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Smart Sensor for NO_x and SO_2 Emissions in Power Station Boilers (SSEPSB)

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Abstract

Analysis of combustion quality from flame images in thermal and gas turbine power plants is of great importance in the domain of image processing and is the primary objective in detection, recognition and understanding of combustion condition. In this work, soft sensors using feed forward neural network trained with Back Propagation Algorithm (BPA) is used for flame image classification. The basic idea behind this work uses the information from the color of the flame images which dependent on the combustion quality. The first step is to define a feature vector for each flame image including 7 feature elements, which are the brightness of flame, the area of the high temperature flame, the brightness of high temperature flame, the rate of area of the high temperature flame, the flame centroid respectively. The quality of the captured images is enhanced using curvelet transform. The concept of object (flame feature) recognition and classification of the flame image is carried out to measure the temperature from the flame color and the flue gas emissions from the flame color. The samples including 51 flame images, parts of which are used to train and test the model. Finally, the entire samples are recognized and classified. Experiments prove this method to be effective for classification of flame images.

Keywords: Back Propagation Algorithm, Curvelet Transform, Feature Extraction, Fisher's Linear Discriminant, Analysis, Flue Gas Emissions, Soft Sensor

1. Introduction

The development of thermal power plant in India is an asset to the nation. The capacity of furnaces is constantly increased, which brings about the problems in detection, control and management. Nowadays all kinds of problems are basically focused on the measurement and processing of signals from these furnaces. The most important condition in large-scale power station secure operation is the credible flame detection, which is also the important method and reference for economical operation[1].

2. Curvelet Transform

The discrete curvelet transform for a 256 × 256 image is performed as is shown in Figure 1. The discrete curvelet transform can be performed in three steps:

- The 256 × 256 image is split up in three subbands.
- The basis subband consists of 256 x 256 image.
- Tiling is performed on band pass subbands Δ1 and Δ2.
- Then the discrete Ridgelet transform is performed on each tile.

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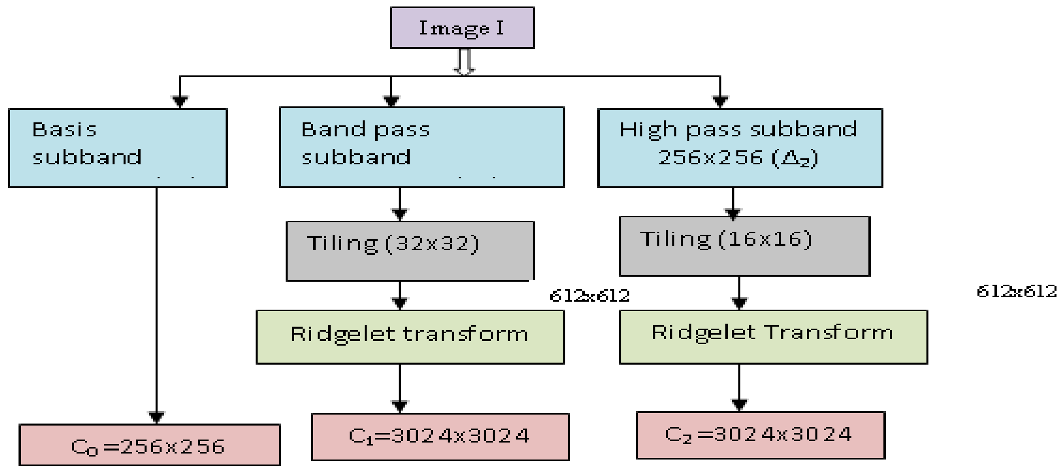


Figure 1. Flowchart for curvelet transform.

3. Materials and Methods

The mapping operation can be linear or non-linear. Fisher developed a linear classification algorithm (Fisher 1936) and a method for constructing a classifier on the optimal discriminant plane, with minimum distance criterion for multi-class classification with small number of patterns (Hong and Yang 1991). The method uses the concept of within class mean (the mean value for the flame images within the same combustion category), between class mean (the mean value of the flame images between the categories of combustion) and the global mean. The relations between discriminant analysis and multilayer perceptrons has been addressed earlier[10] by considering the number of patterns and feature size (Foley 1972). A linear mapping is used to map an n-dimensional vector space onto a two dimensional space. Some of the linear mapping algorithms are principal component mapping, generalized de-clustering mapping, least squared error mapping and projection pursuit mapping.

Table 1. Technical details for coal fired boiler specifications

TYPE	Radiant tower
CIRCULATION	Natural
RH DESIGN PRESSURE	42.5 kg/cm^2(a)
FUEL	Lignite
START-UP FUEL	Light Diesel Oil – Heavy Fuel oil
BURNERS TYPE	Tangential Firing
NUMBER OF BURNERS	12, Lignite and 8 Fuel oil
NUMBER OF MILLS	6
MILLS TYPE	Ventilation Mill MB 3400/900/490
MANUFACTURE	Ansaldo Energia

The flame video is captured from NLC and segregated into frames. The intensity of the flame color in the captured frame varies with respect to temperature and flue gas emissions. The features are extracted and then reduced using FLD. The reduced feature set is used as an input to the BPN classifier and finally the classification performance is validated with certain performance measures. The Figure 6 shows the schematic representation of the flame monitoring system.

4. Experimental Setup

The flame images are obtained from the control room of the thermal power plant boiler. Samples of flame images (51 flame images) for various combustion conditions were collected from the control room. Group 1 refers to complete combustion (flame1 to flame 18), group 2 refers to partial combustion (flame 19 to flame 38) and group 3 refers to incomplete combustion (flame 39 to flame 51). A square image extraction is done by cropping each image to a size of 30 x 30 pixels is done. The Nitrogen Oxide (NO_x) and Sulphur Dioxide (SO_2) emissions were measured from the flue gas at the same instant the flame video was also recorded.

In order to modify the set-up so as to automate the process as shown in Figure 8, the flame video should be transferred to the PC where different image processing and artificial intelligent algorithms can be used. Table 2

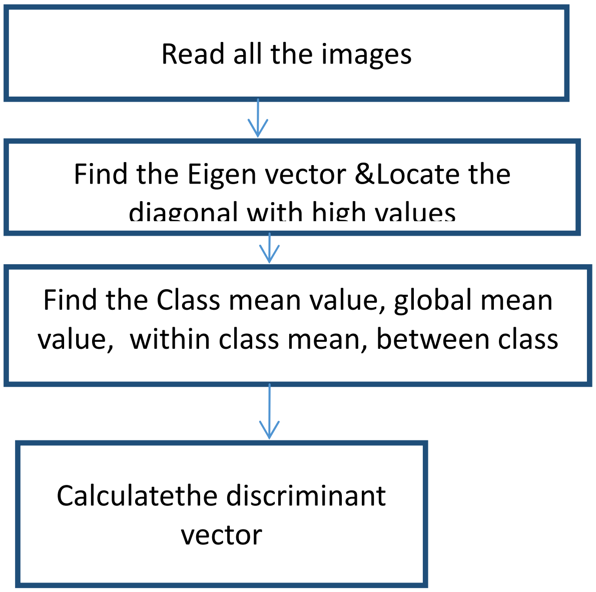


Figure 2. Sequence diagram for FLDA.

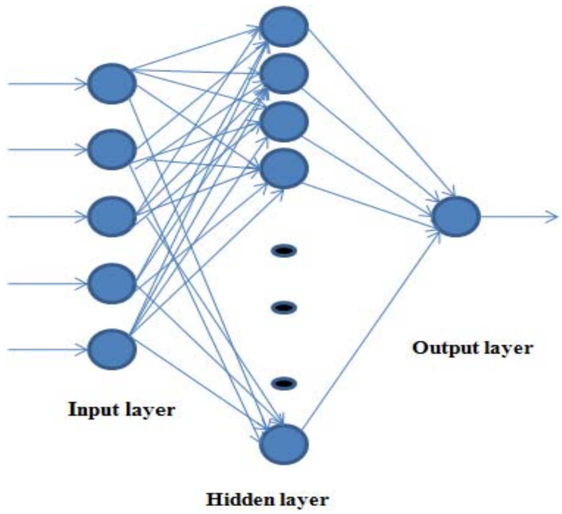


Figure 3. Architecture for feed forward neural network trained with BPA.

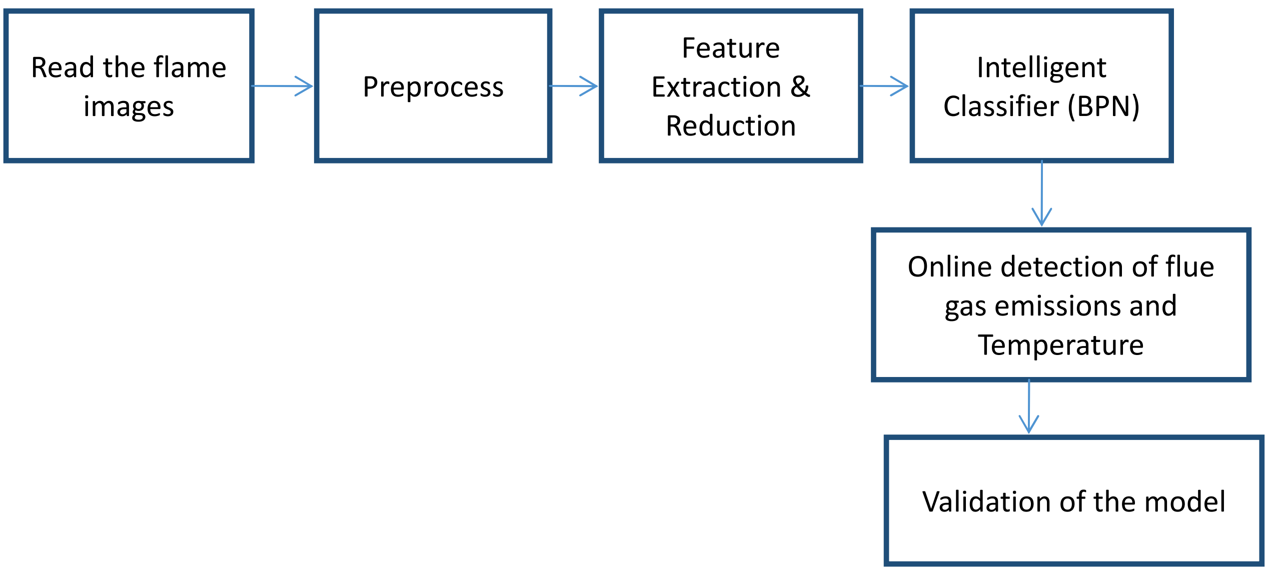


Figure 4. Block diagram for intelligent flame monitoring system.

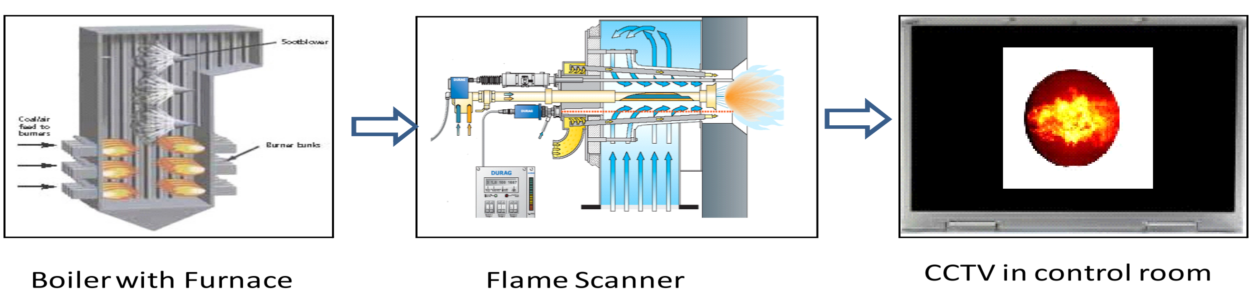
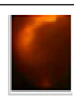


Figure 5. Monitoring of the furnace flame.

below shows the three categories refer to the complete combustion, partial combustion and incomplete combustion conditions. The partial and incomplete combustion conditions are not advisable as it results in wastage of coal as well as affects the power generation.

Table 2. NO_x and SO_2 emissions for various combustion categories

Group	Image	NO_x emissions in mg/Nm^3	SO_2 emissions in mg/Nm^3
1		In the range of 20 to 25	1000 to 1200
2		Greater than 25 and less than 40	1200 to 2000
3		Greater 40 and less than 60	Greater than 2000 and less than 3000

5. Pre-Processing

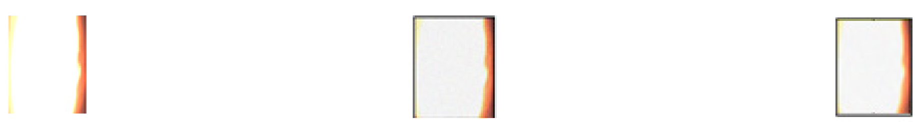
The image is pre-processed to make sure that correct image is used for analysis and monitoring purposes[7]. Median filtering is applied to smoothen the image by removing noise.

The smoothening will remove the speckles of dust captured in the image which is shown in Figure 6. After this the yellowish white region of the flame corresponding to complete combustion is alone extracted as in Figure 7. Plane 1, plane 2 and plane 3 of the images are analyzed for all 51 images to find which plane contains more information about the flame.

The features extracted from each image which are displayed in Figure 8. The features are basic identity patterns present in the image and gets repeated in all directions in the image[9]. The inputs for RBN are φ_1 and φ_2 vectors obtained from FLD, centroid x and centroid y of the flame in the image, number of pixels in the flame portion of the image, orientation of the flame as it gives indication of the speed of air blown, average intensity of the flame in each image, area obtained using region properties of the MATLAB and the rate of area of high temperature flame. The outputs are the temperatures measured for set of images along with the NO_x (milligram per nominal cubic meter-mg/Nm^3) and SO_2 (milligram per nominal cubic meter-mg/Nm^3).

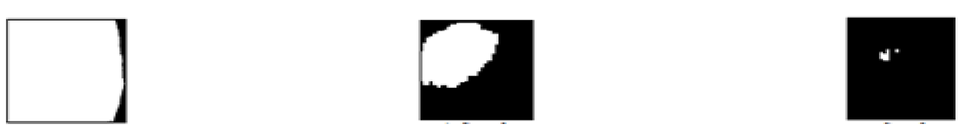
6. Result and Discussions

The images captured are color images, hence hierarchical color correction is done using curvelet transform which helps to maintain the white balance in order to make white portion appear white which indicates the region of complete combustion and the auto contrast adjustment enhances the perceptual quality of an image. The results for hierarchical color correction using iterated TMR filter are depicted in Figures 12 and 13 respectively. Almost equivalent results are achieved to ensure combustion quality when naphtha is used as fuel for gas turbine power plants.



(a) Original Image (b) Corrupted Image (c) Filtered Image

Figure 6. Effect of median filtering on the corrupted flame image.



(a) Group 1 (b) Group 2 (c) Group 3

Figure 7. Results after thresholding and edge detection.

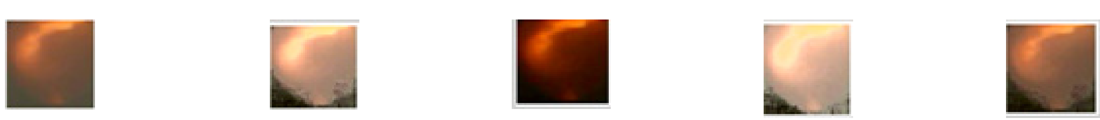
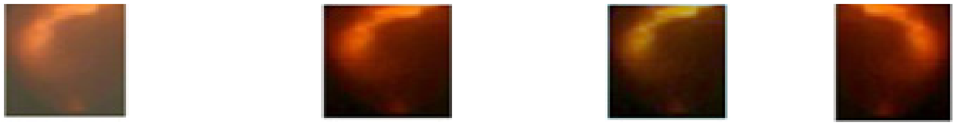
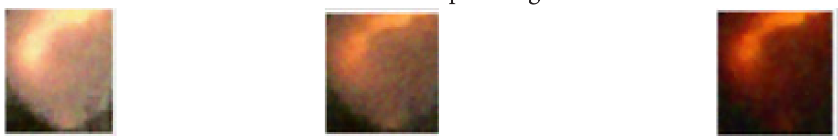


Figure 8. Feature extraction.



(a) Original Image (b) Hierarchical color correction (c) White Balance Image (d) Auto contrast Image

For Group 3 images



(a) Iterated TMR filtered output of for Group 1 (b) Iterated TMR filtered output for Group 2 (c) Iterated TMR filtered output for Group 3

(a) Original Image (b) Hierarchical color correction (c) White Balance Image (d) Auto contrast Image

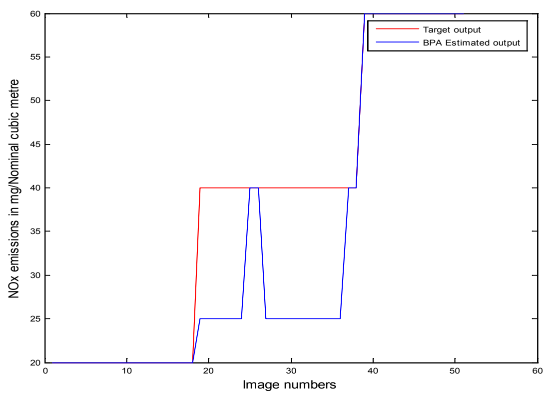
For Group 2 images

Figure 9. Outputs in different conditions.

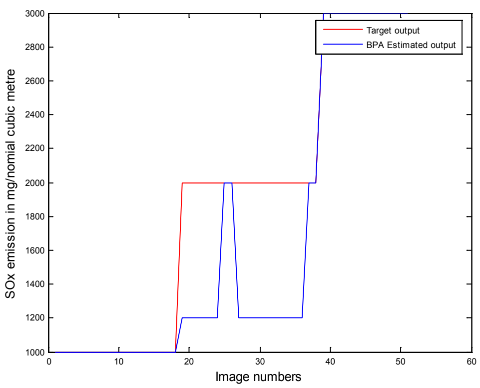
(a) Zoom before Iterated TMR

(b) Zoom after Iterated TMR

Figure 10. Iterated TMR images.



(a) Estimation of NO_x using BPA.



(b) Estimation of SO_2 emissions.

Figure 11. BPA results for flue gas emission estimation.

The following steps were followed to implement BPA for flame image analysis. It includes four major steps which are indicated below:

- Selection of Training data set.
- Selection of ANN parameters (Input neurons, hidden layers, hidden neurons, initial weights, bias, learning rate, momentum factor, iterations, tolerance, learning algorithm etc).
- Selection of appropriate architecture.
- Validation of the ANN estimator

The ANN parameters like mean squared error, no. of iterations, no. of nodes in various layers and the type of the activation function used are shown in the Table 3 indicates that the FFNN is trained to estimate the flue gas emissions for thermal power plants. Figure 12 shows the estimated output for temperature measurement using feed forward neural network trained with BPA. Figure 16 denotes the performance of the BPA classifier for recognizing the flame images and their related parameters. The performance metric used for this purpose are recall and precision. Both the values of recall and precision are closer to 1. Hence the BPA is able to provide an optimal measurement of values.

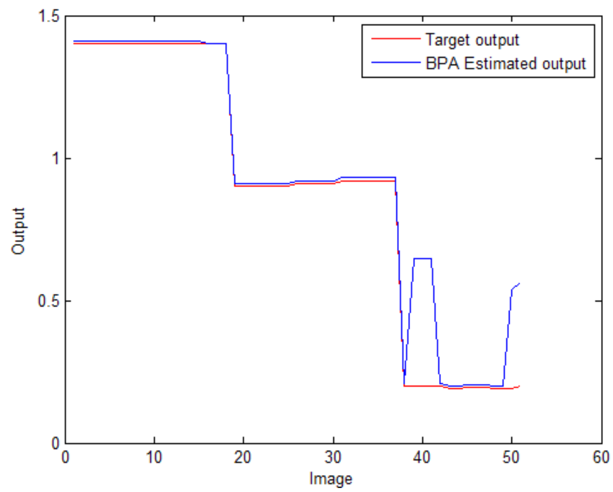


Figure 12. Estimated output for temperature measurement.

Table 3. ANN parameters for estimation by ANN

S. No	Network parameters	Value
1.	No. of nodes in input layer	10
2.	No. of nodes in hidden layer	7
3.	No. of nodes in the output layer	3
4.	Activation function – hidden layer	Sigmoid
5.	Activation function – Output layer	Sigmoid
6.	Mean Squared Error	0.0198
7.	No. of iterations	400
8.	Learning factor	0.8

Table 4. Variation between target and actual values for all the three category of flame images

S.No	Target output	Actual output	Error value
1.	1.4	1.4	0
2.	0.8	0.8	0
3.	0.2	0.6	0.4

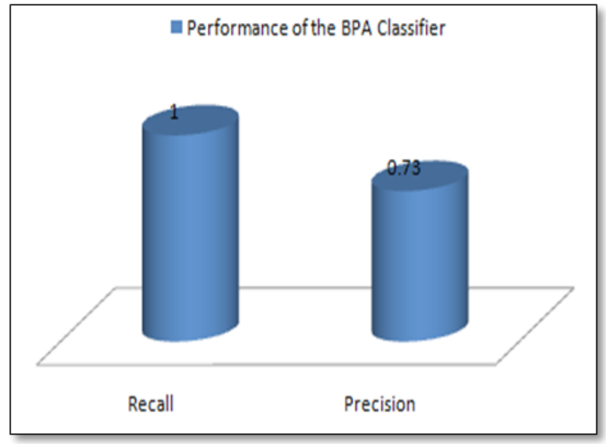


Figure 13. Performance metrics for BPA,

Entropy converts any class for the histogram count calculation so that the pixel values are discrete and directly correspond to a binary value. The information gain is proposed along with the concept which is then extended to gray tone image for defining its global, local and conditional entropy.

Table 5. Entropy for Group 1

Entropy for various stages	Values
Entropy for Unprocessed Image	6.9259
Entropy for White Balance	5.8389
Entropy for Auto color correction	6.3223

Table 6. Entropy for Group 2

Entropy for various stages	Values
Entropy for Unprocessed Image	6.7214
Entropy for White Balance	6.0085
Entropy for Auto color correction	5.9781

Table 7. Entropy for Group 3

Entropy for various stages	Values
Entropy for Unprocessed Image	6.3959
Entropy for White Balance	5.9723
Entropy for Auto color correction	6.3174

7. Conclusion

A different approach to develop an intelligent classifier to monitor and control the combustion quality in power stations was successfully implemented. This BPA classifier is robust when compared to other conventional classifiers. The performance metrics well establishes that the proposed classifier was able to recall all the flame images with slightly reduced precision. Therefore an intelligent sensor for measurement of flue gas emission estimation can be made possible by flame image analysis. Moreover the load generation is consistent at maximum intensities. Hence a correlation can be arrived based on the flame colour and the quality of combustion to ensure complete combustion. As a result an intelligent system can be developed to monitor and control the air fuel ratio. The flue gas emissions are also minimized there by reducing air pollution. The major idea behind this research is to identify the adverse combustion conditions to provide a number of quantifiable parameters to evaluate flame stability and combustion and to develop a PC based system for flame monitoring in thermal power plants.

8. References

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