Smoke detection in outdoor environments: A new approach that incorporates the statistical properties derived from GLCM

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Abstract— **The work aims to introduce a system that detects the presence of smoke in outdoor environments by combining the techniques in image processing and pattern recognition. The proposal of such a system is believed to be a contribution to the society in the current scenario where the toxic smoke is becoming a threat to the ozone layer. Also it assists to track and avoid the possibility of fire accidents. The system interprets the smoke as new texture added to the usual outdoor images and hence a new approach that incorporates the statistical properties obtained from the Gray Level Co-Occurrence Matrix (GLCM) is being introduced through the work. These statistical properties obtained at optimum offsets serve as the feature vectors for the classifier which predicts the presence or absence of smoke. Both k-Nearest Neighbors (k-NN) and Support Vector Machine (SVM) classifiers are experimented and analyzed in the work.**

Index Terms— *Texture; Feature vectors; Contrast; Correlation; Energy; Homogeneity; Offset; SVM classifier; kNN classifier*

I. INTRODUCTION

Recent studies say that the toxic smoke that are expelled on burning materials such as plastics causes much severe damage for the protective ozone layer. Dangerous fire accidents are getting reported very frequently. One might think what the connection between the two statements is. The word ‘smoke’ connects the two. What if we have an automated system that detects the unusual or excess occurrence of smoke? Further pollution and possibility of a deadly fire accident can be avoided by taking the necessary action on time. This is the motivation behind introducing a smoke detection system that incorporates the statistical properties extracted from the Gray Level Co-Occurrence Matrix of the outdoor images.

Smoke can be of different forms. The first type is the smoke that is thickly expelled and the other type is the one that is uniformly spread. In both these cases it can be noted that the smoke dominates over the background. Hence the proposed work interprets the smoke to be a texture that is newly added in the image. The approach towards the presence of smoke in the perspective of texture analysis demands Gray Level Co-Occurrence Matrix to be considered. GLCM reflects the spatial relationship between the pixels of an image so that a particular pattern can be recognized for similar textures. Contrast, correlation, energy and homogeneity which are the most important statistical properties that can be derived from the GLCM are extracted and used as the feature vectors for the classifier. SVM and k-NN are two of the most popular classifiers that are available. SVM classifier categorizes the input by identifying the hyper plane that separates the two classes at a maximum possible gap. On the other hand, k-NN classifier identifies the class of the input by considering a majority vote of its neighbors which are the training samples. The proposed method is experimented using both the classifiers and the performances are analyzed.

The system has a scope of extending to a surveillance system by taking the key frames that are extracted from the video as the input.

II. RELATED AND PREVIOUS WORKS

Due to the rapid advancements in digital imaging technology, vision based systems became very popular. A lot of researches have been conducted on the topic of fire and smoke detection in the field of image processing.

In [1] the authors discussed the novel models for fire and smoke detection based on image processing. [1] Started by mentioning the three important features that vision based systems make use of: color, motion and geometry. The representation of fire and smoke in RGB, YCbCr and HSV color models are explained in detail.

A different method of detecting smoke using k-means clustering is introduced in [2]. The key frames are extracted from the input video and then k-means clustering algorithm is applied which isolated smoke. L*a*b* color space was adopted in this.

A comparative study on the extraction of features using texture and shape is done in [3]. Gray Level Co-occurrence Matrix and Hu-moments are used for the comparison. Texture properties such as contrast, line-likeness, regularity, roughness etc. are discussed in it.

[4] And [5] discussed the role of SVM classifier in two different scenarios. In [4] Object recognition is done using SVM classifier with the histogram of gradient features as the feature vectors. Whereas [5] used SVM classifier for the detection of grape leaf diseases. First the disease affected region on the leaf are detected using segmentation algorithms and then the color and texture properties obtained from the detected region are supplied as the feature vectors for the SVM classifier.

In [6] an application of k-NN classifier in signature identification is explained. In the Hidden Markov Models (HMM) various number of states in transition matrix for each handwritten signature are estimated and used for the training of the k-NN classifier.

A comparative study of k-NN and SVM classifiers in the identification of the fistula state is presented in [7]. The acoustic signals from both healthy patients and those suffering from narrowing fistula were collected and are fed as the feature vectors for the classifiers.

III. PROPOSED WORK

In this section we discuss the proposed framework in detail. It was mentioned that the proposed work approaches the problem of smoke detection in the perspective of texture analysis. Fig. 1 explains the reason. In Fig. 1 (a) and (e) are the photographs taken in two different scenarios under normal conditions. Fig. 1 (c) and (g) correspond to the images of the same outdoor locations in Fig.1 (a) and (e) respectively, taken in the presence of smoke. Fig.1 (b), (d), (f) and (h) are the grayscale images of the RGB images in Fig. 1 (a), (c), (e) and (g) respectively. It is clearly visible that Fig.1 (d) and (h) have certain similarities even though Fig.1 (b) and (f) have nothing much. In both Fig.1 (d) and (h) smoke dominates over the background and creates a unique texture.

Fig. 2 represents the block diagram of the proposed system. It can be seen that Gray Level Co- Co-Occurrence Matrix of the collected outdoor images are calculated first. Statistical properties of each image are derived from the calculated GLCMs and are stored in a database. These feature vectors in the database are used for training the classifier. The calculation of GLCM and extraction of feature vectors are explained in detail in section A.

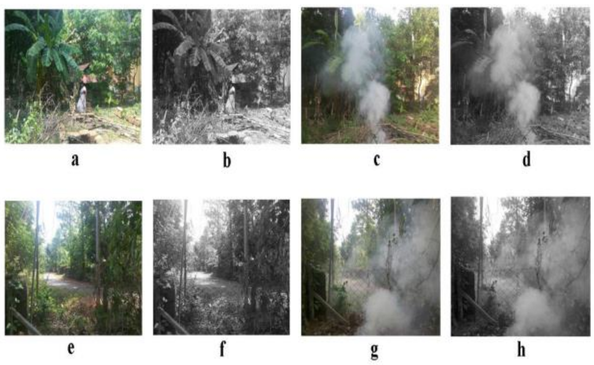

Figure.1 (a) Photograph of agricultural land under smoke free condition; (c) Photograph of agricultural land in the presence of smoke; (e) Photograph of public road under smoke free condition; (g) Photograph of public road in the presence of smoke; (b) (d) (f) (h) Grayscale images of (a) (c) (e) and (g) respectively.

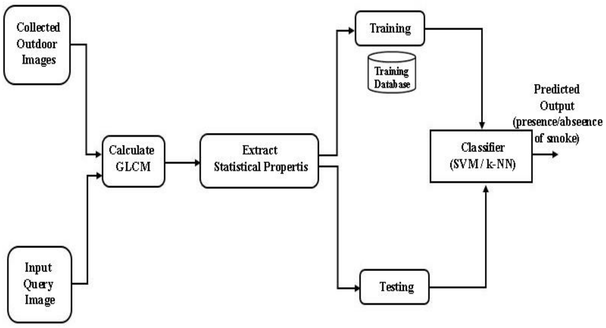

Figure. 2 Smoke Detection System - Block Diagram

A. *Calculation of Gray Level Co-Occurrence Matrix*

As the name suggests, Gray Level Co-Occurrence Matrix calculates the number of times a pair of grayscale values occur together in a specific pattern. The specific pattern which indicates the relative position of the grayscale values with respect to each other is known as offset. The first column in the offset indicates the relative position of the second grayscale value with respect to the first across the rows of an image matrix. Similarly the second column identifies the relative position of the two across the columns. More specifically it can be said that the magnitude stands for the difference of row/column numbers and signs '–' and '+' specifies whether the location of second value is before/after respectively.

On generalizing, we can say that the cell (x, y) of the GLCM with an offset of [a, b] represents the number of times the grayscale values 'x' and 'y' occur together in the image matrix such that the position of 'y' is 'a' rows to the bottom and 'b' columns to the right of 'x'. Fig. 3 illustrates the calculation of GLCM.

2	0	0	7	4
1	4	6	4	3
0	1	7	5	4
0	1	2	4	3

	0	1	2	3	4	5	6	7
0	1	2	0	0	0	0	0	1
1	0	0	1	0	1	0	0	1
2	1	0	0	0	1	0	0	0
3	0	0	0	0	0	0	0	0
4	0	0	0	2	0	0	1	0
5	0	0	0	0	1	0	0	0
6	0	0	0	0	1	0	0	0
7	0	0	0	0	1	1	0	0

Figure. 3 Calculation of GLCM

B. Extraction of feature vectors

The next step after the calculation of GLCM is to extract the feature vectors from it. Contrast, correlation, energy and homogeneity are the statistical properties that are derived in the work. Each one of them indirectly extracts the information about the spatial correlation between the pixels of the image, so that the texture pattern can be incorporated through the feature vectors.

Contrast measures the local variations in the GLCM while correlation measures the joint probability occurrence of the specified pixel pairs. Energy calculates the sum of squared elements in the GLCM and homogeneity gives a measure about the closeness of elements in the GLCM to the GLCM diagonal.

In order to extract the pattern of the texture created by the smoke, the relation between the pixels are to be considered in both horizontal and vertical directions. So GLCM is calculated with two different offsets [0 1] and [1 0]. The four statistical properties are derived from both the GLCMs so that there will be eight feature vectors for each image.

Fig. 4 is a minimal representation of the dataset which considers four different scenarios. Fig. 4 (a), (b), (c) and (d) are the photographs of car porch, school farm, public road and dry paddy field respectively. The corresponding images of the same four scenarios that has the presence of smoke are shown in Fig. (e), (f), (g) and (h) respectively. Similarly a large number of photographs of different outdoor environments with and without the smoke are collected and feature vectors are extracted. Table. 1 depicts the values of the feature vectors that are extracted from a number of the dataset images. In the table, columns from one to four represent the contrast, correlation, energy and homogeneity derived from the GLCM with [0 1] being the offset value. Similarly columns from five to eight denote the statistical parameters obtained from the second GLCM matrix in the same order. The last column signifies the class. The system considers the images without smoke to be under class 0 and those which contain smoke belong to class 1. The sudden variation in the nature of each feature vector with respect to the change of the class is evident in Table. 1.

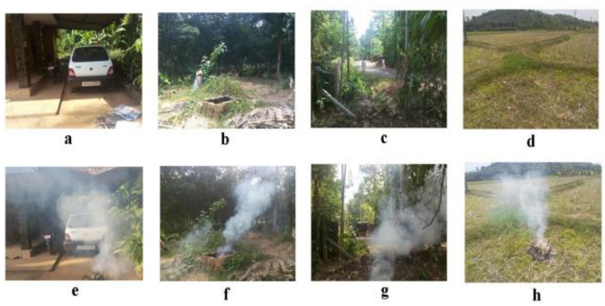

Figure. 4. Representation of the dataset;
(a) (e) Car porch; (b) (f) School farm;
(c) (g) Public road;(d) (h) Paddy field
(In the absence and presence of smoke respectively)

Table 1**.** Feature Vectors of certain images in the dataset

Contrast (1)	Correlation (1)	Energy (1)	Homogeneity (1)	Contrast (2)	Correlation (2)	Energy (2)	Homogeneity (2)	Class
303.7635	0.9662	2.5178e-04	0.2640	386.2881	0.9571	2.3553e-04	0.2554	0
246.3657	0.9715	4.5605e-04	0.2816	333.8904	0.9614	4.1874e-04	0.2704	0
252.7075	0.9715	4.6245e-04	0.2808	343.4692	0.9612	4.2287e-04	0.2693	0
240.2444	0.9409	3.7242e-04	0.2543	312.4302	0.9231	3.6175e-04	0.2477	0
226.7536	0.9399	4.1418e-04	0.2594	299.9537	0.9205	4.0112e-04	0.2521	0
31.7508	0.9923	5.7565e-04	0.4093	40.5902	0.9901	5.6727e-04	0.4059	1
23.5990	0.9927	7.0687e-04	0.4154	27.7474	0.9914	7.0599e-04	0.4147	1
89.5677	0.9840	3.6077e-04	0.3546	138.6081	0.9753	3.4264e-04	0.3457	1
55.8471	0.9925	0.0071	0.3877	73.3200	0.9902	0.0071	0.3825	1
40.2434	0.9924	9.2639e-04	0.4026	44.6671	0.9915	9.3348e-04	0.4043	1

C. Classification

The final phase of the smoke detection system is the classification based on the extracted feature vectors. The classifier is trained using the features extracted from a large number of positive and negative sample images along with the known class identifier.

The system categorizes the dataset samples in to two classes depending on the presence and absence of smoke. The feature vector extracted from the test image is then supplied in to the classifier in order to know the class to which it belongs to. The work considers two classifiers. k-NN and SVM. k-NN is a simple classification algorithm that stores all the possible cases and classifies new cases by considering the distance function as a similarity measure. When a new test sample is introduced for classification, at first the feature vectors are extracted out from it. Then distance of the newly extracted set of features to all those sets that are used for training the classifier are calculated.

Among those, the most nearest k sets are considered. They are the k nearest neighbors of the newly added test sample. The class identifiers of these k nearest neighbors are taken for a majority vote. The class to which a majority of the k nearest neighbors belong is predicted as the class of the test data. There are a number of distance metrics available such as Euclidean, Manhattan, City Block etc. Euclidean distance calculated using (1) is the metric used in this work. In (1) f1, f2, f3…….fn and v1, v2, v3…….vn denote the feature vectors of test sample and a neighbor respectively.

$$\sqrt{\left((f1-v1)^2+(f2-v2)^2+(f3-v3)^2+............+(fn-vn)^2\right)} \tag{1}$$

Fig. 5 (a) shows the working of k-NN classifier on smoke detection system with only the first two features considered. The circled points are the nearest neighbors and the blue colored point is the new test point. It can be seen that there are 5 circled points since the value of k used by the system is 5. Among those five, four circles belong to class 1 and one to class 0. Considering majority it can be concluded that the input image had smoke presence.

SVM classifier categorizes the input by detecting the hyper plane that splits the two classes at a maximum possible gap. After finding out the optimal hyper plane, the new test point is mapped on to the coordinate system and its position relative to the hyper plane decides the class to which it belongs. Fig. 5(b) illustrates how the system works with SVM classifier by considering only the first two feature vectors. The new sample point falls to the left side of the hyper plane that separates the two classes in the best possible way. Hence the test image is predicted to be the one that has smoke texture.

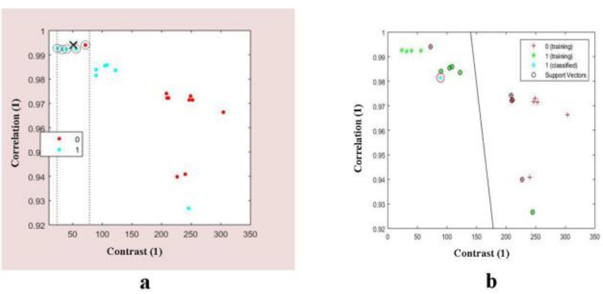

Figure. 5. Classification in the smoke detection system (a) using k-NN classifier; (b) using SVM classifier.

IV. EXPERIMENTAL RESULTS

The proposed method was tested on the system with windows 8.1 with 2GHz CPU and 6 GB memory. The proposed work was implemented using MATLAB 2015b. Around 200 images were collected from different outdoor environments. Among this 200 images, 100 are the images contain smoke and the other hundred do not. Since our system's objective is to detect smoke, let's consider the presence of smoke in an image as the positive instance. The 200 images are tested in the system and arrived at a confusion matrix for both the classifiers. Tables 2 and 3 shows the confusion matrices obtained when the system is trained and tested using SVM and k-NN classifiers respectively. Considering presence of smoke in an image to be a positive instance, classifying images that contains smoke correctly becomes True Positive (TP) and classifying them wrongly becomes False Negative (FN). Similarly True Negative (TN) is the situation when smoke free images are classified correctly and False Positive (FP) occurs when they get wrongly classified. Accuracy defined as the ratio of the sum of TP and TN to the total size of the sample space is calculated from both the confusion matrix and is obtained as 97% for SVM classifier and 95.5% for k-NN classifier.

Table. 2 Confusion matrix obtained on using SVM classifier

		Predicted Condition	
		Smoke is present	Smoke free
Actual Condition	Smoke is present	98 (TP)	2 (FN)
	Smoke free	4 (FP)	96 (TN)

Table. 3 Confusion matrix obtained on using k-NN classifier

		Predicted Condition	
		Smoke is present	Smoke free
Actual Condition	Smoke is present	94 (TP)	6 (FN)
	Smoke free	3 (FP)	97 (TN)

The system was applied in two different ways. The first one was the general smoke detection. That is use the system to detect the smoke in any outdoor images. Even though certain challenges were there regarding the different background in the image, increasing the number of sample images for training the system cleared all the hindrances. The second one is a much easier application in where the system is to be used to detect smoke in a specific environment alone. In such a case, since there will not be much variations in the environment, even training the system using a limited number of datasets will work. An accuracy of 100% was obtained when the system was used for this application.

Fig.6 (a) and (b) demonstrates the user interface of the smoke detection system using k-NN and SVM classifiers respectively.

a b

Figure. 6 User Interfaces – (a) Smoke detection system using SVM classifier; (b) Smoke detection system using k-NN classifier

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