IMAGE BASED SMOKE DETECTION WITH LOCAL HURST EXPONENT

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ABSTRACT

Smoke is an important sign for early fire detection. Image based detection methods are more useful than other methods which use some special sensor devices.When treating image information of smoke, it is important to consider characteristics of smoke. In this study, we consider that the image information of smoke is a self-affine fractal. We focus on the nature of smoke and present a new smoke detection method based on the fractal property of smoke. We use the Hurst exponent H, which is one of the widely known exponent of fractals. We calculate H of smoke from a relation between H and the wavelet transform of the image. So we detect smoke areas in images with H through the wavelet transform. Moreover, to obtain the accurate detection result, we use the time–accumulation technique to smoke detection results of each image. In experiments, we show the effectiveness of our method with the fractal property of smoke.

Index Terms— smoke detection, fractal, Hurst exponent

1. INTRODUCTION

For early and certain fire detection, a smoke detection method is one of the important and challenging problems especially in open areas, such as port facilities, chemical plants and power plants. In such areas, direct fire or flame detection methods [1, 2, 3] are very limited because sources of the fire or flames cannot always fall into the field of view of sensors due to their positions and sizes. So smoke detection is needed for early fire detection in such cases. For smoke detection, especially in the above situations, we consider that image based methods are useful. In most of such areas, surveillance cameras are already set and we can easily obtain image information of target areas using them. So we adopt a computer vision approach for smoke detection.

Smoke gradually grows and always exists until the sources of smoke disappear. When we treats the image information of smoke, we have some difficulties mainly due to following characteristic properties of smoke: (i) semi–transparency (ii) non–stationary shape (iii) sensitiveness to environmental conditions (background, wind, lighting conditions, etc.). Conventional image processing techniques do not consider these smoke's properties for their target images. So previous studies[4, 5], which use conventional image processing techniques, cannot obtain robust results of smoke detection by the effect of above properties of smoke in some cases.

In this study, we present a new smoke detection method which considers characteristic properties of smoke. That is, we assume that smoke is a fractal[6, 7]. From this assumption, we can characterize the fractal nature of smoke with *Hurst exponent* (H), which is a widely known and used exponent of fractals. H is defined on two-dimensional regions of images and it takes unique value for each fractal–type. So we can characterize the fractal regions in given images using H.

We firstly extract moving objects or areas as candidates of smoke regions. From these candidates, we classify smoke regions using H. To obtain H of a region in the image, we use *Averaged Wavelet Coefficient* (AWC) method[8, 9]. AWC estimates the values H of the regions in an image from the relation between H and the wavelet coefficient of the region. Using estimated value of H, we determine whether the region is a smoke area or not. To obtain more accurate results of smoke detection, we also accumulate the results of determination based on H about time.

2. PRELIMINARIES

2.1. Pre–processing

We consider smoke is a moving object in an image sequence. So extracted regions as moving objects are candidates of smoke regions. As pre–processing, we detect moving objects in the image sequence as candidates of smoke regions. We use 30 frame–per–second rate image sequences, $f(t)$ ($t = 0, 1, 2, \cdots$ (frame))), as input image sequences in the following processing. We extract regions of moving objects with the image subtraction technique. As the growth–speed of smoke is considered, we subtract an original image sequence at one second intervals and obtain subtract images at every 5 frame of $f(t)$. That is, the subtracted image frame $g(t)$ is written as $g(t) = |f(t) - f(t - 30)|$ ($t = 30, 35, 40, \cdots$).

2.2. Fractal property of smoke

Since smoke is considered as Brownian motion at the molecular level, we assume that smoke is a *fractal*. Moreover, we assume smoke is a *self-affine-fractal*($\mathcal{SAF}$)[10]. From this assumption, smoke has some features of the fractal and hence it is characterized with index numbers.

In this study, we use *Hurst exponent* H to measure the property of $\mathcal{SAF}$ of smoke. Using this H, we determine smoke areas in an image. Note that, in addition to the assumption above, we also assume that the subtracted image $g(t)$ is $\mathcal{SAF}$. After the pre–processing, we use $\mathcal{SAF}$ property of the subtracted image $g(t)$ in our method.

3. PRINCIPLES

The assumption of $\mathcal{SAF}$ on smoke provides us how to determine which regions are smoke in the image. That is, we can use the Hurst exponent H in the smoke detection. Here we describe the definition of H and how to use it in our method.

3.1. Hurst Exponent of $\mathcal{SAF}$

If an image $h(x, y)$ is $\mathcal{SAF}$, $h(x, y)$ satisfies the following relation under the transformation $(x, y) \to (\lambda x, \lambda y)$:

$$h(x, y) \simeq \lambda^{-H} h(\lambda x, \lambda y) \tag{1}$$

where H is called Hurst exponent. That is, $h(x, y)$ is controlled by the scaling parameter λ and H. From the relation (1), we obtain the characteristic value H which reflects the $\mathcal{SAF}$ property of $h(x, y)$

3.2. Calculation of Hurst Exponent

To calculate H of an image $h(x, y)$, we use a relation between the (discrete) wavelet coefficient [11] of $h(x, y)$ and H as follows[8, 9] :

$$\begin{aligned} &W\{h(x, y), a, b_x, b_y\} \\ &= \frac{1}{a} \int\int \psi^* \left(\frac{x-b_x}{a}, \frac{y-b_y}{a}\right) h(x, y) dxdy \end{aligned} \tag{2}$$

$$W\{h(x, y), a, x, y\} \propto a^{H+1} \tag{3}$$

where ψ is a mother wavelet that has *scale parameter* a and *translation parameter* b, and $*$ denotes the complex conjugate. From the relation (3), we obtain H of $h(x, y)$ by changing a of the wavelet coefficient W.

3.3. Local Hurst exponent H_l

When we treat real data, it is known that the numerically calculated H has fluctuation[8][1]. To avoid this, we adopt an averaging method named AWC. In AWC, the wavelet coefficient value W at (x, y) is calculated by averaging out with its neighborhood's W. That is, AWC is mathematically defined as the following equation[9] :

$$\begin{aligned} &\overline{|W(h(x, y), a, x_0, y_0)|} \\ &= \frac{1}{w^2} \sum_{x=x_0-(1/2)w, y=y_0-(1/2)w}^{x=x_0+(1/2)w, y=y_0+(1/2)w} |W(h(x, y), a, x, y)| \end{aligned} \tag{4}$$

where w is the parameter that defines the range of the neighborhood at (x, y).

From Eq. (4), we obtain the Hurst exponent without the numerical fluctuation. We call this *Local Hurst exponent* H_l. To calculate the H_l of each point in $g(t)$, we define the (Local) Hurst exponent of the point in the target rectangle as H_l. As using AWC, the detection process of smoke becomes the rectangle–based. So we scan whole of the image $g(t)$ with the rectangle window whose window size is w and calculate H_l of these rectangles.

To avoid the computational complexity, we set the value of H_l of every point in the same rectangle window to be that of the center point of the rectangle. Based on these H_l, we determine which rectangles are smoke.

3.4. Extraction of smoke regions using H_l

To extract smoke regions in images, we compare H_l of the target (rectangle) region with H_l of *ideal smoke*, which is the set consists of preliminary prepared smoke regions. This ideal smoke set consists of manually selected rectangle regions of smoke, and the rectangle's size is $w \times w$ as same as the window size in Eq. (4). We scan $g(t)$ with the rectangle window and calculate the value of H_l of each rectangle region. If H_l of the target rectangle is *similar* to the H_l of the ideal smoke, we determine it as smoke. We set the condition whether the rectangle is smoke or not as H_l of the rectangle is in 95% confidence interval of ideal smoke's H_l for any given a in the relation (3). We label the target rectangle $l_g(x, y; t)$ to 1 when the target is determined as smoke, else we set it to 0 as Eq. (5).

$$l_g(x, y; t) = \begin{cases} 1 \ ((x, y) \ is \ determined \ as \ smoke) \\ 0 \ (else) \end{cases} \tag{5}$$

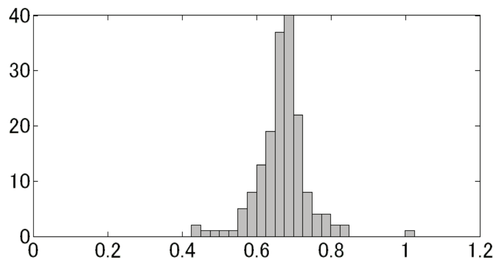
where (x, y) is a point in the target rectangle.

3.5. Time Accumulation

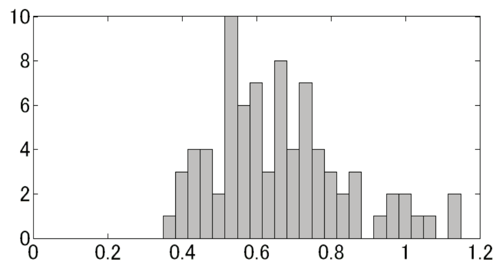
In the smoke detection with the real scene analysis, we have sometime difficulties using only one index due to the effects of several conditions. For example, there exist not only smoke but some moving objects in the real scene as noises. To solve this problem, we consider the property of smoke as moving objects, that is, smoke almost appears at the same place during the fire (the source of smoke) exists. We accumulate the results with H_l about *time* to realize this. The accumulation is defined as follows:

$$\mathcal{A}_g(x, y; t) = \sum_{t=\tau}^{\tau+T} l_g(x, y; t) \tag{6}$$

[1]This fluctuation is caused from the numerical calculation of the wavelet coefficient.



(a) H_l of smoke (171 images)



(b) H_l of the car (82 images)

Fig. 1. Distribution(Histogram) of H_l.

where $l_g(x, y; t)$ is the label of (x, y) described in Eq. (5) and the accumulation time T is must be selected manually. This point-wise accumulation of the label about time provides us more accurate information which point is similar to smoke. That is, if $\mathcal{A}_g(x, y; t)$ takes the high value, we can say that point is similar to smoke. Based on this $\mathcal{A}_g(x, y; t)$, we proceed the point-wise extraction of smoke regions.

4. EXPERIMENTS

To evaluate our method, we do experiments using an image sequence obtained from a fixed surveillance camera in a real scene. The image size of this sequence is $720 \times 480(px)$, and it contains smoke and other moving objects such as humans and cars. An example frame of this image sequence is shown in Fig. 2 (a). In the following experiment, we set the window size w in Eq. (4) the fixed value, $32 \times 32(px)$, and the scanning window size of the rectangle is same.

4.1. Hurst Exponent of ideal smoke

To measure the similarity between the target region and smoke, we prepare the smoke image set as the *ideal smoke*, which consists of 171 images of smoke manually selected. To calculate H_l, we use *Coiflet* as the mother wavelet in Eq. (2) in this case. Fig. 1(a) shows the distribution of H_l of smoke. As a comparison, Fig. 1(b) shows the distribution of H_l of the car image set, which is a example of non–smoke object and it consists of 82 images of the car manually selected. From Fig. 1, the distribution of smoke is sharply-peaked and hence smoke has almost same values of H_l. This also shows that smoke is the fractal, that is our assumption. However, the the distribution of cars are not peaky and this results the car is not a fractal.

4.2. Detection result

Firstly, we scan the subtracted images $g(t)$ using the rectangle window and calculate the H_l of the rectangles. To obtain H_l, we numerically calculate the wavelet coefficient W of the rectangle at $a = a_i = 2^{-i}$ $(i = 1, 2, \cdots, 5)$. As described in 3.4, the rectangle is determined as smoke when H_l of the rectangle is in 95% confidence interval of ideal smoke's H_l for any given a_i. Fig. 2 (b) shows the result of the detection using only H_l. The condition to determine the rectangle as smoke is strict in the numerical calculation using real data. So it is not enough using only H_l to detect smoke areas.

Next, we proceed the time accumulation. The result of the accumulation is affected by the accumulation time T and the threshold value of $\mathcal{A}_g$ in Eq. (6). In this experiment, we choose the case of $T = 10(frame)$ and the threshold value of $\mathcal{A}_g$ to be 8, which is 80% of T. Fig. 2 (c) shows the result of the time accumulation using this setting. We confirm that the time accumulation works well to detect the smoke area.

5. CONCLUSION

In this study, we present the new method of smoke detection based on the characteristic property of smoke as a fractal. As the characteristic of the fractal nature of smoke, we use the Hurst exponent H defined on the image information. To determine which regions of images are smoke, we use H of each regions. There is a relation between H and the wavelet coefficient of the image, we can obtain H by changing the parameter of the wavelet coefficient. So the value of H of each target region is calculated from this relation. We employ the averaging method, AWC, to avoid the numerical fluctuation of H.

In our method, the moving objects in images is extracted as the candidate regions of smoke. Instead of ideally defined H, we use the local Hurst exponent H_l, the averaged value of H calculated with AWC, to determine whether these candidate regions are smoke or not. Moreover, to obtain more accurate results, we accumulate the result of detection in each image about time. The time–accumulation works well, as smoke has different properties from other moving objects which even has the similar value of H compared to smoke's one.

To evaluate our method, we examine it with some examples of image sequences. In the example images, there exist smoke and other moving objects which are considered as obstructions. Experimental results show the effectiveness of our method.

There remain some problems for further works. One is that we need a more accurate estimation of the smoke region. To obtain the accurate regions of smoke in the images, it is useful to use the statistical distribution of the *ideal smoke* set. And we need the automatic threshold setting method, which can reduce the bad effect of lighting and environmental conditions. Additionally, it is needed to evaluate using more data obtained in different conditions such as day-and-night time, complex backgrounds, and moving objects of varied categories and sizes.

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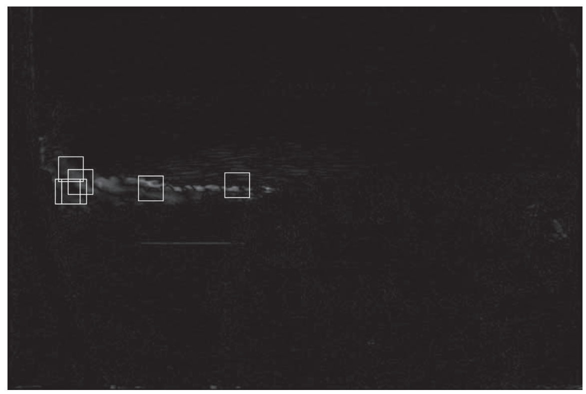
(a) Original image



(b) Detection result (using only H_l)

(c) Detection result (using time-accumulation)

Fig. 2. Example images of smoke detection.