corresponding blocks.

The Fisher Discriminant Ratio is commonly used as a metric tool. Specifically, for measuring a distance between distributions. Where J(w) is the computed FDR.

$$J(w) = \frac{|\widehat{m_1} - \widehat{m_2}|}{|\widehat{s^2}_1 - \widehat{s^2}_2|}$$

The hypothesis of this proposal lies at the heart of measuring the change of an image when a convolution is applied. The change is measured by comparing blocks of the image into equal sub-images ranging in pixel-by-pixel sizes. When both images undergo a Gaussian convolution, the information makeup of each block may be different. The difference depends on the initial information makeup of the image. The effect of the Gaussian kernel on edges, information homogeneity and information heterogeneity can be captured by the FDR.

The final step is to calculate the threshold of the change in variance. The median of the FDR array is used as the threshold to classify whether a pixel is smoke or non-smoke. Once the FDR array is sorted, the final image can be reconstructed by marking the pixel to its respective class.

Experimental Results:

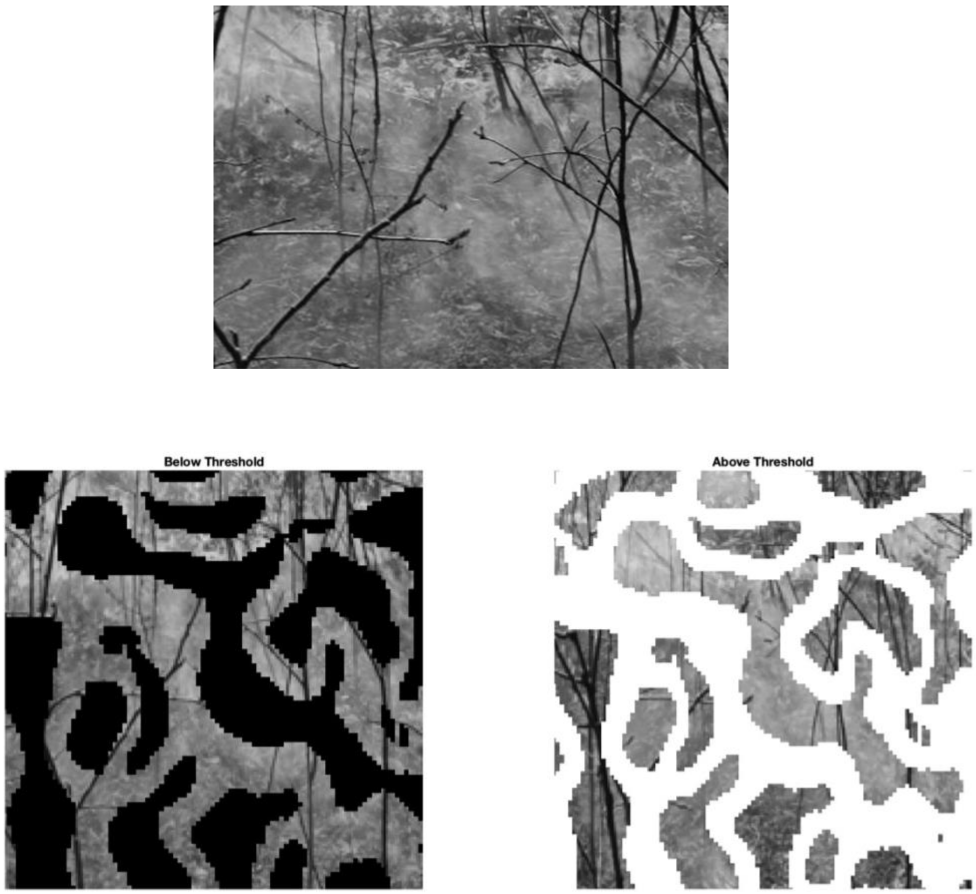

Figure 1. The top image contains smoke in a forest. The bottom left image labels smoke pixels as black. The bottom left image labels non-smoke pixels as white. The threshold for this image = 56.53.

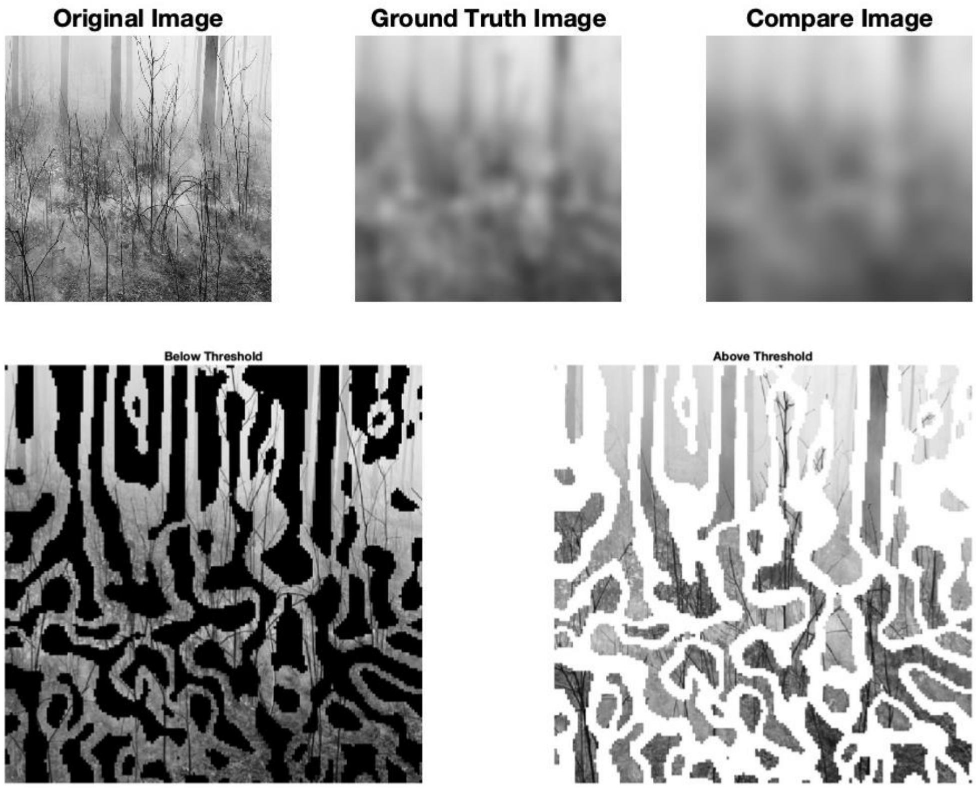

Figure 2. The original, ground truth, and comparison image are displayed and labeled. The compare image is blurred significantly more than the ground truth image. Ground truth image Gaussian sigma parameter: 5. Compare image Gaussian sigma parameter: 20.

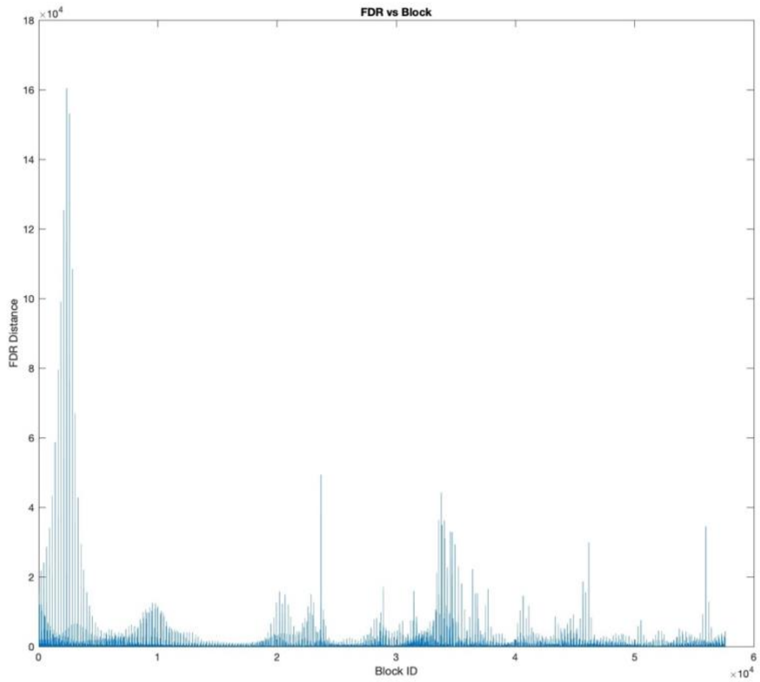

Figure 4. A graph of the FDR distance attributed to a unique block. Block ID represents the block number. The distribution of distances categorizes the image's response to the Gaussian kernel.

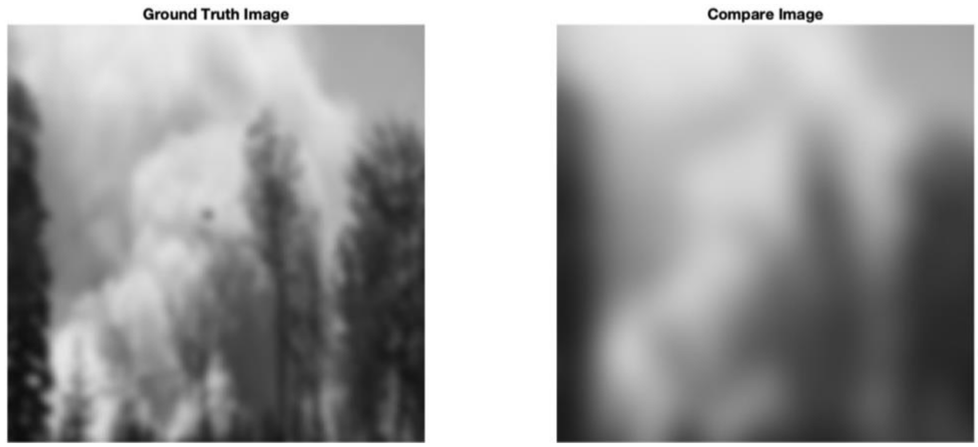

Figure 5. Comparison of the Gaussian variance parameter between ground truth image and compare image. $\sigma_{GT} = 5$; $\sigma_V = 20$

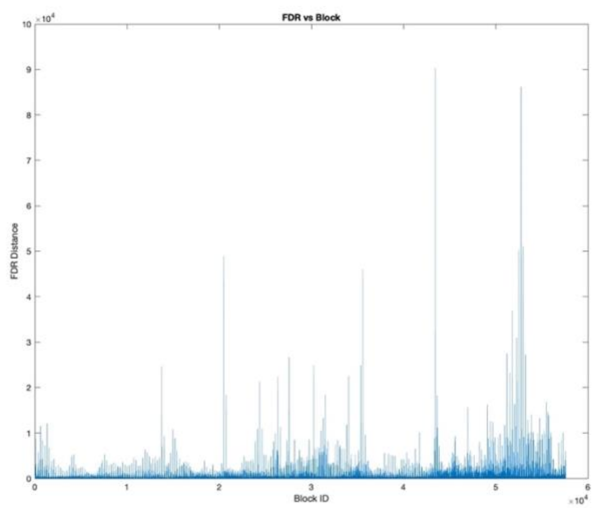

Figure 6. The FDR distribution of the image shown in figure 6. $\sigma_{GT} = 5$; $\sigma_V = 20$

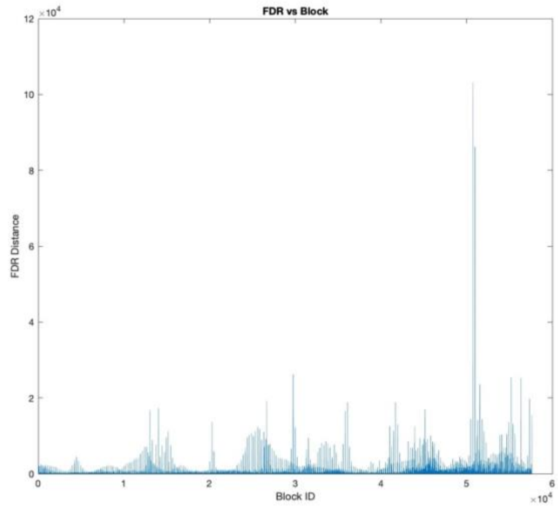

Figure 7. The FDR distribution of the image shown in figure 6. $\sigma_{GT} = 10$; $\sigma_V = 20$. The distribution has a more uniform shape when compared to figure 7. The uniformity directly contributes to inaccurate labeling of the image.

Discussion and Conclusions:

The experimentation dataset contains hundreds of images with diverse backgrounds, quality, lighting, time-of-day, and smoke/fire ratios. In the experimental results section above, it is demonstrated that the Gaussian blur and FDR thresholding algorithm works accurately, and with a 2x2 pixel region precision. Figures 2 and 3 show that even in a highly complex environment, where smoke is present both in the foreground and background. The algorithm was able to locate pixels in and around tree branches and leaves. A well-defined contour of the smoke is clearly labeled, and the non-smoke regions are in agreement with the smoke regions. Figure 4 is a plot of the FDR ratios and the respective blocks. Upon testing more images it became clear that the starting variance parameters of the Gaussian kernels made a substantial impact on the FDR distributions. Figures 6 and 7 confirm this effect by showing the different distributions of each Gaussian kernel settings.

The potential of this algorithm can be recognized by the demonstration shown in this proposal. However, there is no standard protocol in place to fully characterize the algorithm and its performance. The tested images were compared by eyesight, and therefore a standard accuracy metric is not provided. There are issues to be aware of, such as the false labeling of non-smoke pixels due to noise and texture. The phenomenon of different Gaussian variance parameters affecting the FDR distribution is already noted. Further work can be done by categorizing the dataset and observing the FDR distributions under different ratios of the starting Gaussian variances. In conclusion, a novel image processing algorithm to detect smoke in an image was proposed. The similarity of the Gaussian blur and smoke was exploited to threshold and segment the image into smoke and non-smoke classes. The algorithm has demonstrated itself

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