# Smoke Detection: Revisit the PCA Matting Approach

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Abstract

This paper revisits a novel approach, PCA matting, for smoke detection where the removal of the effect of background image and extract textural features are taken into account. This article considers an image as linear blending of smoke component and background component. Under this assumption this paper discusses a model and it's solution using the concept of PCA.

Keywords: Smoke detection, Image separation, Eigenvalues and eigenvectors,

## 1. Introduction

Early smoke detection is the most important key to prevent the fire event. There are several techniques to identify the smoke, however those techniques require some constraints. For example, photoelectric and ionization detection techniques detect some specific particles produced from smoke and fire [4]. Photoelectric detectors use the photometry to detect the fire. Ionization detect fire using the quantity of ionized air molecules. Both of the detectors require the specific amount of particles around them. In other words they can detect the smoke or fire if they get surrounded by enough smoke particles from at least certain distance. Photometry and ionized air molecules depend on air concentration, sunlight, the presence of wind and many other components. So these techniques are highly dependent on many parameters. May be photoelectric and ionization detectors are good enough for enclosed spaces, house, shopping mall, etc.

There are other methods, visualization methods, which do not suffer similar drawbacks. Real-time video-based surveillance techniques detect the smokes and fire at the early stage. Vision-based techniques are very good for enclosed and open spaces. These techniques also detect the location and intensity of the fire or smoke. Vision-based smoke detection techniques require pattern recognition procedure where the images are divided into small windows. Then those small windows are classified as smoke or non-smoke. These techniques depend on the quality of the visual features for classification. Vision-based smoke detection is a challenge because of the quality or characteristics of the smoke [4]. Vision-based smoke detection technique depends on the shape, color, motion, air quality, degree of transparency and a lot of different parameters. There are a lot of drawbacks of this technique. For example, texture feature extraction from an image along with thin smoke will get the visual characteristics of both smoke and background.

In this paper we will discuss a novel approach for smoke detection which is described in a current literature [4] where the removal of the effect of background image and extract textural features are taken into account. In this paper an image is considered as linear blending of smoke component and background component. Under this assumption we will discuss a model and it's solution using the concept of PCA.

## 2. Model and solution using PCA

Early detection of area of the smoke and location of the smoke definitely reduce the risk of the explosion of the fire. To get the early detection and localization of the smoke, a video could be divided into overlapped and non-overlapped small-sized image windows. Basically, we have to determine the image windows which are covered by the smoke. In this paper we will focus on that idea.

Suppose, $f_t \in \mathbb{R}^N$ be a smoke window with N pixels at time $t$. According to the fundamental models, smoke would serve as a medium to attenuate the light reflected from the background before it reaches the camera due to scattering if there is existent [4]. At the same time smoke will behave like a light source through the scattering due to atmosphere. So, $f_t$ will be determined by the attenuation model and airlight model. Suppose that the scattering coefficient of smoke does not change in a specific degree within a visible range and there is no fixed point of light source, then $f_t$ could be modeled as a linear blending model of $s_t$ and $b_t$ such that

$$f_t = \alpha_t s_t + (1 - \alpha_t)\, b_t + n_t \tag{2.1}$$

where $n_t \in \mathbb{R}^N$ represents the noise, $b_t \in \mathbb{R}^N$ represents the background under clean air (no smoke), and $s_t \in \mathbb{R}^N$ represents the air light (scattering) component by the smoke of infinite thickness. $\alpha_t \in [0, 1]$ is the blending weight at time $t$. It is assumed that $\alpha_t$ is constant in small window of smoke as well as the thickness of the smoke is fixed in that small window. For simplicity we will drop the subscript $t$ from now. Assuming that $f$ is collected by stationary camera, we can use background modeling techniques such as Gaussian Mixture model (GMM) to determine $b$ [3]. Therefore, we can model the problem to estimate $\alpha$ and $s$ under given $f$ and $b$ by minimizing the residual noise:

$$\min_{\alpha,s} ||f - \alpha s - (1 - \alpha)\, b||_2^2 \quad \text{s.t. } \alpha \in [0, 1] \tag{2.2}$$

The above equation is solvable because there are $N$ equations and $N + 1$ free variables. We could have infinite number of solutions. May be we will get an unique solution by constraining either $s$ or $b$ or both. Suppose smoke surface holds the similar property of smoothness.

Suppose each image window has $N$ pixels as a point in an $N-$dimensional space, pure smoke images, being similar in overall textural configuration, are likely to lie in a low-dimensional subspace. If this subspace is located, it could be well describe pure smoke images. Using principal component analysis (PCA), given a set of pure smoke images, $N \times N$ covariance matrix is computed, and it's eigenvalues and eigenvectors are computed [2, 1]. The eigenvectors are ranked according to the corresponding magnitude of the eigenvalues, a subset of eigenvectors with large eigenvalues can be selected to form the subspace of pure smoke. Suppose $P \in \mathbb{R}^{N \times L}$, $(L < N)$, be a matrix, where $L$ is the dimension of the obtained subspace. Each column of $P$ is an eigenvector chosen according to the required criterion. Then a pure smoke image $s$ can be expressed as

$$s = Py \tag{2.3}$$

Where $y \in \mathbb{R}^L$ is the coefficient vector of projecting $s$ onto the subspace $P$ of pure smoke. Substituting equation (2.3) into equation (2.2) we get

$$\min_{\alpha, s} ||f - \alpha Py - (1 - \alpha)\, b||_2^2 \quad \text{s.t. } \alpha \in [0, 1] \tag{2.4}$$

It is clear that equation (2.4) is a quadratic function of $\alpha$ (or $y$) when $y$ (or $\alpha$) is fixed. We can solve for $\alpha$ and $y$ alternately and get $s$ using the equation (2.3). Specifically, suppose $\hat{s}$ be the current solution of $s$ when $\alpha$ is fixed then we have

$$\hat{s} = P \left(\alpha P^T P\right)^{-1} P^T \left(f - b + \alpha b\right) \tag{2.5}$$

By fixing $y$, the current solution $\hat{\alpha}$ for $\alpha$ can obtained as well using the following

$$\hat{\alpha} = \frac{(b - Py)^T (f - b)}{(b - Py)^T (Py - b)} \tag{2.6}$$

## 3. Smoke Detection Framework

For each foreground window $f$ and it's associated background window $b$, the blending parameter $\alpha$ and smoke component $s$ are computed. For a threshold of $\alpha$ we classify as smoke or non-smoke. Here below the framework is described.

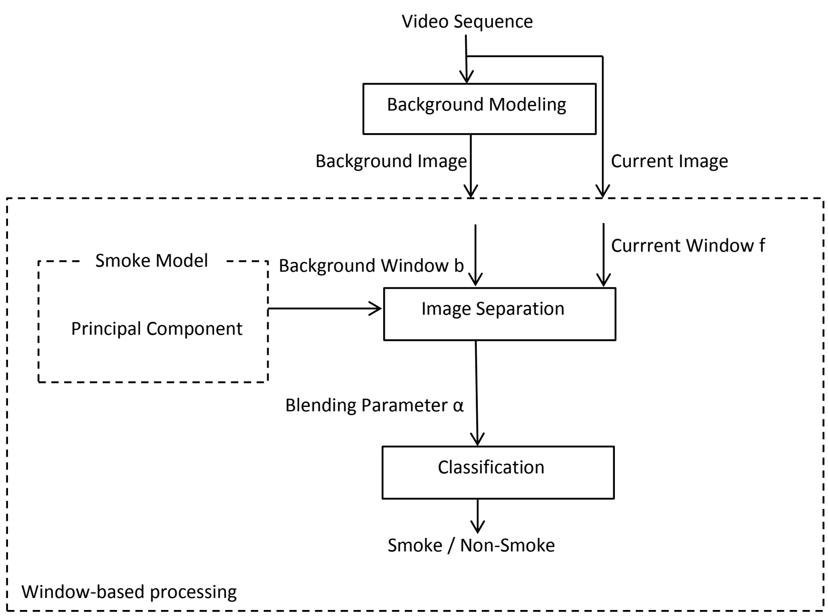



Figure 1. Framework for smoke detection

## 4. Subspace $P$ of pure smoke

To calculate the PCA components of pure smoke we take 1005 pure smoke windows of size $20 \times 20$ pixels. There are 400 pixels in each window. We define a vector of size 400 for each window. In other words we define 400 dimensional vector for each window. Each component of the vector is a pixel value of the 400 pixels. Then we created a matrix of dimension $1005 \times 400$. Then using principal component analysis (PCA) we have a matrix of principal component vectors of size $400 \times 400$. Then we took the 20 principal component vectors corresponding to the 20 highest eigenvalues. That is the matrix $P$. So $P$ is a matrix of size $400 \times 20$. In other words in each column of $P$ the number of pixels, $N = 400$, and there are 20 columns, $L = 20$, of $P$ each of them are the eigenvectors corresponding to the highest 20 eigenvalues. Here below the graph of eigenvalues corresponding to their index, and the images of the 20 eigenvectors corresponding to the 20 highest eigenvalues are shown.

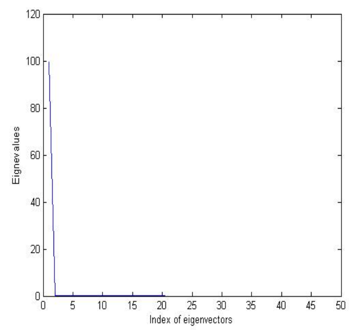



FIGURE 2. *PCA on pure smoke images (eigenvalues are decreasing rapidly)*

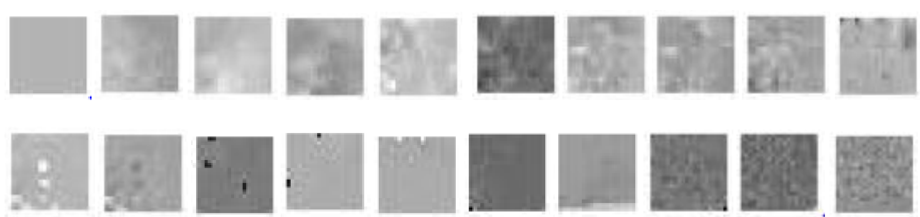


FIGURE 3. First 20 eigenvectors of PCA

## 5. Simulation and result

We take two types of background images without smoke from different scenario. Then we take four consecutive foreground images from type I and two consecutive foreground images from type II with smoke to determine the location of the smoke using the above method. To do that we divide the foreground images and the background images into windows of size $20 \times 20$ pixels. We convert each of

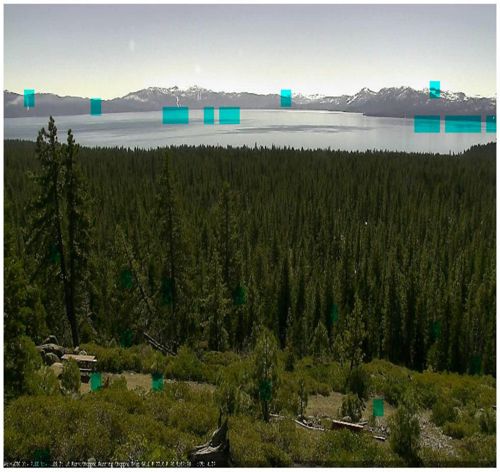
those windows into a vector of dimension 400. For each background window and corresponding foreground window we estimate $\alpha$ and $s$ using the equation (2.5) and (2.6) . By fixing $\alpha$ we calculate $s$ and then using that $s$ we calculate $\alpha$. And then we use the calculated value of $\alpha$ to get $s$. We continue this procedure for 50-100 iterations. Using the range of the blending parameter, $0.85 \leq \alpha < 1$ we classify whether the corresponding window contains smoke or not.
To identify the location of the smoke window we put a window of size $40 \times 40$ pixels on that window. In the figure 5, 6 and 8, the windows ($40 \times 40$ pixels) are indicating the location of the smoke in the window of size $20 \times 20$ pixels.

(A) Background image (no smoke)

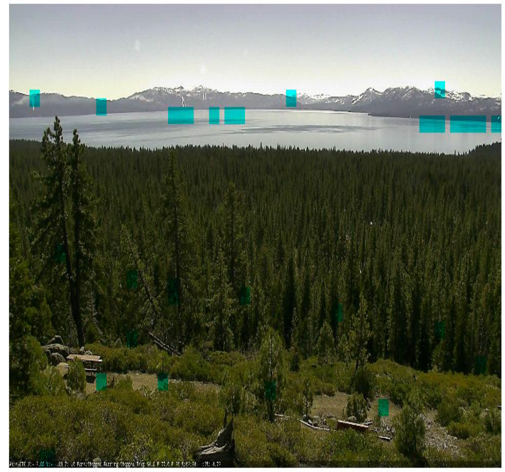

(B) Foreground image (smoke inside the circle)

FIGURE 4. Background and foreground images (type I)

In figure 5 and 6 we can see that there is a window on the smoke in each figure. However, there are several windows which are not on the smoke. Those are on the water, sky and some other smoke on the colored region. May be those places look like smoke.

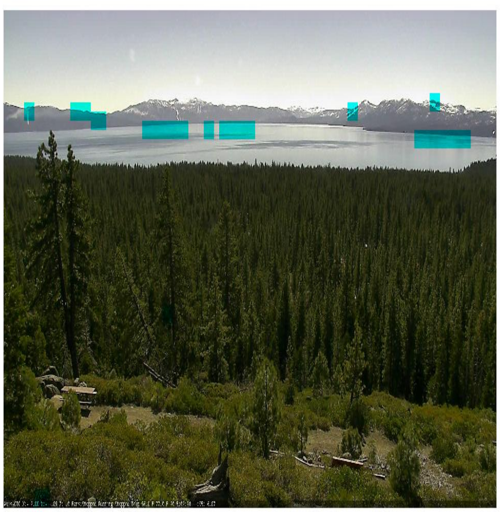


(A) First consecutive foreground image

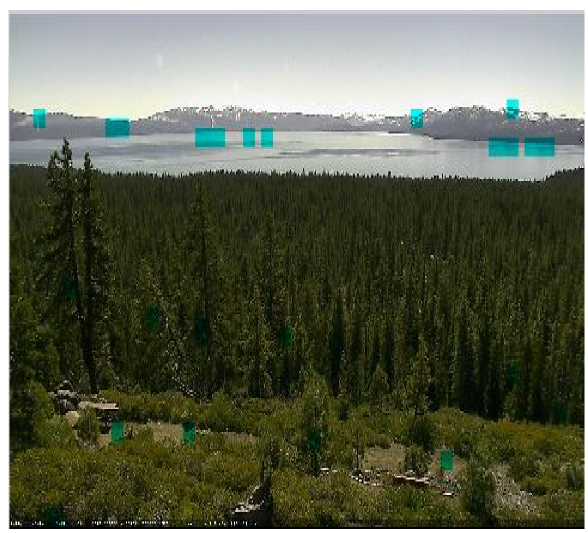


(B) Second consecutive foreground image

FIGURE 5. Windows indicate the location of smoke (type I)



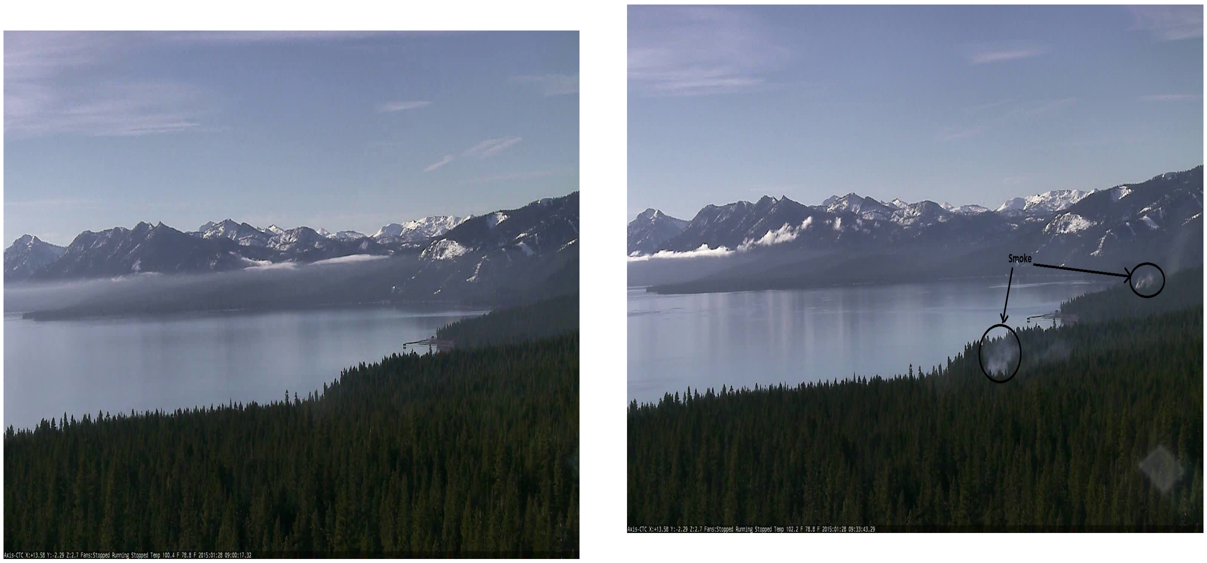
(A) Third consecutive foreground image



(B) Fourth consecutive foreground image

FIGURE 6. Windows indicate the location of smoke (type I)

In fugure 8 we can see that the windows are on the smoke. However, there are several windows which are not on the smoke. Those places are located as smoke

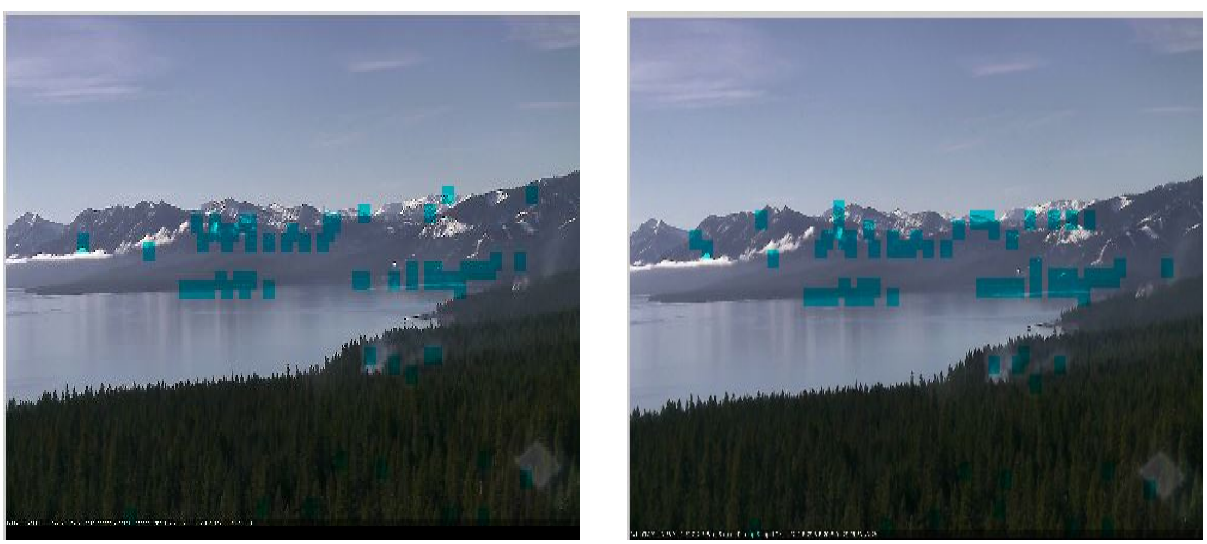



(A) Background image (no smoke)

(B) Foreground image (fog, clouds, and smoke inside the circles)

Figure 7. Background and foreground images (type II)

since fog, clouds and water look like smoke. Those places are classified as smoke because of their colors.



(A) First consecutive background image

(B) Second consecutive background image

Figure 8. Windows indicate the location of smoke (type II)

## 6. Conclusion

In this paper we discuss considering an image is a linear blending of smoke component and background component. Under the above assumption we model the problem and solve the corresponding optimization problem. Basically we focus on the characteristics of the blending parameter, $\alpha$ assuming that $\alpha = 1$ indicates the solid object instead of smoke.

The method, PCA matting, depends on many parameters to determine whether there is any smoke in the window or not. First, training pure smoke windows play the most important character in this procedure. To get the PCA vectors of the pure smoke for training purpose we use white, gray and black colored smoke (user defined). Because of that most of the time it classifies the white, gray and black color as smoke regardless of the existence of smoke. Second, setting the bar for $\alpha$ is another key to get the smoke location. Relatively high value of $\alpha$ gets the more success. Third, number of iterations to get the optimal value of $\alpha$ and $s$ is not unique. It depends on the quality and the intensity of the smoke. Fourth, calculation is not always quite correct since most of the time the matrix $\alpha P^T P$ is singular. Fifth, selecting the size of the window plays potential character. For small window it shows relatively good result. Sixth , searching by overlapping windows appears good result instead of non-overlapping window. Seventh, the position of the smoke on the image plays another role. There are some other factors which control the result of this method. Finally, it seems if there would have pure smoke database and if the water, sky, and snow from the images could be removed then the method would work better.

## References

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