# Classification of Flame and Fire Images using Feed Forward Neural Network

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*Abstract*—**Flame edge determination and classification is an active research area of wide application. Edge detection techniques for flame images can be used in applications such as flame image monitoring, early detection of fire, evaluation of fire, and the measurement of flame and fire parameters. This paper mainly gives importance on edge detection and classification of flames. The boundaries of flames are detected perfectly by using auto adaptive edge detection algorithm and classification of flame levels are done by using resilient back propagation algorithm in feed forward neural network.**

***Keywords*- Edge detection; feature extraction; edge image analysis; shape measurement; flame classification.**

## I. INTRODUCTION

There are many reasons why it is important to identify flame edges. First, the flame edges form a basic foundation for the determination of flame characteristic parameters namely flame location, size and shape. Second, the flame edge definition can decrease the amount of data processing and remove unwanted information such as noise within the image. Third, edge detection can be used to segment multiple flames which become helpful for multiple flame monitoring in some industrial furnaces using multi-burner system. Flame monitoring is widely used in fossil-fuel-fired combustion systems and power generation plants [1].

Numerous methods are reported for identifying flame edges for geometric flame characterization [2, 3]. One of these methods uses a software tool to analyze fire images, for which a mouse could be used to trace the flame edge [4]. This manual edge-detection method does not indicate the usefulness of fire edge detection. Another adequate method is to extract contours of flame by detecting the changes in intensity over a flame image horizontally line by line as in [5], but this method can be only adapted for simple and steady flames. References [6, 7, 8] succeeded to identify fire in live video using hidden Markov models and wavelet transform methods. Another efficient method to detect and analyze fire information on a video is developed by inspecting the shape regularity and intensity saturation feature [9].Reference [10] suggests the use of background subtraction and Prewitt edge-detection method for detecting flames in fire protection systems. Also a Chan-Vese active contour model is proposed for flame edge detection in a power plant [11]. An improved canny edge detector was used to detect moving fire regions on large space fire images as in [12]. A new method using FFT and wavelet transform for the contour analysis for forest fire images in a video is presented in [13]. An algorithm for early fire detection is proposed [14] and tested on video clips. All of the above methods despite having its own advantages such as fire detection or shape reconstruction in a complicated background, early fire detection followed by activation of a fire alarm, also have some limitations. For detecting the flame's size, shape and the geometric characteristics, it is required to attain a clear, continuous and closed edge of the flame. Many conventional methods for edge detection have been tested and the results were unsatisfactory. It is therefore adequate to develop an efficient method for fire and flame image processing. In this paper, a new edge detection algorithm called Auto adaptive edge detection for flame and fire images has been proposed. Also classification process of flame and fire edges are carried out by feed forward neural network using resilient back propagation algorithm.

The remainder of this paper is organized as follows. Section II explains about the methodology. Section III discusses the experimental results. Finally, conclusion and suggestion for future work is given in section IV.

## II. METHODOLOGY

In this section the detailed procedure for flame edge extraction and classification of flame levels is given. The basic strategy is to use auto adaptive edge detection algorithm to identify the superfluous and coarse edges in a fire/flame image and then to identify the principal edges, removing the unwanted ones and finally classifying the flame level as high level or low level using feed forward neural network. The following are the logical steps involved.

### A. Auto adaptive edge detection algorithm

Step1) Covert the colour image of the flame in to gray level and adjust the gray level according to its statistical distribution. Let's consider a discrete gray scale image 'x' and let the total number of occurrences of gray level of 'i' be '$n_i$', then a pixel of gray level 'i' has the probability of occurrence[15]

$$P_x(i) = p(x = i) = \frac{n_i}{n}, 0 < i < L \quad (1)$$

where 'L' is the total number of gray levels in the image, 'n' the resultant pixels in the image, and $p_x(i)$ the pixels histogram with 'i', normalized to [0,1].The cumulative distribution function(CDF) corresponding to $p_x$ is defined as

$$CDF_x(i) = \sum_{j=0}^{i} p_x(j) \quad (2)$$

This is the accumulated normalized histogram of the image.

Next, a transformation of form $y = T(x)$ is created to produce a new image {y}, such that its CDF will be linearized across the value range with number $K$ which is a constant , i.e.

$$CDF_y(i) = iK \quad (3)$$

Step2) Noise removal of the flame image is done by using a Gaussian filter. Gaussian smoothing [16] is performed using standard convolution methods after selection of a suitable mask. As the Gaussian mask width increases, it reduces the sensitivity of detector to the noise in the flame or fire image making the detected flame or fire image edge so accurate but the localization error in the detected flame/fire edges also increases slightly with the Gaussian width. The discrete approximation to Gaussian functions as shown in Fig.1 is used in the implementation.

$\frac{1}{115}$

| | | | | |
|---|---|---|---|---|
| 2 | 4 | 5 | 4 | 2 |
| 4 | 9 | 12 | 9 | 4 |
| 5 | 12 | 15 | 12 | 5 |
| 4 | 9 | 12 | 9 | 4 |
| 2 | 4 | 5 | 4 | 2 |

Figure 1. Discrete approximation to Gaussian functions.

Step3) The basic edges of the flame is found out by using Sobel operator. Here, the gradients of all the pixels in the image are found out. The edges, since having high gray level contrast are highlighted and all other pixels not having peak gradients are suppressed. If the gradient magnitude is greater than high level threshold ($T_H$) then it taken as an edge and otherwise not an edge. The Sobel operator uses a pair of 3×3 convolution masks, estimating the gradient in the x-direction (columns) and y-direction (rows). The Sobel operator is expressed as follows [17].

$$M_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \quad (4)$$

$$M_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \quad (5)$$

Step4) Adjust the threshold value which can be achieved by taking an initial threshold value based on prior results of identical flame images and adjusting this value for improved result. The result is evaluated by how many edges there are. The parameters are improved with the increase in edge pixels detected in the edge image. Another threshold $T_E$ is set to limit the total number of edges, i.e., if the number of edge pixels increases above $T_E$, the automatic adjustment will be stopped. At this point, a preliminary edge image (PEI) with edges identified will be obtained from the original flame image.

Step5) Removing all unrelated edges in PEI

a) Any edge point in the Preliminary edge image is selected, that point is removed from PEI and plotted on to a newly allocated temporary edge image.

b) Using the selected point as the center, search in a 3×3 area. Check if the neighbouring pixels are edge pixel or not, if yes then store the location of all neighbouring pixels. In eight neighbouring pixels, operations are taken for three different cases as follows.

i) If there are no neighbouring pixels, selected point turns out to be an isolated point and it should be removed from the Preliminary edge image. Stop the search and move to step (5d).

ii) If there is one neighbouring pixel, then the selected point turns out to be an endpoint. This point should be removed from PEI and it is plotted on to a temporary edge image (TEI), and is added to the end point list. New searches are then started from the found neighbor and move to step (5c).

iii) If there are two or more neighbouring pixels, the selected point turns out to be an intersection with more than three bifurcations or a normal transition point in an edge line. One of the neighbouring points is set as the new search center, and a new search process is started. The other positions are stored as unchecked conjunction points, and then, move back to Step (5b).

c) After checking the conjunction points and if all the points have been searched as center then one temporary edge image is accomplished. The lengths of any two end points in the temporary edge image are computed, and the longest one is picked out. Then, move to Step (5d).

d) Check if all the pixels in the Preliminary edge image are moved to the temporary edge image then move to Step (6).

Step6) The pixels of the longest edge are selected in the final edge image which should follow the same size as that of original input flame image.

Step7) Flame image is classified based on feed forward neural network using resilient back propagation algorithm. The flowchart of the process is shown in Fig.2.

LMS algorithm is used for find out proper threshold value. LMS algorithm is a class of adaptive filters in which the filter coefficients that produce the least mean square of the error signal between the actual result and required result is found out. Here steepest descent algorithm is used to calculate the filter weights that reduce the cost function. From the steepest descent method, the equation for weight vector is given by [18]

$$w(n+1)=w(n)+1/2\ \mu[-\nabla(E\{e^2(n)\})] \quad (6)$$

where $\mu$ was the step size parameter which controls the convergence characteristics of the LMS algorithm and $e^2(n)$ is the mean square error between the former output y(n) and the reference signal which is given as

$$e^2(n) = [d^*(n) - w^h x(n)]^2 \quad (7)$$

The gradient vector in the above mentioned weight update equation can be calculated as,

$$\nabla_w (E\{ e^2(n)\})= -2r(n) +2R(n) \quad (8)$$

Where r(n) and R(n) are covariance matrices defined as below:

$$r(n)=x(n)d^*(n) \quad (9)$$

$$R(n)=x(n)x^h(n) \quad (10)$$

The weight update is given by,

$$w(n+1)=w(n)+\mu x(n)[d^*(n) - x^h(n)w(n)] \quad (11)$$

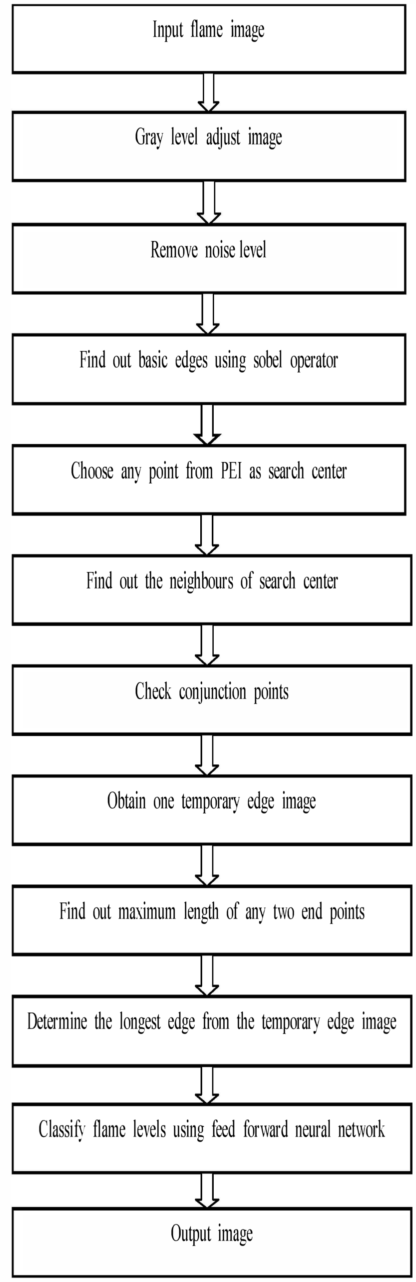


Figure 2. Methodology used for flame edge detection and classification

So

$$w(n+1)=w(n)+\mu x(n)e^*(n) \quad (12)$$

In this process, the two parameters $T_H$ and $T_L$ need to be automatically adjusted. Here starting value of $T_H$ and $T_L$ based on priory result of similar flame images are given, and set one of the parameters constant for adjusting the other one. For example, assume that $T_H$ is constant, then $T_L$ is adjusted in each step. The Euclidean distance measure of a curve's start point $C_s$ and endpoint $C_e$, denoted as D, is used for the judgment of the new threshold $T_L$. The coordinates of start point $C_s(S_a, S_b)$ and endpoint $C_e(E_a, E_b)$ should be stored in the memory in the tracing process. So D can be calculated as

$$D = \sqrt{(E_a - S_a)^2 + (E_b - S_b)^2} \quad (13)$$

After LMS computation process, a $T_L$ is suitably chosen. If D adequately small then the computation process terminates and if D value is still greater than the required value, again LMS algorithm is applied to $T_H$. If D value is zero no other adjustment of $T_H$ and $T_L$ value is necessary so auto adaptive process ends but if D value is still big enough a further adjustment should be executed.

### B. Feed forward neural network

Feed forward neural network is the simplest type of artificial neural network where there are no cycles or loops in the network. Here the connections between units does not form a directed cycle and the information moves in the forward direction from the input nodes, through the hidden nodes if there are any to the output nodes. By using this feed forward neural networks the flame image is classified as low level or high level. Mainly feed forward neural network are of two types namely single layer and multilayer network. In single layer only input and output layer exist and in multilayer three layers namely input, hidden and output layer exists.

### C. Resilient Back propagation algorithm (R prop)

Multilayer neural networks are trained by using steepest descent algorithm with sigmoid transfer functions as in fig.3.

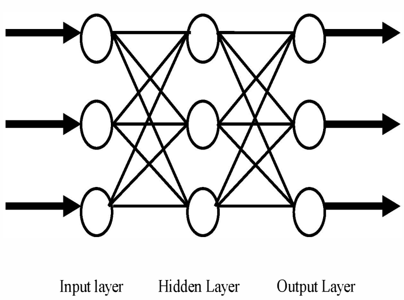


Figure 3.Feed forward neural network

The sigmoid functions are also called squashing functions because an infinite input range is compressed to finite output range. Sigmoid transfer function has some characteristic such as the input becomes large as their slope converges to zero. This creates a big problem when using steepest descent training algorithm for multilayer neural network with sigmoid functions because the magnitude of the gradient shall be small causing only small change in bias and weight values even though the biases and weights are nowhere near their optimal values. The main function of the resilient back propagation algorithm is to remove negative effects of the magnitude of the partial derivatives. The direction of the weights is determined only by using the sign of the derivative; the derivative magnitude has no effect on updating the weights. The size of change in weight is decided by a separate update value. The update value for each bias and weight was increased by a factor delt_inc whenever the performance function derivative with respect to that weight has occurrence of same sign in successive iterations. The update value is decreased by a factor delt_dec whenever the performance function derivative with respect to that weight has sign difference from the previous iteration. If the performance function derivative is zero, then the update value stays the same. If there is continuous change of weight in the same direction for several iterations, then the magnitude of the weight change will be increased. If the weights are oscillating the weight change will be decreased. The main parameters involved for training are epochs, show, goal, time, delt_inc, delt_dec, min_grad, max_fail, delta0, deltamax. The performance of resilient back propagation algorithm does not show much sensitivity to the training parameter settings.

## III. RESULT AND DISCUSSION

### A. Auto adaptive edge detection process flow

Input selected for this edge detection algorithm process is flame images. For the purpose of getting the gray level adjusted image the given input image is first converted into the luminance image. The gray level adjusted image is obtained by adjusting the gray level of a flame image according to its statistical distribution. The image is smoothened to eliminate the noise. The sobel operator uses a pair of 3 × 3 convolution masks for estimating the gradient in the *y*-direction (rows) and *x*-direction (columns). PEI image is achieved by giving the first pair of $T_H$ and $T_L$ initial values according to the a priori results of similar flame images and then adjusting the values for a better result and finally sobel edge image is obtained. The output of each step is shown in Fig.4

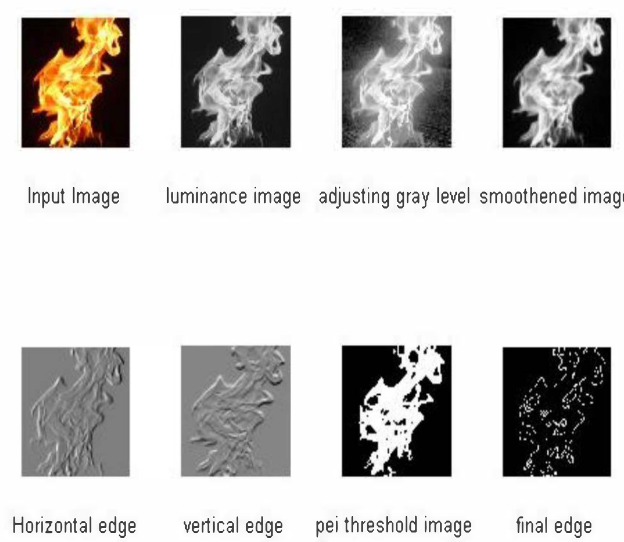


Figure 4. Edge detection process

B. Comparison of edge detection process

Our proposed sobel is compared with the prewitt, canny and laplacian operators. The edges obtained from the other methods are unclear and discontinuous, while the results obtained using adaptive edge detection algorithm show clear and continuous edges with parameters automatically adapted as in Fig.5.

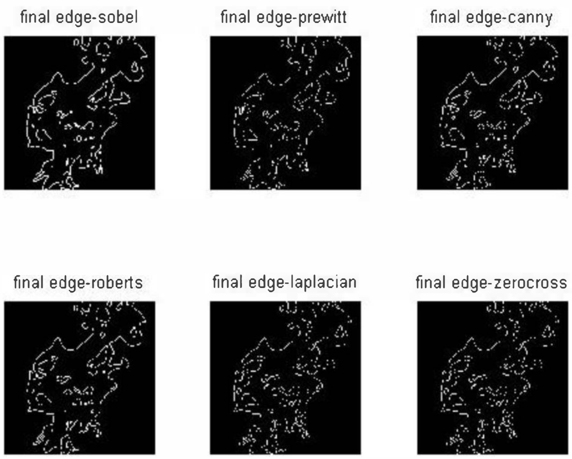


Figure 5. Comparison of proposed and conventional methods

C. Neural network training process

Classification of flame image is carried out by using feed forward neural network. Resilient back propagation algorithm is used for training the network as shown in Fig.6.The advantage of using this algorithm is faster training, less memory requirement, updating of weights within limited time.

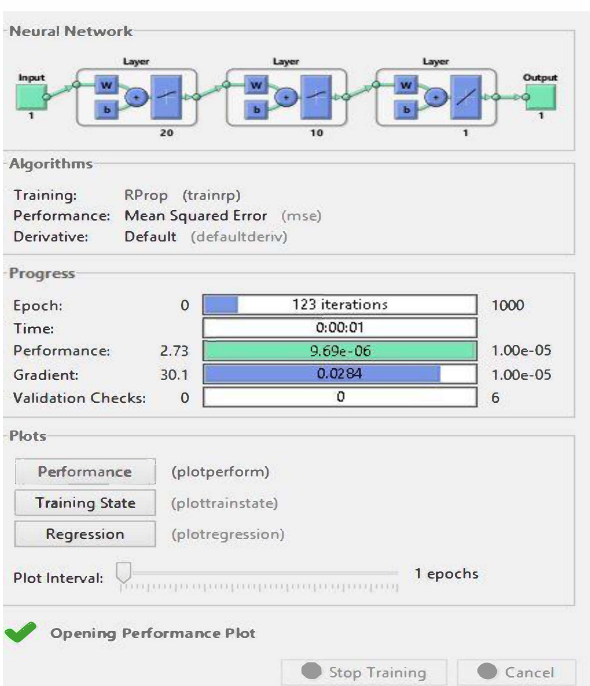


Figure 6. Neural network training tool box

D. Performance plot of feed forward neural network

The neural network training process is repeated as long as we get a linear performance plot as in Fig.7. Here the best training performance is obtained as 9.69e-06 at epoch 123 which is and always should be less than or equal to 1.00e-05.

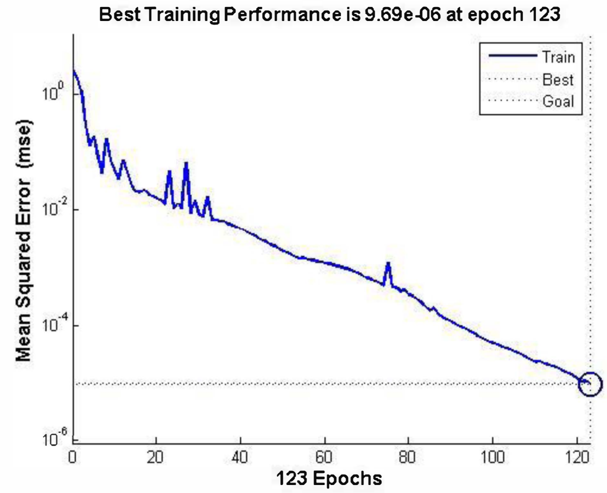


Figure 7. Neural network performance

E. Flame classification using feed forward neural network

After the training of the feed forward neural network using resilient back propagation algorithm, the new network which is returned and the calculated area under the flame edge is utilized to classify the flame as low level or high level. Here the input flame image is identified as a high level flame and a dialog box appears as in Fig.8.


Figure 8. Flame classification using neural network

IV. CONCLUSION AND FUTURE WORK

In this paper a new flame edge detection algorithm have been developed and the performance is compared with the conventional methods. Experimental results have demonstrated that the algorithm developed is much more effective in identifying the edges of irregular flames compared with the conventional methods. The main advantage of this method is that the fire and flame edges detected are continuous and clear. Furthermore with change of scenarios, the parameters in the algorithm are auto adjusted. The clearly defined combustion region forms a good basis for flame parameter quantification [19] such as flame volume, spread speed and surface area. Artificial neural network is an adaptive mathematical module which works similar as human brain functions. Feed forward neural network is the simplest type of artificial neural network where there are no cycles or loops in the network. Here the connections between units does not form a directed cycle and the information moves in the forward direction from the input nodes, through the hidden nodes if there are any to the output nodes. By using this feed forward neural networks the flame image is classified as low level or high level.

The future expansion of this work is to evaluate the performance of the proposed algorithm in real life flame detection scenarios. Also work can be done to characterize the geometric features for flames and establish their relationship with combustion conditions such as air/fuel inputs and emissions.

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