Smoke Detection Prescreening in Sequential Images

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Abstract

This paper investigates the use and optimization of particular image processing techniques as applied to the problem of early detection of smoke in chronologically sequential images taken in nominally undeveloped regions. In particular, we are studying techniques used to eliminate as many potential regions in the image from detailed investigation by other means in the vision processing pipeline. This work is intended to reduce the sophistication necessary to eliminate or confirm the presence of smoke in these images, either by automated or human means.

Keywords: Computer Vision, Machine Intelligence, Image Processing.

1 Introduction

The fundamental focus of this application of the Gaussian Background Elimination functionality available by means of OpenCV [5] is in the initial stage of a larger application development for the automated detection of smoke resulting from ligneous combustion in sequential photographs taken circumlocated in proximity to Lake Tahoe on the Nevada/California geographical border in the United States of America as shown in Figure 1. Multiply differentiable specifics of these fires and the resulting particulate exudate characterize them as well as create features easily distinguishable with Gaussian Background elimination.

The system of cameras and computers, with their associated computer connections was initiated as a joint project between the Nevada Seismological Laboratory and the Forest Guard team. [9] This project combined human observation of these image sequences communicating through social media to detect fires. The Tahoe region is particularly susceptible to wildfires as it is a fire climax ecosystem with a relatively dense human population intermingled with highly inflammable coniferous trees and regular cycles of drought and overgrowth.

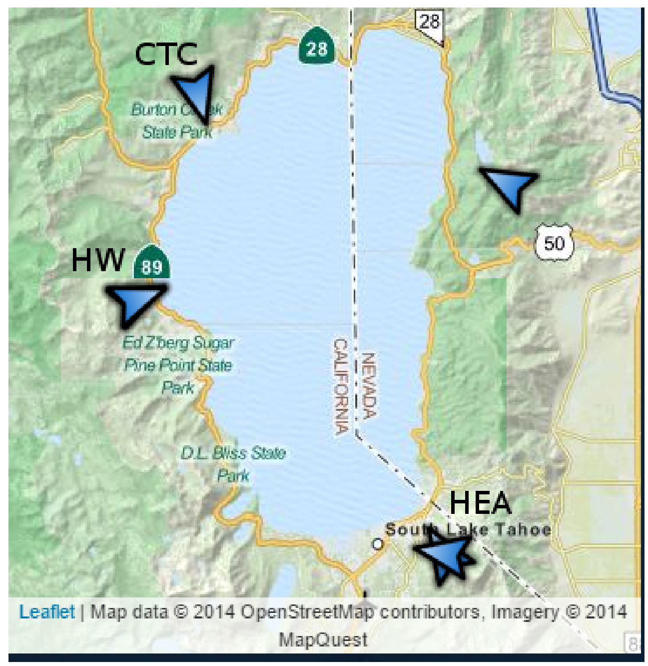

Figure 1: Tahoe Fire Camera Map.[10]

The characteristics of ligneous fires in rural environments typical of the Western United States induce oxidative exudate with readily differentiable specifics, the most notable of which being chromatic invariability. Additionally, the rate of ascent is also relatively consistent as is growth in proportion to geometric proximity to the camera.

In this paper, we will discuss the characteristic of preliminary image screening techniques used for automated smoke detection in coordination as well as for screening of trivially negative potential smoke occurrences. Next, we will discuss the details of the Gaussian Background

Elimination technique used in this investigation with the specific characteristics which specifically contribute to its unusually efficacious success in distinguishing ligneous smoke from other fluctuations in the image sequences. Following this discussion, our results will be given to establish a baseline for this technique in its most fundamental formulation. Finally, we will discuss modes of modification for ultimate development as part of the automated smoke detection system being worked upon by persons at the University of Nevada, Department of Geology [11] as well as others.

2 Background

2.1 Image Detection Pipeline

The image detection pipeline is composed of multiple components, both in parallel and sequential. The portion we are investigating in this paper is the initial triage at the beginning of the image detection pipeline as shown in Figure 2. The purpose of this is to definitively eliminate as many locations in the image as possible as not smoke so more refined smoke detection algorithms can focus on fewer locations and be possessed of more time to investigate possible smoke locations in greater detail. The later stages in the pipeline are also modular and interchangeable.

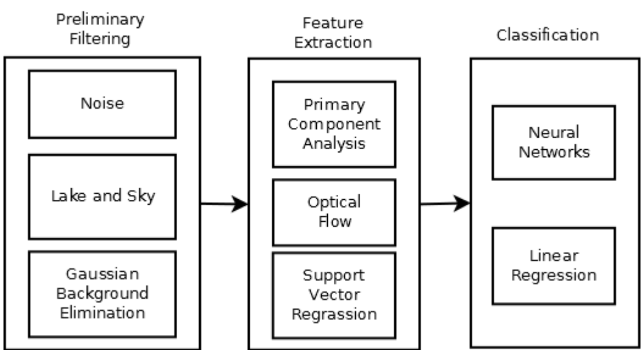

Figure 2: Image Detection Pipeline.

2.2 Optical Flow

One of the most common methods for automated determination of smoke or fire in sequential image or video media is by means of optical flow techniques, often supplemented by neural network feature detection optimization as shown by Kolesov. [7] This is a more sophisticated technique applicable to multiple smoke detection applications, as well as the entire detection pipeline from initial image discrimination through operator notification of exception to be examined.

The primary techniques used in this particular method of smoke detection are morphological, chronological and transitional. For the stage of smoke detection we are examining here, however, we are focusing on positively assuring the non-exception of any possible smoke incident, as much as possible, and so this technique is beyond the scope of our current technique under examination.

2.3 Manual and Automated Region Exclusion

Another method to remove obviously negative regions from consideration for future automated processing is region exclusion, either by manual or automated methods. For this particular application, manual region exclusion has been used very successfully, as the cameras are stationary and the regions to be excluded are easily blocked from consideration by a human operator designating areas as not of interest. The two most common for this particular application are the sky and the water.

The water is a major complication in automated visual processing of the images, as it is always moving, at least in every season except winter and the sky is even more difficult, as there is little optical difference between clouds and ligneous smoke. There are techniques for the automation of this process, but with fixed cameras, the ease with which a human operator can distinguish and immediately eliminate such regions is far more practical.

The technique used in this paper, however, was not combined with this technique, so as to give it a considerably greater challenge and so to show potential applicability to unknown camera locations or moving cameras, either in field of view and rotation, or in all axis.

2.4 Digital Filtering

The primary concept behind this particular implementation of Gaussian Background Elimination for the purpose of automated smoke detection is based in the fundamental concept of a basic digital filter, as discussed in any introductory text book on the topic, such as the text DSP First. [8]

The most fundamental variety of digital filter which can be readily implemented is a finite impulse response filter, or FIR. A simple diagram is shown below in Figure 3. In this diagram, each of the rectangles represent a signal at a certain time, above it are the weights assigned to each time and they are added together to give the final signal output.

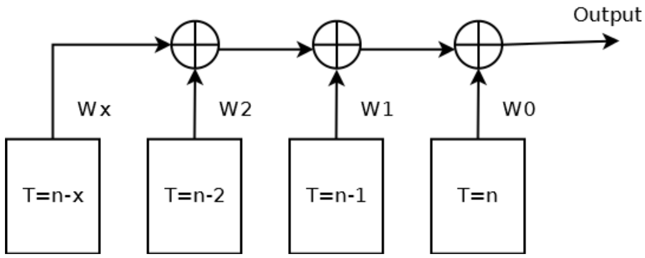

Figure 3: Finite Impulse Response Diagram.

Different filter response profiles are given by adjusting the weights. The primary functionality of Gaussian Background elimination [6] and implemented in Open CV uses exactly this methodology. This technique, while very simple and fundamental to filtering time variant signals in the digital domain, works exceptionally well for excluding simple binary integer type image changes between frames in video, or in this particular case, between discreet images taken over periods of time.

In addition, Gaussian Background Elimination, as its close relative, the Finite Impulse Response digital filter, is readily modified for optimal inclusion and exclusion of preferred changes over time, in this case those which occur over multiple frames and are clustered in space as well as chronological sequence. This clustering generates a unique visual effect in the bi-chromatic output display generated by the Gaussian Background elimination filtering technique.

3 Implementation Details

3.1 Development Environment

The fundamental environment and package manager used for this was the Anaconda [1] package from Continuum Analytics with the IDE being Spyder, a specialty scientific and technical Python editor. The version of Python [4] being used is 2.7.4. Anaconda automatically includes NumPy 1.7.1, SciPy 0.11.0 and Matplotlib 1.2.1. The version of Open CV [5] we used was 2.4.2.

The only adjustments made were for the changes in versions subsequent to publication of documentation for the packages used, particularly Open CV, as the Python variant is not the primarily used variant of Open CV.

3.2 Code

The nature of Gaussian Background Elimination in this context, is to remove all pixels which are not changing by designating them as black with the remainder being white. These are the pixels which are nominally of interest. Simple subtraction of pixels is not sufficient to eliminate the majority of false positive incidents of pixel variability as numerous pixels change only slightly over time, but constantly, or are very slow changing.

The normal or Gaussian distribution, on the other hand, is a standard measure of change from a nominally labeled standard point. For the purposes of this initial investigation, the standard deviation we were determining to be significant was 2.5. This is a major change, preventing very small changes from triggering as a nominal pixel of interest, and thus eliminating very slow changes from triggering our pixel of interest specification.

There are other means of determining changes in background in order to isolate foreground or changing pixels from stable or background pixels, as discussed in Brutzer. [2] However, given the nature of smoke, which is a naturally occurring modification against an equally natural background, the normal or Gaussian distribution was indicated as potentially characteristic and thus nominal measure of change.

This is what was found when we used the filtering code against the image sequences, distinguishing the foreground, *id ext* the smoke, as conglomerates of white pixels against a background of black and a scattering of unrelated white pixels. This clustering, in specific, was very visual characteristic of an igneous oxidation exudate incident in the sequential images under consideration in our examples under examination.

4 Results

The primary characteristic of smoke, as detectable by human and computer vision systems, is in the distinct manner of transitional behavior characteristic of oxidative exudate. Due to this characteristic, notably leveraged by Gaussian Background Elimination, the non-sequential images do not give significant image representation of the actual smoke in many of the image sequences.

As a result of this difficulty, discrete still images don't demonstrate the distinctive behavior shown of the filtered output. Therefore, the results are a comparison between the ability of a human to visually recognize smoke in the original video sequence and the computer manipulated black and white images produced by the background elimination filter. In reference to Figure 1, the Fire Camera Map in Section 1, CTC refers to the California Tahoe Conservancy camera, labeled CTC on the map and in the tables, Heavenly refers to the Heavenly Ski Area camera, labeled HEA on the map and Heavenly in the tables, while Homewood refers to the Homewood Ski Area camera, labeled HW on the map and Homewood in the tables. In the tables, foreground (FG), mid-ground (MG) and background (BG) refer to the location of the smoke in these image sequences. These labeles are sometimes a big disingenuous, as such labeling often does little to truly help locate the smoke in the images. The lighter areas on the top of the images are an artifact of the graphic rendering system used. All output from the Gaussian Background elimination filter is either true black or white, with no intermediate shades of grey.

The following images, Figure 4 through Figure 7 show two images, before and after filtering. In the final figure of the set, the collection of white at the head of the arrow is exemplar of the optimal result of the smoke detection filtering implemented by the Gaussian filtration function. Note, the filtered image results are true black and white, not graduated between the two monochromatic extrema despite an artifact of the image generation process in the upper portion of the image.

Despite this particular challenge, the smoke in the sequential images generated as the output of the digital filter is notably easier to distinguish, particularly once the characteristic of white pixel conglomerates being significant of smoke is taken into consideration. This is one of the primary avenues of exploration for the future.

The unmodified images show clearly the difficulty inherent in visual examination of single images contributing to the detection of smoke in naive single image examination. It is not that the filter removes all possible regions of interest, but rather has the ultimate effect of raising the contrast on the subject of interest into far greater visibility both to the human eye as well as any computer vision system. This is the ultimate advantage to using this technique as a primary filter to determine areas of interest to investigate further.

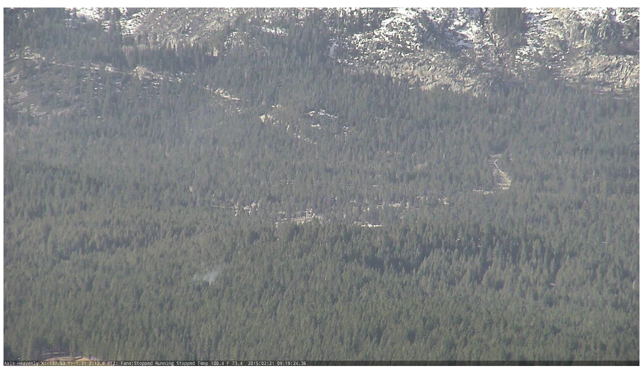

Figure 4: Unfiltered Heavenly Foreground Smoke 1.

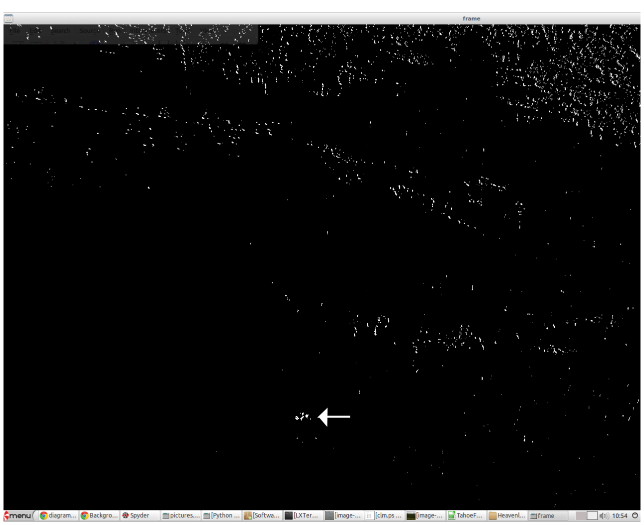

Figure 5: Heavenly Foreground Smoke 1.

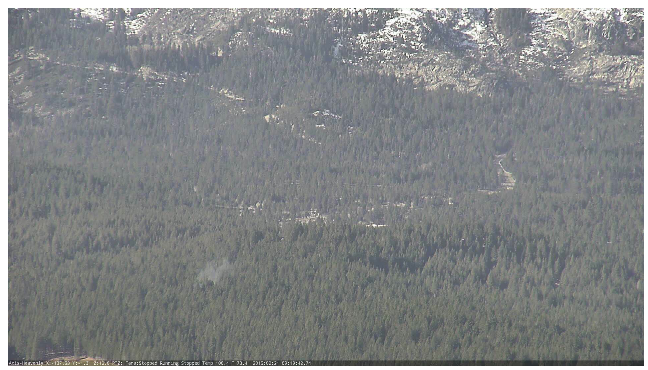

Figure 6: Unfiltered Heavenly Foreground Smoke 2.

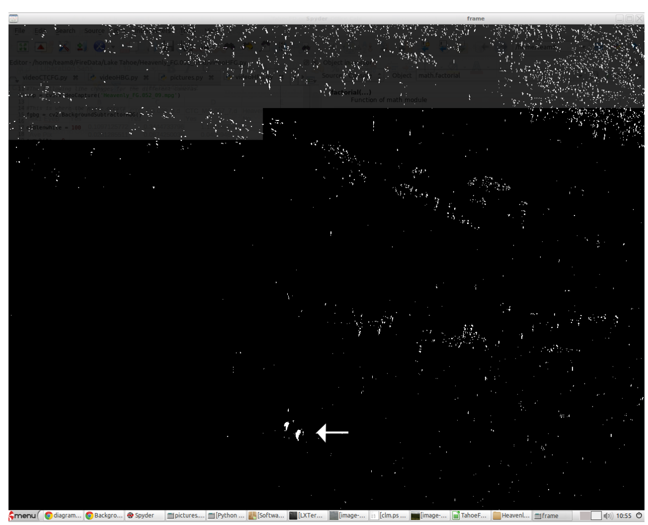

Figure 7: Heavenly Foreground Smoke 2.

The computer images, in particular ones with large foreground object movement such as the Homewood chairlift discussed below, were significantly more difficult for the computer to distinguish between single pixel modifications and the more numerous grouped pixel modifications. However, note, this should not be a significant challenge to a normal smoke feature detection system, such as in Chunyu. [3]

In all the following tables, visual detect refers to the ability for a trained human observer to detect the smoke in the filtered video sequences. This detection was then correlated with the original video sequence. Often when a human had significant difficulty detecting the smoke in the filtered video sequence, there was a concomitant difficulty in detecting the smoke in the original video sequence, in the most extreme cases to being unable to find the smoke without additional external to the sequence cues, such as another human giving a suggestion as to where to begin searching in the images. Percentage white refers to the computer generated pixels of interest, which are all white in comparison to those which are not of interest at all, which are black. In no case, however, once a human was aware of the exact area of interest, did the computer absolutely show no white at all in that region. The difficulties were often more in the category of false positives, as desired for a preliminary filtering system. The percentages represent the fraction of white pixels, or pixels of potential interest. The maximum percentage represents the absolute largest fraction of pixels in the entire image to possibly be relevant for further examination. The Average percent white represents the more typical fraction of pixels of potential interest.

The first table, Table 1 below, shows the CTC data in three versions as given in the example data set. It is unknown at this time, where these sequences were taken, exactly, other than overlooking Lake Tahoe. The critical numbers to examine are the percentage of pixels that are most definitely not smoke. Most critical, is the significance of the fact these numbers are taken from raw images, not images where obviously non-smoke regions have already been excises, such as the lake and sky.

	CTC BG	CTC FG	CTC MG
Visual Detect	Yes	Yes	Yes
Max Percent White	0.1097	0.3445	1.193
Ave Percent White	0.0281	0.0874	0.0406

Table 1: CTC Video Results

The ultimate conclusion, however, is the percentage of pixels that can *a priori* be eliminated from consideration given this particular technique. In addition, as this technique, as implemented in Open CV, takes a trivial length of time to implement, it allows for far more complex feature recognition techniques which may take significantly more time to implement.

	HW BG	HW MG
Visual Detect	Late	Yes
Max Percent White	65.00	1.438
Ave Percent White	1.703	0.4150

Table 2: Homewood Video Results

The following Table 2 and Figures 8 and 9, contain a chairlift, for example, which causes a large number of pixels to register as moving and thus tagged as being of potential interest. However, many of these can be easily excluded as non-smoke by any reasonably accurate automated visual smoke detection system. Additionally, because much of this movement is periodic, it would be relatively trivial to eliminate this movement from future recognition as potential smoke pixels.

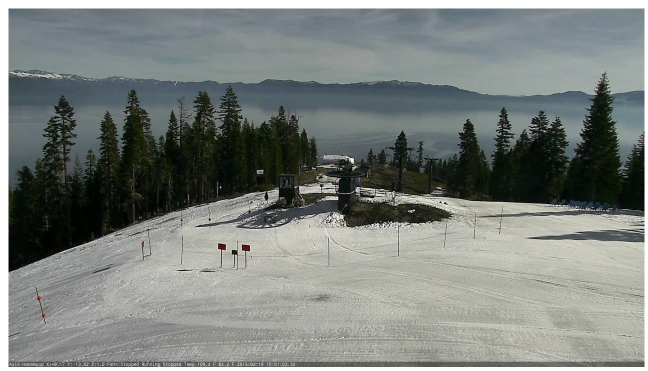

Figure 8: Unfiltered Homewood Chairlift.

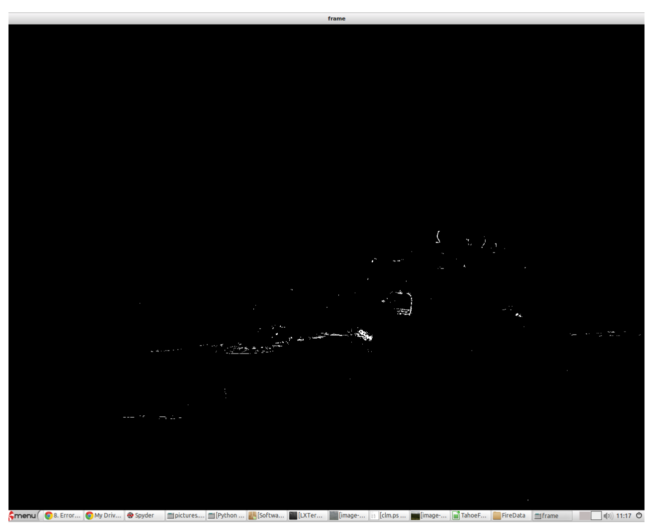

Figure 9: Homewood Chairlift.

The final set of images under consideration was for the camera aimed at a portion of the Heavenly ski resort and is referred to in Table 3. This entire sequence of images was extremely difficult to distinguish the smoke from other lightening behaviors relative to the stable background. Or in this particular sequence of images, the relatively unstable background, which was a significant part of the difficulty in distinguishing the smoke in this sequence. There was a great deal of other atmospheric lightening, particularly moisture which appears as a lighter haze against the darker background, or very similar to smoke. This one was also extremely difficult to distinguish in the original footage by even a trained human observer.

	H BG	H FG
Visual Detect	No	Yes
Max Percent White	6.955	1.438
Ave Percent White	0.1643	0.4150

Table 3: Heavenly Video Results

5 Conclusion and Future Work

5.1 Conclusion

This technique, using Gaussian Background Elimination, as implemented in Open CV, is an effective and useful primary filtration technique to triage large high resolution sequential images before the application of other potentially more complex, in time or memory, techniques on the entire image.

As a preliminary investigation, this method was particularly effective, more than was at first expected on initial contemplation. And as such, this method certainly warrants significant future investigation.

In particular, the primary changes we would like to see implemented are in the Gaussian filter itself. As wood smoke, the only kind under investigation in this case, is always white or at least lighter than its surroundings, the Gaussian could be fixed to be a certain value less than the nominal background. This would make the Gaussian a fixed Mahalanobis distance from any pixel value and thus achievable with a constant time delay filter.

The next point of optimization for this initial filtering device is to associate it with an automated feature extraction and classification system, completing the pipeline and generating entirely computer observed and sorted data. There is a large amount of additional data to be used to both train and test such a classifier and this filtering system appears to be a very useful initial starting technique for further development.

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