Smoke Detection in Digital Frames

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Abstract: This paper uses Machine learning (image mining techniques) for detecting smoke through an image or frame using difference in luminance and chrominance of the red and blue color. The smoke generated usually has peculiar color which can be used for it to be differentiated between a fog and smoke. This paper uses the color model and principal component analysis to effectively differentiate between smoke and other background objects. The methods used for color modeling is YCbCr and the algorithm proposed in Tian, Li et al's. [1] has been implemented for the principal component analysis.

INDEX TERMS- Smoke Detection, YCbCr, PCA, Digital Frames

I. INTRODUCTION

Deep breathing is the solution to many health problems as one inhale fresh and oxygen rich air. But is it true for our nation. Do we have fresh air especially in the cities which are congested, full of public, vehicles and industries?

This study is for the people who are smokers not by choice but due to circumstances, be it people smoking in public areas, harmful particulates released by various industries specially in urban areas, vehicle with outdated PUCs, roadside burning of both biodegradable and non-biodegradable garbage. Air pollution exposure can trigger new cases of asthma, worsen a previously existing respiratory illness, and provoke development or progression of chronic illnesses including lung cancer and obstructive pulmonary diseases [5] [6].

The existing methods for smoke detection involves use of some kind of hardware and these hardware vary from fancy smoke detector to infrared sensors .Optical smoke detectors have a very high response time though they generate good results but the results are not cheap as installing them in public areas could be expensive and would require proper hardware management as they are easy to get tempered.

In this paper, a method is purposed which is quite efficient and cost effective at the same time than the traditional methods. This is done by using image mining techniques. It was achieved namely by implementing color modeling and the Principal component analysis for detection of smoke. Both techniques when implemented independently have some flaws as the color modeling generates excellent results when there is light smoke in the atmosphere but if the smoke is dense the accuracy is greatly affected and PCA always require some kind of dimensional modeling so that it can detect smoke which can be achieved by using color models . Since it only requires image it can be implemented on any device which has a camera. This paper is only for detecting the presence of smoke in an image and not in a video as it does not take into consideration the temporal characteristics of the smoke.

II. RELATED ARTCLES AND DISCUSSIONS

The traditional method of smoke detection required hardware like sensors and had many shortcomings like the life of hardware, battery of sensor, substantial amount of smoke for detection, proximity of smoke to the sensor as discussed in [3,13,4]. So in this day and age of technology the idea for early and accurate detection of fire and smoke by the help of video surveillance has been extensively studied. In [7] a method for automatic monitoring systems to detect early fire and smoke is described, it uses motion history detection algorithm to register possible smoke and fire positions in a video and then analyze the spectral, spatial and temporal properties in the stream of images.

This paper doesn't require the study of temporal properties as the detection n being done is in a single image. This project is used to detect smoke in our surroundings by the help of images taken by the user and differentiate it with fog.

In [7] the spectral probability density is represented by comparing the flame and smoke histogram model, where HIS color space is used. In this paper YCbCr model is used as it is explained in [8] that it is able to distinguish luminance and chrominance information and that RGB is easily convertible to YCbCr and vice-versa. [9] also discusses about the various advantages of YCbCr model in smoke detection.

The main problem with smoke detection is the matting problem which is nothing but specifying if a region of pixels contains smoke or not as discussed in [10]. This problem arises because of the background present in any image. The spatial models for detecting smoke as discussed in [2] which are highly important for matting problem as it helps in studying the structure of the smoke. [2] discusses the various affects of the atmosphere on the smoke like atmospheric scattering , airlight, attenuation excreta.

I.

The detection algorithm mentioned in [11] is a very good example to showcase the use of color model in detection of faces. Many things can be learned and implemented for smoke detection using YCbCr color model from it.

The detection of smoke in images using YCbCr has also been briefly discussed in [13] but it can only be used in enclosed areas like offices, banks, excreta. This problem is reduced with the implementation of PCA in this paper.

[12] proposes a method of smoke detection in stationary camera video using the multiple features of smoke. It does so in three steps, the first uses YUV model for color filtering, the second step involves extracting the features and finally they are inputed to SVM (Support Vector Machine) classifier which makes decision on candidate smoke region.

III. ROPOSED SMOKE DETECTION APPROACH

A block diagram of the purposed smoke detection method is shown in the Fig.1. To ensure the efficiency and robustness, the purposed method is applied in the block based manner.

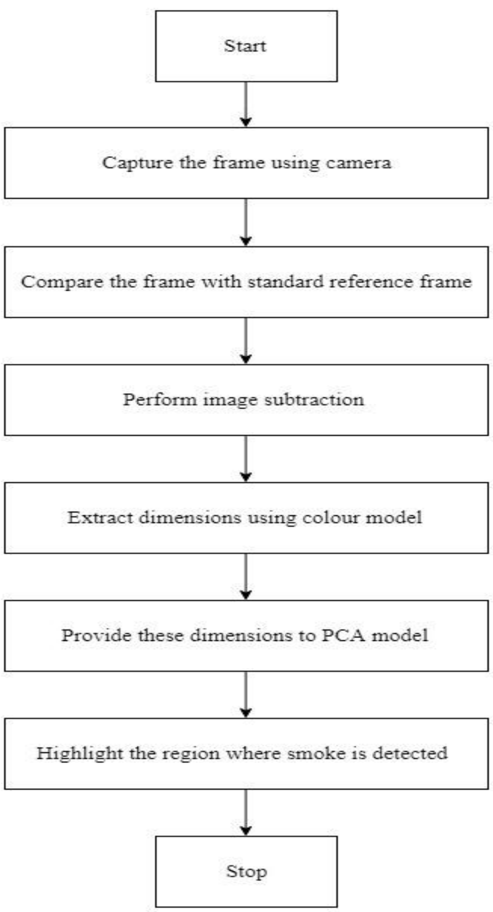

Fig.1. Block diagram of the proposed method

IV. WORKING

A. COLOR SPACE SELECTION

There are a variety of color spaces present for example RGB, YUV, HSV, HIS, YIQ, etc but YCbCr was used for this project because there are some special characteristics to this color space as it separated the brightness and chrominance effectively [8, 9] and YCbCr can easily be extracted through linear transformation from RGB space and the computational efficiency is relatively high since it has to deal with only Cb and Cr which compensates for the computation cost.

B. CALCULATING LUMINANCE AND CHROMINANCE

Since YCbCr color model is used there is a need to compute the value of Y and C for both red and blue which means there is a need to do RGB band separation but an RGB image has 3 component which are red, green and blue thus the memory consumption increases .To solve it three over-lapping matrices are created in which RGB is separated respectively [2]. The background of the image can cause great hindrance while detecting smoke from an image thus it is of utmost importance to correctly compute the brightness and saturation of the image so as to reduce returning false positive for the image. The color of the image as mentioned above comprises of 3 colors i.e. red, green, and blue which are used for calculating the chrominance.

For calculating the chrominance of red

Cr = red component / RGB

For calculating the chrominance of blue

Cb = blue component / RGB

For calculating Luminance

$$Y = 0.22 * R + 0.587 * G + 0.114 * B$$

C. LINEAR MODELING

Each image is treated as a collection of subsections of pixels $f\ (t)\ R\hat{}N.$ If, as is reasonable, assumption that the scattering coefficient only varies slightly within regions of smoke is made, regions of the image (represented by f(t)) can be treated as a linear combination of the background vector of the image without smoke in it (b(t)) and a smoke vector (s(t))

$$f(t) = \alpha(t)s(t) + (1 - \alpha)b(t) + n(t)$$

With n(t) ε R^N representing the noise in the model. With the assumption of the airtight model s(t) can be thought of as the scattering component with an infinite thickness. This

Seemingly strange assumption allows for the airtight model to be incorporated to be used in this linear fashion.

In the above equation α (t) can be thought of as a blending parameter that is ε [0; 1]. The equation depends on both the thickness of the smoke as well as the scattering (smoke) coefficient at time t. So while the blending will vary from region to region, a further assumption can be made that α won't vary within a specific region of smoke, due to the likely uniform thickness in a specific small region.

This results in the salient region selection which can formulate as a two variable estimation problem of α(t) and s(t) by minimizing the following:

$$min" f(t) - \alpha(t)s(t) - (1 - \alpha(t))b(t) "\hat{}2 \mid \alpha(t) \in [0, 1]$$

But this equation has two unknowns and as there is only one equation, the result is in an infinite amount of solutions. So the best hope for the estimation of both variables is by constraining either b(t) or s(t) and as the background from different cameras will be completely different but in each of the image the smoke should retain a similar structure, so it is better to constraint s(t) for the principal component analysis method.

D. PRINCIPAL COMPONENT ANALYSIS

A given pixel region of pure smoke, with high probability, lies in a lower dimensional sub-space than the totality of the image in which it is contained. Principle component analysis was used to select the salient dimensions which correspond to the subspace. In order to find this subspace firstly the covariance matrix corresponding to N pure smoke images is computed, which results in an N x N matrix, followed by computing the corresponding Eigen values and vectors. Once you have the Eigen values, sort the two sets according to magnitude of Eigen values and select the first Eigen vectors up to the upper bound of dimensionality you desire. This results in the information dense dimensions of smoke to be retained and then can be used in the detection process.

The subspace can be represented as a matrix $E\ z\ R\hat{}N\,l$ where L is the reduced dimensionality (thus a general assumption is that L < N). As chosen from the aforementioned process, each column of E is an Eigen vector corresponding to pure smoke, an "Eigen smoke". Assuming that the dimensionality reduction retained all of the salient dimensions (as hoped!) the smoke vector can be written at any time-step as $s(t) = E\,y(t)$ where $y(t)$ R and can be thought of as operational vector by which s(t) is projected onto E. This means to incorporate formulation of s(t).

$$min" f(t) - \alpha(t)Ey(t) - (1 - \alpha(t))b(t) "\hat{}2 s.t : \alpha(t) \in [0,1]$$

When modeling α(t) or y(t) constant, this equation becomes quadratic and allows for clean analytical solution to both α(t) and y(t) by which s(t) can be found via E.

V. RESULTS

Due to the massive size of Tahoe images [14], it is at least minimally helpful by decreasing the number of regions to pass on to the classifier. The results from different data sets from both the Tahoe and South California region are included.

In all results that follow, the color of the points correspond to different α values. Specifically green is plotted if α 0:9, blue if 0:5 α < 0:9, and red if 0:3 < α < 0:5. The clusters of green dots in the figure show the detection of smoke in that region.

VI. CONCLUSION

By using the YCbCr color model along with Principal component analysis a lot of false positive results were generated. Smoke was successfully detected in the Tahoe data set and South California data [14] set but it also developed an intrinsic flaw, that when there are partial dark cloud the result was false negative but since this method is used for detection of harmful smokes in ones surroundings that generally doesn't involve any dark clouds it is highly unlikely to come face to face with the flaw. Thus this method can be applied to implement the smoke detection in ones surrounding.

VII. REFERENCES

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