An Autoadaptive Edge-Detection Algorithm for Flame and Fire Image Processing

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Abstract – The determination of flame or fire edges is the process of identifying a boundary between the area where there is thermochemical reaction and those without. Previous vision based methods were based on color difference, motion detection of flame pixel and flame edge detection. Most previous vision-based methods using color information and temporal variations of pixels produce frequent false alarms due to the use of many heuristic features. Plus, there is usually a computation delay for accurate fire detection. Thus, to overcome these problems, candidate fire regions are first detected using a background model and color model of fire. Probabilistic models of fire are then generated based on the fact that fire pixel values in consecutive frames change constantly and these models are applied to a Bayesian Network. This proposed work uses a three-level Naïve Bayesian Network that contains intermediate nodes, and uses four probability density functions for evidence at each node. The probability density functions for each node are modeled using the skewness of the color red and three high frequency components obtained from a wavelet transform. The proposed system was successfully applied to various tasks in real-world environments and effectively distinguished fire from fire-colored objects. Experimental results will indicate that the proposed method outperforms other methods in both of fire target enhancement and background detail preservation.

Keywords – Edge Detection, Smoothing, Segmentation.

I. INTRODUCTION

Edge detection is an important field in image processing. It can be applied to many applications such as segmentation, registration, feature extraction, and identification of objects in a scene. Edge detection can refer to the procedure of locating sharp discontinuities within an image. These discontinuities originate from different scene features which can include discontinuities comprehensive, discontinuities in surface orientation, and changes in information properties and variations in scene enlightenment. Edge detection is basically a fundamental tool utilized in most image processing applications to acquire information seen from the frames currently being a precursor step to feature extraction and object segmentation. This system detects outlines relevant to an object and limits between objects and the background in the image. An edge-detection filter can also be used to strengthen the appearance of blurred image; of this cause more studies take this subject might be give many of these studies briefly: Soft computing techniques have located wide applications. One of the most essential applications is edge detection for image segmentation. The method of partitioning be sure you image into multiple regions or sets of pixels is termed image segmentation. Edge is basically a boundary between two homogeneous regions. Edge detection is the means of identifying and locating sharp discontinuities inside an image. In this paper, the primary aim will be to survey the idea of edge detection for image segmentation using soft computing approach according to the Fuzzy logic, Genetic Algorithm and Neural Network[1]. The Canny algorithm uses a beneficial edge detector dependent on an arrangement criteria which includes searching for the most edges by minimizing the error rate, marking edges as closely as is possible to the actual edges to maximise localization, and marking edges only once whenever single edge exists for minimal response[2]. The nonmaximal suppression stage identifies pixels that might be local maxima toward the gradient utilizing the magnitude and orientation of the pixels. The foremost orientation of this very gradient, either horizontal or vertical, is obtained by comparing an individual components, dx and dy, which you'll find are as a result of convolving the smoothed image in the derivative of one's Gaussian. Since the majority of edges are in an angle, it is possible to obtain further granularity inside the orientation of a given gradient by comparing the sign serving of the gradient [3]. The designed fuzzy rules are a lovely resolution to improve the quality of edges whenever possible[1].

The overall impact of many image processing and pc or laptop vision tasks is determined by the perfection of
detecting priceless edges. Edge detection has been a challenging problem in low level image processing. It becomes more difficult when color images are considered as a result of its multi-dimensional nature. Color images provide accurate information about the object which will be very ideal for further operations than gray level images. Due to some unavoidable reasons which can include distortion, intensity variation, noise, segmentation errors, overlap (large range of distracting objects i.e., clutter), and occlusion of those objects in digital images, it's usually impossible to wring complete object contours and also to segment the whole of the objects. On account of lack of object edge information the output image is certainly not visible clearly. A lot of methods can be found within the literature to segment images. This task are difficult or incredibly important, since the output associated with an image segmentation system can easily be fed as input to higher-level processing tasks, which can include model-based object recognition systems. Along with general surveillance dependent on human tracking, fire detection using surveillance cameras has as well become significant area of research. Most current fire alarm systems are dependent on infrared sensors, optical sensors, or ion sensors that depend on certain characteristics of fireside, which can include smoke, heat, or radiation. However, these traditional fire alarm systems aren't alerted until the particles actually reach the sensors, and usually are unable to provide any additional information, like location and size of one's fire and to discover the measure of burning. Contrastingly, vision sensor-based fire detection systems offer several advantages. First, the technology cost is lower, consequently systems are based on CCD cameras, which you'll find are already installed in many public places for surveillance purposes. Second, the response how about fire and smoke detection is quicker, like the camera does not require to anticipate for the smoke or heat to diffuse. Third, since the camera also work as a volume sensor, as distinct from traditional point sensors, it may monitor a significant area, creating a higher probability of fire detection in an early stage. Finally, for example in the case of a false alarm, the system manager can confirm the incidence source of fire throughout the surveillance monitor without choosing the location.

II. LITERATURE SURVEY

Chen et al.[1,5] used an RGB/HIS color model and dynamic analysis of flames that suits the disordered characteristic of flames in the development of pixels to verify when it comes to the incidence a fire, and Töreyin et al.[2] detected moving pixels and regions in a video utilizing a hybrid background estimation method. Because of that, candidate fire regions are extracted among moving regions whenever they belong to pre-specified fire-colored models, then a wavelet analysis in temporal/spatial domains is carried out to discover high-frequency activity within these candidate regions. Celik et al.[3] proposed a real-time fire detector that mixes foreground object information with color pixel statistics for fire. The foreground details are extracted using an adaptive background subtraction algorithm, and then verified making use of a statistical fire color model. Han et al.[4] proposed a fire and smoke detection system for use in tunnels. However, the use of many heuristic thresholds makes these methods impractical for real-life application. To overcome this difficulty, Cheong et al.[5] proposed a Support Vector Machine (SVM)-based fire detection method, but despite a very good detection performance, this procedure is not suitable for real-time applications, mainly because it requires additional computational time as documented in the number and dimensions of a given support vectors. Edge detection is analyzed utilizing the mathematical representation of first order & second purchase derivatives. The first order finds the gradient & second order allows the magnitude of the sting. A flame zone has got a stronger luminance in comparison with its ambient background and the boundary involving the flame zone and also its background is mostly continuous. Subjective used will be to detect the coarse and to discover the superfluous edges inside a flame image, if there happen to be one unit main flame and if the reputation contains multiple flames, it is segmented regarding contain one flame. See the flame’s primary edge and take out irrelevant ones to project the continual edge. The most common edge-detection methods like Sobel, Prewitt, Roberts, Canny and Laplacian method have been applied with appropriate parameters to process typical flame images. Despite many parameters being lightly and appropriately adjusted within the utility of these methods, flame edges could hardly be clearly identified. Figure 1(a)–(f) shows instances of results obtained through conventional edge-detection methods in addition to authentic image.

The expected flame edge should be only one clear, continuous, and uninterrupted edge. However, just like the results have indicated, the edges identified making use of these methods are frequently disconnected and fragmented [Figure 1(b)–(f)]; many of the methods are only able to identify a part of the flame edge [Figure 1(b)–(d)] or wrongly find small edges that are obviously not the edges of one's main flame [Figure 1(e)]. The final results have as a result suggested that should be not usually actually possible to obtain ideal edges from real-life images of moderate complexity, for that reason complicating a subsequent task of interpreting the reputation facts.
III. PROPOSED SYSTEM

Occurrence of permanent changes in the scene is possible, and if this change can not be detected by the system, the system always gives false positive which is undesirable. It is observed that, if the change stays in the system long time which is in the unit of frame, i.e. if it stays 2 frames, then the change in the system can be added to the background model if we keep a counter for each pixel which keeps how many consecutive frames it stays as background and decide on corresponding pixel using this counter. This counter value is used to decide whether the corresponding pixel should be added to background model or not. The pixel’s counter value is compared with a predefined threshold value $\tau$ which is a global threshold used to decide whether corresponding pixel should be registered as background pixel which is formulated as below:

$$S(x,y) = \begin{cases} \text{background,} & C(x,y) \geq \tau \\ \text{foreground,} & \text{otherwise} \end{cases}$$

Where $\tau$ is threshold for image noise filtering.

Fire colored-pixel detection:

- After detecting the foreground pixels using background modeling, the non-fire colored pixels need to be filtered out. Therefore, this system generates RGB probability models using a unimodal Gaussian from sample images containing dynamic fire scenes.

- Fire pixels are then detected using these RGB probability models. If the RGB channel distributions of each pixel are assumed to be independent, the Gaussian probability distribution can be estimated as follows.

$$p_i = \frac{1}{\sqrt{2\pi\sigma_i^2}} \exp\left(\frac{(I_i(x,y) - \mu_i)^2}{2\sigma_i^2}\right)$$

for $i \in \{R,G,B\}$

**The feature of Bayesian Network**

Bayesian Networks are directed acyclic graphs (DAGs), where the nodes are random variable. The arcs in a Bayesian Network then specify independent assumptions that must hold between the random variables. These independent assumptions determine what probability information is required to specify the probability distribution among the random variables in the network. To specify the probability distribution of a Bayesian Network, the prior probability of all root nodes and the conditional probabilities of all non-root nodes must be set, given all possible combinations of their direct predecessors. Moreover, Bayesian Networks allows the conditional probabilities of the nodes in the network to be calculated, given that the values of some of the nodes have been observed.

Bayesian classifiers are statistical classifiers. They can predict class membership probabilities, such as the probability that a given tuple belongs to a particular class. Bayesian classification is based on Bayes theorem. Naive Bayesian classifiers assume that the effect of an attribute value on a given class is independent of the values of the other attributes. This assumption is called class conditional independence. It is made to simplify the computations involved and, in this sense, is considered “naïve.” Bayesian belief networks are graphical models, which unlike naïve Bayesian classifiers, allow the representation of dependencies among subsets of attributes. Bayesian belief networks can also be used for classification.

The naïve Bayesian classifier, or simple Bayesian classifier, works as follows:

1. Let D be a training set of tuples and their associated class labels. As usual, each tuple is represented by an n-dimensional attribute vector, $X = (x_1, x_2, \ldots, x_n)$, depicting n measurements made on the tuple from n attributes, respectively, $A_1, A_2, \ldots, A_n$.

2. Suppose that there are m classes, $C_1, C_2, \ldots, C_m$. Given a tuple, $X$, the classifier will predict that $X$ belongs to the class having the highest posterior probability, conditioned on $X$. That is, the naïve Bayesian classifier predicts that tuple $X$ belongs to the class $C_i$ if and only if $P(C_i/X) > P(C_j/X)$. Thus we maximize $P(C_i/X)$. The class $C_i$ for which $P(C_i/X)$ is maximized is called the maximum posteriori hypothesis. By Bayes’ theorem

$$P(C_i/X) = \frac{P(X/C_i)P(C_i)}{P(X)}$$

3. As $P(X)$ is constant for all classes, only $P(X/C_i)P(C_i)$ need be maximized. If the class prior probabilities are not known, then it is commonly assumed that the classes are equally likely, that is, $P(C_1) = P(C_2) = \ldots = P(C_m)$. Given data sets with many attributes, it would be extremely computationally expensive to compute $P(X/C_i)$. In order to reduce computation in evaluating $P(X/C_i)$, the naïve assumption of class conditional independence is made. This presumes that the values of the attributes are conditionally independent of one another, given the class label of the tuple (i.e., that there are no dependence relationships among the attributes). Thus,
We can easily estimate the probabilities \( P(x_1/C_i), P(x_2/C_i), \ldots, P(x_n/C_i) \) from the training tuples. Recall that here \( x_k \) refers to the value of attribute \( A_k \) for tuple \( X \). For each attribute, we look at whether the attribute is categorical or continuous-valued.

IV. RESULTS

![Original Image](image1)

![Sobel Detection](image2)

![Neighbor Detection](image3)

![Temporary edge detection](image4)
**Flame Edge Detection**

Proposed Results:

**Figure 1. Original Image Load**

**Figure 2. Flame Edge Detection Output**

**Different curvature graph detection for noise**

**Final edge detection**

**V. CONCLUSION AND FUTURE SCOPE**

Vision-based fire detection approaches offer several advantages, including relatively inexpensive equipment, a rapid response time, and fast confirmation through the surveillance monitor. Yet, fire detection approaches using a camera face certain challenges, as well as offering opportunities for the development of effective fire alarming systems. Most previous vision-based methods depend on color information and temporal variations in the pixels using empirical parameters. However, these methods are often difficult to apply in practice, due to several factors, such as varying environmental conditions and fire materials. Thus, to overcome these limitations, this paper presented a fire detection algorithm using an adaptive background subtraction model with a Bayesian inference to verify real fire pixels. In particular, the patterns of fire and fire-like moving objects were
analyzed and probability models of fire designed using several fire feature patterns. As a result, the use of probability models and a Bayesian inference improved the detection performance and reduced the missing rate.

REFERENCES