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Catastrophe Prevention in Highly Industrialized Areausing Image Processing

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ABSTRACT: In our daily life we find it is imperative to have a smoke and fire extinguisher in each and every industry according to the norms of the government. If there is exits smoke, fire or poisonous gases there is pandemonium of either abrogate the area or turning on the fire extinguisher. Also trained persons can only turn on the extinguisher. If an industry fires means it really affects the human lives, economy and its infrastructure. Lot of commercial smoke and fire detectors exist. But all of them are formidable to use at large areas due to their increased cost and maintenance needed. So fire detection systems are earning a lot of attention among researchers to prevent the economy and public safety. In this research video images are captured from the industry and its surrounding environment and pre-processing of the captured images are done. Features are extracted as frames and decision tree algorithm is used to detect the occurrence of smoke, fire and leakage of poisonous gas in the highly industrial area. During the implementation phase we observed that this automated technology is more efficient with an alarm and an alertmessage.

KEYWORDS: Classification,Detection, Feature,Flame.

I. INTRODUCTION

During the last several decades there has been a growing awareness of the expanding risks and consequences of major industrial disasters. In most countries, development, growth, and sustenance of industrial facilities are given utmost importance due to the influence in the socio-economic development of the country. Therefore, special economic zones, or industrial areas or industrial cities are developed in order to provide the required services for the sustained operation of such facilities. Such facilities not only provide a prolonged economic support to the country but it also helps in the societal aspects as well by providing livelihood to thousands of people. Therefore, any disaster in any of the facilities in the industrial area will have a significant impact on the population, facilities, the economy, and threatens the sustainability of the operations. Disaster refers to the event of serious interruption that leads to extensive losses of human lives and deterioration of the environment and physical facilities. The disasters in industrial facilities are classified as technological disasters as they are essentially man-induced disasters. The line of sight and the early stage of the fire process problem could be solved with the second type of sensors. A new technology called wireless sensor network (WSN) is nowadays receiving more attention and has started to be applied in forest fire detection. The wireless nodes integrate on the same printed circuit board, the sensors, the data processing, and the wireless transceiver and they all consume power from the same source batteries. Unlike cell phones, WSN do not have the capability of periodic recharging. The sensors are devices capable of sensing their environment and computing data. The sensors sense physical parameters such as the temperature, pressure and humidity, as well as chemical parameters such as carbon monoxide, carbon dioxide, and nitrogen dioxide.

II. LITERATURESURVEY

Chen et al [5] presented an early fire-detection method based on video processing. They used RGB model based chromatic and disorder measurement to extract real fire and smoke pixels in video sequences. Based on the intensity and saturation of red component, fire pixels are detected. Further dynamic analysis of extracted fire pixels is carried out using both growth and disorder features to determine whether it is a real flame or a flame-alias. Iterative checking on the growing ratio of flame gives the condition for alarm-raising. Background estimation algorithm [13] and chrominance model [5]are used by Torian et al [14]to detect flames in video. In addition to motion and colour information, Hidden Markov model is used to detect flame flicker process. Two Markov models are proposed to distinguish flame flicker process from motion of flame coloured moving objects. Same Markov models are used to evaluatespatial

colour variance in flame. Horng et al[6]used an HSI colour model to extract fire flame features. Based on these features, fire-like colours are separated from the image and fire regions are segmented. Image difference method and colour masking technique are used to separate fire coloured background objects from flames. A method for estimating the burning degree of fire flames is also proposed. Shi and Cao [7] used threshold and Binarization processing to find the highlighted regions in gray scale video images. An improved version of frame-difference method is proposed to filter the interference of rapidly moving objects with high brightness e.g.to differentiate lamps of motorcycles from flames. Colour and motion information extracted from video sequences are used to detect fire and provide fire alarms by Huang et al [8]. First, fire regions are localized using three simple decision rules using the RGB Colour model. In the second stage, additional decision rules utilizing both the growth of fire region and the invariability of the centroid of the fire region. The method seems to be computationally efficient. Video based wildfire detection is particularly important at night, when smoke is not visible. Gunay et al [11] proposed a method for video based fire detection at night which comprises off our sub-algorithms -slow moving video object detection, bright region detection, detection of objects exhibiting periodic motion, and interpretation of the motion of moving regions in video. Atleast mean square (LMS) based decision fusion approach is used to combine the individual decisions of the sub algorithms to obtain a fire/no-fire decision. Yamagishi and Yamaguchi [12] presented a flame detection algorithm based on thespace-timefluctuation data onthe flame coloursss area. Chen et al [2] proposed an algorithm of early fire image detection and identification based on Discrete Fractal Brownian Incremental Random Field model (DFBIR). Initially, the high-brightness regions with colours that match the flame colour model are identified (YUV model).

III. PROPOSED METHODOLOGY

Fire, smoke and poisonous gas can be considered an unfortunate phenomenon that can cause catastrophic damage to property and environment. It can also pose an immense threat to human safety and lives, especially when this hazard gets out of control. When fire breaks out, especially in an open space, it often remains undetected by the conventional smoke sensor-based detection systems until it reaches a severe stage. Therefore, skilfully designed video based smoke and fire detection systems, using surveillance cameras in open space environments, can be the key to providing early warning signals. These systems utilise videos obtained from surveillance cameras and subsequently process them to detect either smoke or the initiation of a fire. However, the chaotic variations of shapes, movement, colours, texture, and density of smoke and fire make the detection process a rather challenging task.

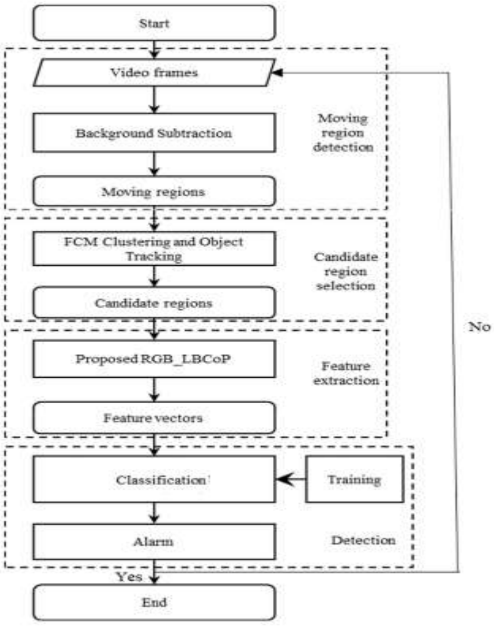

Figure 1: Propose Architecture

For candidate region selection, background subtraction is widely used because of its performance and simplicity. Different methods have been proposed besides background subtraction method to detect candidate regions. In this research, the approximate median subtraction method and the fuzzy c-means algorithm are used for candidate region selection due to their improved performance. For this research, approximate median subtraction method is utilised in order to exploit its high efficiency. It mainly operates on grey level images. This method is a combination of frame differencing between current frame and a reference image. The reference image is a successive median of the image sequence which is prepared using the following steps:

Let I୨ (i,j) denotes the intensity value of a pixel in an image. The estimated background intensity value of the same location is calculated as follows:

$$B_{n+1}(i,j) = \begin{cases} B_{n+1}(i,j) + 1, & \text{if } I_n(i,j) > B_n(i,j) \\ B_{n+1}(i,j) - 1, & \text{if } I_n(i,j) < B_n(i,j) \end{cases}$$

where B୨ (i,j)is the previous estimate of the background intensity value at the same position in the preceding frame. Using equation, background is updated after every frame. Primarily, the value of *B*୧ (*i*,*j*) is set to the intensity of *I*୧ (*i*,*j*). A pixel positioned at (*i*,)is shifted if

$$|I_n(i,j) - B_n(i,j)| > T$$

Here, T is the threshold value which is defined experimentally. The FCM algorithm tries to cluster the data set X into c number of clusters. The standard objective function is defined by

$$J_m = \sum_{i=1}^{c} \sum_{k=1}^{n} \mu_{ik}^{m}\, d^2(x_k, v_i)$$

Where d (x,) is the Euclidian distance between the data point x□ and the centroid value v of the i[th] cluster, μ is the degree of membership for data point x in the i-th cluster. The objective function is minimised by repeatedly adjusting the values of μ and v based on the following equations:

$$\mu_{ik} = \left[\sum_{j=1}^{c} \left(\frac{d^2(x_k, v_i)}{d^2(x_k, v_j)} \right)^{\frac{1}{m-1}} \right]^{-1}$$

$$v_i = \frac{\sum_{k=1}^{n} \mu_{ik}^{m} x_k}{\sum_{k=1}^{n} \mu_{ik}^{m}}$$

GLCM is one of the well-known global feature descriptors. It introduced the co-occurrence probabilities for calculating texture features which is also known as Grey Level Dependency Matrix. The GLCM is defined as a two dimensional histogram of grey levels between pixels separated by a fixed spatial relationship. The GLCM computes the spatial relationship between the reference and the neighbouring pixels within an image either in horizontal, vertical or in diagonal distance. The GLCM of an image is calculated using a displacement vector d, defined by its radius δ and orientation θ. based on the accuracies from various researches, radius δ value varies from 1, 2, 4 to 10.

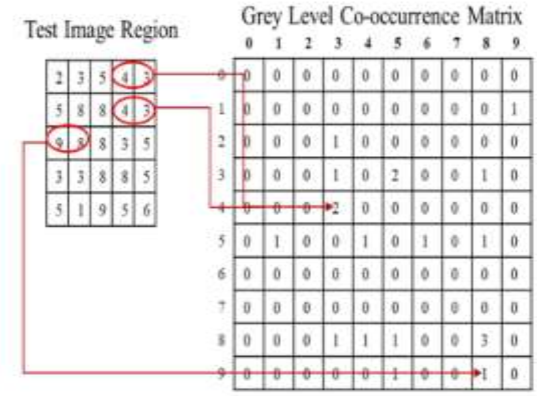

Figure 2: GLCMconsidering two neighboring pixels

The LBP code for each pixel is achieved by thresholding its P neighbors in a circle of radius R as per the following equation:

$$LBP_{P,R}(x_c, y_c) = \sum_{p=0}^{P-1} s(g_p - g_c)2^P$$

Where g denotes the grey scale value of the centre pixel, g is the greyscale value of its neighbouring pixel, and s is a function defined by (x)= 1 x≥00 x<0.

. In this research we have analysed how a pre-trained CNN (pre-trained on ImageNet) model can lead to enhanced performance for smoke and fire detection.

In addition, we have extracted the learned features from the convolutional layers and fully connected layers to investigate their performance in smoke and fire and poisonous gas detection. Moreover, a lightweight CNN model is proposed in this work to detect poisonous gas, smoke and fire which is inspired by AlexNet. All the pixels of the moving regions are partitioned into various clusters according to the membership value μ. The overall computational steps are given below:

Step 1: Compute the number of clusters c and initialise the centroid value v

Step 2: Calculate the membership value, μ, using equation which is repeated, to make easier for the reader to follow:

$$\mu_{ik} = \left[\sum_{j=1}^{c} \left(\frac{d^2(x_k, v_i)}{d^2(x_k, v_j)} \right)^{\frac{1}{m-1}} \right]^{-1}$$

Where d $(x,)$ is the Euclidian distance between the data point x and the centroid value v of the ith cluster, μ is the degree of membership for data point x in the i-th cluster, m is the fuzzy factor, and c is the cluster centroid.

Step 3: Update the centroid value using the following equation:

$$v_i = \frac{\sum_{k=1}^{n} \mu_{ik}^{m} x_k}{\sum_{k=1}^{n} \mu_{ik}^{m}}$$

Step 4: If the termination condition, ma[ ] , is satisfied, stop the iteration. Otherwise, repeat from step 2

Step 5: Assign all the pixels to the clusters based on the maximum membership value

It is essential to select the optimal number of clusters and the initial values of the cluster centroid to achieve good clustering accuracy. Support Vector Machine (SVM) is a supervised machine learning algorithm which is extensively used in video-based poisonous gas, fire and smoke detection due to its robust performance for two classes ((eg)smoke or non-smoke).

IV. RESULT AND DISCUSSION

For RGB_LBP, we have computed the LBP features in the three (R, G, and B) channels and then concatenated the features obtained from the three channels to form a single feature vector. While performing detection utilising the aforementioned feature extraction methods, we have maintained the identical processing stages for moving regions detection, candidate regions selection and classification. This way, we were able to compare performance of the different feature extraction methods in detection. From each positive video, only that segment has been chosen for experimental analysis which records from initiation until an occurrence of detection. For negative video, the whole segment is used for calculating false alarm rate. The accuracy is measured by computing the true positive rate (TPR) of the methods.

$$TPR = \frac{Number\ of\ TP}{Number\ of\ TP + Number\ of\ FN}$$

Video	Frame rate (fps)	Proposed
Video 7	24	**95.71**
Video 8	24	88.89
Video 9	25	97.30
Video 10	15	**95.46**
Video 11	25	**100**
Video 12	25	**100**
Video 13	30	**97.45**
Average		**96.40**

Table 1: True Positive Rate (TPR) of the Proposed Method

V. CONCLUSION

Feature extraction is one of the key challenges of video based poisonous gas , smoke and fire detection due to chaotic variations in colours, shade, motion, and density. To improve the discriminative and representative power of the features, this work focused on the correlation between dynamic textures features along with colours. Subsequently, a framework has been developed, named Local Binary Co-occurrence Patterns for the RGB colours space (RGB_LBCoP), To extract local and global texture features for video based detection. To explore the texture features, this research utilized an efficient co-occurrence encoding scheme along with rotation invariant uniform LBP and extended it to integrate RGB colours information. The proposed approach cannot only capture the local and global information, but also enables the measurement of higher order statistical texture information that helps to describe the complex structure of input in video streams. This research investigated the capabilities of the proposed method and its performance compared with other state-of-the-art methods. Experimental analysis on publicly available smoke video datasets demonstrates that the proposed algorithm outperforms the other methods by achieving an average True Positive Rate (TPR) of 96.40%.

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