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A Novel Flame Edge Detection Algorithm via a Novel Active Contour Model

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Abstract

Flame edge detection from color images is a challenging research area recently. In this paper, an extension of active contour model is proposed by adding the two information types to both internal and external energy terms. Therefore, the combination of these two forces allows for flexible initialization of the contours. This energy is then incorporated into a level set formulation with a level set regularization term that is necessary for accurate computation in the corresponding level set method. Edge extraction of different flame images using C-V model and the classical edge detection operators are compared and analyzed. Experimental results show that the existing methods do not emphasize the continuity and clarity of the flame and fire edges while the proposed method identifies the continuous and clear edges of the flame fire.

Keywords: *Edge detection, fire, flame, active contour*

1. Introduction

Aspect ratio of an image is a concept used to describe the ratio of the width of the image to its height. Image rendering or capture devices (e.g. widescreen TV, computer LCD monitors) typically adopt a specific aspect ratio from a set of about half a dozen possibilities.

To meet the stringent standards on combustion efficiency and pollutant emissions, quantitative flame monitoring is becoming increasingly important in fossil fuel fired combustion systems, particularly in power generation plants[1].In fire safety engineering ,flame image processing is also emphasized in a digital imaging based multifunctional flame monitoring system. As one of the important steps in flame image processing, edge detection is often the precursor and lays a foundation for other processing. There are several reasons why it is necessary to identify flame edges. First, the flame edges form a basis for the quantitative determination of a range of flame characteristic parameters such as shape, size, location, and stability. Second, the definition of flame edges can reduce the amount of data processing and filter out unwanted information such as background noise within the image. It is also used to segment a group of flames. This method is used to detect the flame edge to distinguish real and false alarms by online detection of flame in video [2].

In flame and fire edge detection several conventional edge-detection methods have been examined to determine their effectiveness, such as morphological method, wavelet transform method, neural network method, fuzzy detection method , IFS detection method and so on [3]. However, classical edge detection methods are mostly utilized in flame

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edge detection [4], such as Roberts operator, Sobel operator, Prewitt operator and Canny operator which based on first-order differential operator, and Log operator which based on second-order differential operator. As there may be some noise in flame images and sometime the flame image is not very clear [5], the edges detected by those operators may be discontinuous. By adjusting the parameters in this method the results achieved were still unsatisfactory. In the conventional edge detection methods, the flame image edge curves are not connected, and the false edges were detected. It is therefore desirable to develop a dedicated edge detection method for flame and fire image and video processing.

Recently, partial differential equations based on active contour model [6] are widely used in image segmentation. Existing active contour models can be categorized into two major classes: edge-based models and region-based models [7]. Edge-based models utilize image gradient to stop the evolving contours on the object boundaries. Typical edge based active contour models have an edge-based stopping term and a balloon force term to control the motion of the contour. One fact is that the segmentation results are very poor for the objects with strong noise or edge blurs in their interior areas. The reason is that those edge detectors greatly depend on the gradient of the input image. Region-based models aim to identify each region of interest by a certain region descriptor to guide the motion of the active contour. Typically, area information based Chan-Vese (CV) model is a very popular region-based active contour model [7]. It uses the global image information, without depending on gradient. It should be noted that it can better handle image segmentation problems such as strong noise and edge blurs. Thus, this model has widely been used in image segmentation for past decades. But, in the CV model, the image intensities are assumed to be statistically homogeneous. However, the assumption does not hold for some general images, which limits its applications.

Thus a new edge detection algorithm is proposed in this paper to process a combustion image and to identify flame and fire edges. Here section 2 of the paper deals with the introduction of CV model. Section 3 proposes a new edge detection of flame and fire image with detailed description. Section 4 shows the experimental results of edge detection with some discussions and comparisons, followed by conclusions in Section 5.

2. Related Works

2.1. Chan-Vese Model

Chan and Vese [7] proposed an active contour model which can be seen as a special case of the Mumford–Shah problem [3]. For a given image I in domain Ω, the CV model is formulated by minimizing the following energy functional:

$$E(C,c_1,c_2)=\lambda_1\int_{inside(C)}\left|I(x,y)-c_1\right|^2dxdy+\lambda_2\int_{outside(C)}\left|I(x,y)-c_2\right|^2dxdy,\ (x,y)\in\Omega \tag{1}$$

where c_1 and c_2 are two constants which are the average intensities inside and outside the contour, respectively. With the level set method, we assume

$$\begin{cases} C=\{(x,y)\in\Omega:\phi(x,y)=0\}, \\ inside(C)=\{(x,y)\in\Omega:\phi(x,y)>0\}, \\ outside(C)=\{(x,y)\in\Omega:\phi(x,y)<0\}, \end{cases} \tag{2}$$

$$c_1(\phi)=\frac{\int_\Omega I(x,y)\cdot H(\phi)dxdy}{\int_\Omega H(\phi)dxdy},\quad c_2(\phi)=\frac{\int_\Omega I(x,y)\cdot(1-H(\phi))dxdy}{\int_\Omega(1-H(\phi))dxdy} \tag{3}$$

By incorporating the length and area energy terms into Eq. (1) and minimizing them, we obtain the corresponding variational level set formulation as follows:

$$\frac{\partial \phi}{\partial t} = \delta(\phi)\left[\mu div\left(\frac{\nabla \phi}{|\nabla \phi|}\right) - \nu - \lambda_1 (I - c_1)^2 + \lambda_2 (I - c_2)^2\right] \quad (4)$$

where $\mu \geq 0, \nu \geq 0$, $\lambda_1 > 0$, $\lambda_2 > 0$ are fixed parameters, μ controls the smoothness of zero level set, ν increases the propagation speed, and λ_1 and λ_2 control the image data driven force inside and outside the contour, respectively. ∇ is the gradient operator. $H(\phi)$ is the Heaviside function and $\delta(\phi)$ is the Dirac function.

The CV model has good performance in image segmentation due to its ability of obtaining a larger convergence range and being less sensitive to the initialization. However, the CV model is only adapted for 2-phase image. If the intensities with inside C or outside C are not homogeneous, the constants c1 and c2 will not be accurate. As a consequence, the CV model generally fails to segment images with intensity inhomogeneity.

3. An Active Contour Model Combined With the Region and Edge Information (ACRE)

In this section, we present and discuss in detail the proposed model which combines the region information and edge information. For convenience, the proposed model is called ACRE. From the previous steps, a contour is initialized near or around the object of interest based on its strong saliency value. To evolve this contour, ACMs usually use either edge information or region information to define their energy functional. In this paper, an extension of ACMs is proposed by adding these two information types to both internal and external energy terms. A strong point when integrating region information into an energy functional is that this model has much larger convergence range and the initialization of the curve can be anywhere in the image. The Chan-Vese minimal variance criterion, or fitting term, for color images is given in [8] using region statistic information by

$$F_1(C) + F_2(C) = \int_{inside(c)} \frac{1}{3}\sum_{i=1}^{3} \lambda_i^+ (I_i - c_{1,i})^2 dxdy + \int_{outside(c)} \frac{1}{3}\sum_{i=1}^{3} \lambda_i^- (I_i - c_{2,i})^2 dxdy \quad (5)$$

where C is any curve and the optimal $c_{1,i}$ and $c_{2,i}$ are depending on C. In this term, λ_i^+ , λ_i^- > 0 are weights which control evolving speed of the curve. Usually, these parameters are constants set by experiments that can be very difficult to correctly tune for specific images [9]. Based on its meaning, a measure of information content, the image entropy is described as

$$E_{in} = -\sum_{k=1}^{n} p_k \log_2 p_k \qquad k \in inside(C)$$

$$E_{out} = -\sum_{k=1}^{n} p_k \log_2 p_k \qquad k \in outside(C) \quad (6)$$

where p_k is the probability of the k^{th} color level. This entropy reflects the diversity of intensity of the image. To apply this improvement, we assume that $\lambda_1 = E_{in}$ and $\lambda_2 = E_{out}$ to let the evolvement be faster and more smoothly.

For color images, edge information is defined by classical Riemannian geometry results [10]. In this case, the value of each pixel at (u_i , u_j) is treated as an Ndimensional vector. Using the standard notation of Riemannian geometry, they describe : $g_{ij} = \frac{\partial I}{\partial u_i} \cdot \frac{\partial I}{\partial u_j}$ and build a metric tensor $\left[g_{ij}\right]$. From this matrix, its eigenvectors θ_i and corresponding eigenvalues λ_i are obtained. Values of λ_i are called the maximal and minimal rate of change, respectively. As [10], the " strength" of edges in the vector-valued case is not simply the rate of maximal change but how λ_1 compares to λ_2. Therefore, the first approximation (or gradient) of edges should be a function $f = f(\lambda_1, \lambda_2)$.

In this paper, we select

$$f_{edge} = \lambda_+ - \lambda_- \tag{7}$$

Finally, the vector-valued edges are used to define an edge stopping function as

$$g = \frac{1}{1 + (f_{edge} * S(I))} \tag{8}$$

where $S(I)$ is the saliency map. This equation can increase the effect of pixels which are both in salient regions and at the object boundaries more than others to speed up the evolution of the contour to edges of the object.

Finally, to improve performance of the ACM in different situations, we propose a new energy functional, which combines both the edge and region information, defined as

$$\varepsilon(\phi) = \int_\Omega \frac{1}{3}\sum_{i=1}^{3} E_{in}^i (I_i - c_{1,i})^2 H(\phi) dxdy + \int_\Omega \frac{1}{3}\sum_{i=1}^{3} E_{out}^i (I_i - c_{2,i})^2 (1 - H(\phi)) dxdy$$
$$+ \mu \int_\Omega g\delta(\phi) |\nabla \phi| dxdy \tag{9}$$

where μ is a contant, H is the Heaviside function, and δ is the univariate Dirac function by

$$\delta\phi(x) = \begin{cases} 1 & \phi(x) = 0 \\ 0 & |\phi(x)| < \varepsilon \\ \frac{1}{2\varepsilon}\left\{1 + \cos\left(\frac{\pi\phi(x)}{\varepsilon}\right)\right\}, & otherwise \end{cases} \tag{10}$$

As shown in Figure 1, if ε is too small, the values of $\delta\phi(x)$ tend to be near zero to make its effective range small, so the energy functional has a tendency to fall into a local minimum. The object may fail to be extracted if the initial contour starts far from it. However, if ε is large, although $\delta\phi(x)$ tends to obtain a global minimum, the finial contour location may not be accurate. So in this paper, we choose $\varepsilon = 1.5$.

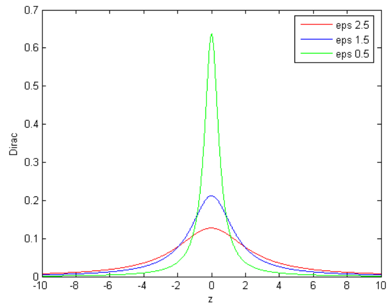


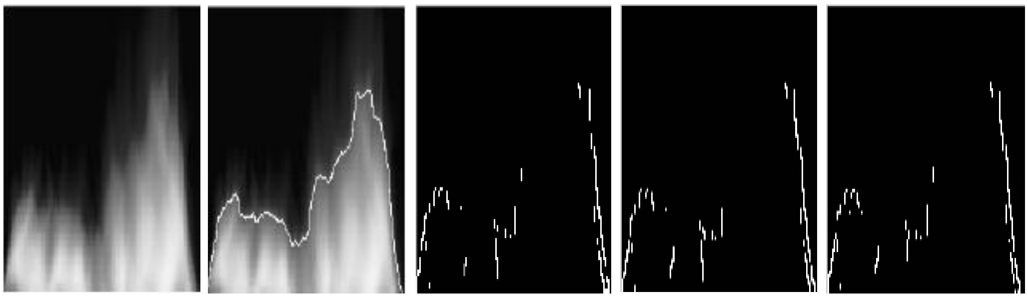
Figure 1. The Dirac Function W.R.T Different Epsilon Values

4. Experimental Results

Our algorithm is implemented in Matlab 7.0 on a 2.8-GHz Intel Pentium V PC. In each experiment, we choose ε = 1.5, $\mu = 0.01 * 255^2$. Thousands of flame images were proposed using the algorithm to evaluate its effectiveness. Some of the flame images were taken for propane Bunsen flames burning in open air. Some images were obtained from the internet with courtesy of permission of use. The experimental results are obtained by image segmentation of ACRE model and four classical edge detection operators [9], comparing the final results and characteristics of them.

4.1. Experimental Results of Simple Fire Images

Our first experiment is carried on different flame images without complicated background using ACRE and four classical edge detection operators. Some edge detection results are showed in Figure 2, Figure 3.



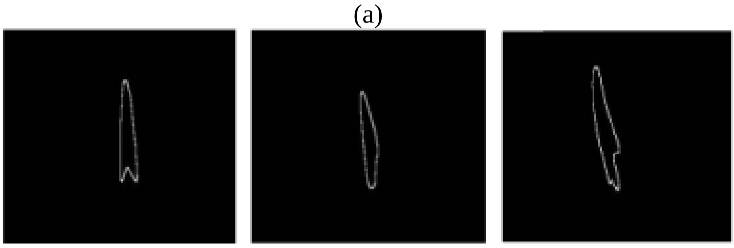
(a)Original image *(b) our method* *(c) Roberts* *(d) Sobel* *(e) Log*

Figure 2. Flame Edge Detection Results

From the result of Figure 2, we can see that when the edge strength of primary flame images is different, the edge detection results are also different using different methods. The edges detected by ACRE model are continuous and clearer than those detected by the four classical methods. Moreover, the edges detected by the four classical methods are discontinuous, especially in the first flame image which has weak edge strength, and from these discontinuous edges it is hard to extract flame feature parameters.

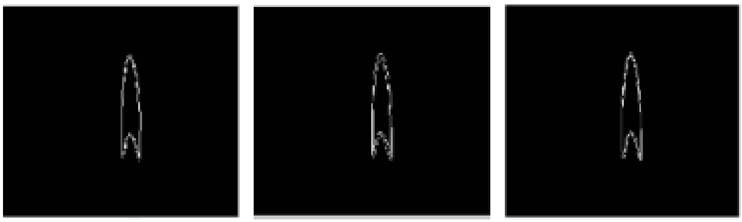
1 2 3

(a)



1 2 3

(b)



1 2 3

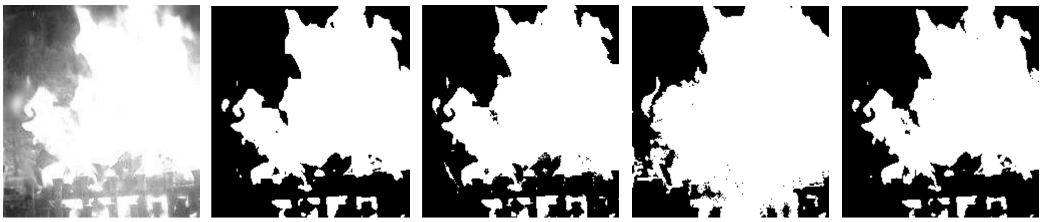
(c)

Figure 3. Edge-Detection Result For A Flame Video (A) Frames In A Flame Video (B) Detected Flame Edge From the Video Sequence Using the Proposed Method ACRE.(C) Detected Flame Edge From the Video Sequence Using (1) Roberts (2) Sobel (3)Log

To evaluate the robustness of the system for continuous edge detection many flame videos are also tested. Figure 3(a) shows a series of frames acquired from a flame video. Figure 3(b) shows the edge detection results by proposed algorithm. Figure 3(c) shows the edge detection results by various operators. It is clear that the flame edges obtained using the proposed algorithm show clear and continuous edges.

4.2. Experimental Results of Fire Images with Complex Background

To verify the effectiveness of our method in the complex background, our second experiment is carried on the complex fire images.



(a) (b) (c) (d) (e)

Figure 4. Segmentation Results of Mine Fire Disaster Image. (A) The Mine Fire Disaster Image (B) Roberts (C) Sobel (D) Log (E) Our Method

Figure 4 shows the typical processed flame images with edges identified with different edge operators. It is clearly noted that the proposed algorithm can clearly detect the edges of the flame which the common edge detection method cannot achieve.

5. Conclusions

In the paper we first introduce the importance of accurate edge detection in flame image, and then propose the image segmentation method using ACRE model. Finally, we use the ACRE method and classical edge detection operators to detect the edges in different flame images. The experimental results show that the advantage of this method is that the flame and fire edges detected are clear and continuous. This algorithm provides a useful addition to fire image processing and fire analysis in fire safety engineering. Our future work is conducted to extract flame feature parameters from the detected flame edges for further furnace flame image monitoring and combustion.

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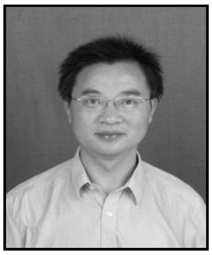

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