STUDY OF STATISTICAL AND COMPUTATIONAL INTELLIGENCE METHODS OF
DETECTING TEMPORAL SIGNATURE OF FOREST FIRE HEAT PLUME
FROM SINGLE-BAND GROUND-BASED INFRARED VIDEO

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COMMITTEE MEMBERSHIP

TITLE: STUDY OF STATISTICAL AND COMPUTATIONAL
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PLUME FROM SINGLE-BAND GROUND-BASED
INFRARED VIDEO

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ABSTRACT

This thesis will analyze video from land-based, cooled mid-wave infrared cameras to identify temporal features indicative of a heat plume from a forest fire. Desirable features and methods will show an ability to distinguish between heat plume movement and other movements, such as foliage, vehicles, humans, and birds in flight. Features will be constructed primarily using combinations of statistics and principal component analysis (PCA) with intent to detect key characteristics of fire and heat plume: persistence and growth. Several classification systems will combine and filter the features in an attempt to classify pixels as either heat or non-heat. The classification systems will be tuned and compared with common metrics of error rate and computation time. It was found that the movement pattern of a heat plume could be distinguished from the similar movement pattern of foliage by detecting outlier movement patterns, a phenomenon associated with the growth property of fire. Outlier movement patterns were best detected by thresholding the quotient of mean and median of a set of variance measurements over time. The best tested classifier in terms of minimizing false positives without losing the heat signal came from PCA of a dual-range moving average difference.

Keywords: Forest Fire Smoke Heat Temporal Detection Features Classification

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1 INTRODUCTION

1.1 Motivation

Forest fires threaten lives and property. The past 10 years from 2002 to 2012 in California have *officially* seen 26,128 fires, affecting an average of 971,000 acres per year [1]. Early detection of forest fires would lead to an earlier deployment of fire fighting resources, which could preclude damage. In the interest of saving lives and property, this thesis examines methods for use in detection of forest fire by infrared video.

1.2 Background

The simplest method of early forest fire detection is to post a diligent human observer at an effective vantage point, and instruct the observer to raise an alarm when they see fire or smoke. Thankfully, modern technology provides many useful alternatives. The most ubiquitous fire detection system, as seen in buildings, relies on a device on a wall that detects smoke, heat, or carbon monoxide, indicators of combustion [2]. This detection scheme is referred to as “point detection.” Unfortunately, it only works well in an enclosed environment, in somewhat close proximity. Another category is “beam detection,” which uses cameras or lasers to monitor an enclosed space. Though longer-range, they can suffer from indirect sunlight at some times of day, or from misalignment, perturbation, or dirty lenses [3]. There’s no school like the old school, and a group from the University of Nevada, Reno are blending old and new by installing a remote 360-degree, solar powered camera that streams video to a public website, where thousands of volunteers can check on it and manually raise an alarm [18].

Satellite solutions can work, but they have their own limitations. They can suffer from atmospheric conditions and coarse resolution in space and time. For example, the well-known MODIS algorithm, the subject of many current papers, implemented on the TERRA satellite and

launched in 1999, has a spatial resolution of 250 m: hardly suitable for detecting small forest fires [19]. Satellite systems are better suited to conservative fire detection algorithms that detect 30-40% of fires that account for 80-99% of burned biomass, according to a study on forest fires in Brazil [20]. It appears that only ground-based systems can detect fires early enough for tactical response.

Many papers address the subject of smoke detection and fire detection. Of those that consider detection from video sources, the trend veers towards considering multiple dimensions of the event, in spatial, temporal, and spectral domains [4], [5], [6]. More domains and more features, if combined wisely, can add robustness to the system. Unfortunately, these come at the cost of increased sensing system requirements. If an adequate system could be demonstrated to detect smoke or heat plume from a single camera, it would reduce cost and complexity, be more easily maintained, more light-weight, and more widely accessible.

1.3 Context

This thesis explores just a few aspects of an on-going and wide-spanning inquiry into early forest fire detection under Professor Saghri. Other Master's theses and senior projects have explored related topics.

1.3.1 Ryan Radjabi

Applies multi-temporal principal component analysis (PCA) with nonlinear mapping on mid-wave infrared video to identify fire and heat plume activity.

Ryan did his project first, so he pioneered some of the data manipulation and processing techniques.

1.3.2 Tim Davenport

Applies multi-temporal and multi-spectral principal component analysis (PCA) on blue, green, red, mid-wave, and long-wave IR, then applies texture analysis to identify heat plume activity and raise alarm.

Tim refined and expanded Ryan's work in terms of data manipulation, and the breadth and complexity of processing techniques. Some of the lowest-level data manipulation code of this thesis is based on Tim's, and has been modified and further expanded.

1.3.3 George Moussa

George performs texture and motion analysis in the visible spectrum, in time- and frequency-domain. At the time this paper was written, George was in the early stages of his research.

1.4 Problem Statement

Given infrared video footage of a scene containing an active barbecue pit at mid-day, study features that indicate the presence of heat plume. Heat plume is the warmth that rises from a combustion source, as measured by an infrared camera. Heat plume should not be confused with smoke plume, which is detected in the visible domain due to scattered light as a result of particulate by-products of combustion. Design a system that detects the heat plume and raises an alarm. The available infrared channels include cooled mid-wave (CMWIR), cooled long-wave (CLWIR), and uncooled long-wave (UCLWIR).

An active flame is trivially simple to detect with an intensity threshold, so this problem does not include flame detection, but rather focuses on the heat rising from the flame, which has a higher probability of showing up in line-of-sight than the flame itself, by virtue of its relative size. Infrared can detect heat from a fire by day or night, making a more robust solution.

1.5 Theory and Methods

To detect heat plume, a system must know the characteristics of the heat plume, and those of the background. Assume that heat plumes come from fire. Then heat plumes share some noteworthy characteristics of fire, specifically, **persistence** and **growth** [13]. In the case of fire, persistence and growth can be measured by pixel intensity over time, in visible or infrared. However, a fire can be considered a point source, where the heat plume emerges from that point source, which this thesis assumes is obscured. Furthermore, the heat of the fire pixel would dominate that pixel's DC component, where the heat plume wavers and simply adds to the natural background intensity of the pixels it passes through. These two points imply that persistence and growth can't be measured by intensity, but rather by *movement*. Relying on movement creates a challenge: many elements of a scene move in patterns very similar to that of the heat plume. People walking and cars moving pose a simple challenge, but by far the most difficult phenomenon to distinguish from heat plume has been the foliage, because both heat plumes and foliage move and vary in the wind.

This thesis will attempt to identify features that indicate persistence and growth, and incorporate those features into a classifying system that detects the eruption of a heat plume. A standardized system of measuring error rate will compare different classification systems.

The features will derive from statistics employed in such a way as to represent time-relevant information. These statistics will consist of variances, weighted means, medians, thresholds, and deliberate combinations of these. In addition to statistical methods, Principal Component Analysis (PCA) will contribute to the feature base. Classification systems will combine and filter multiple features with thresholds and morphological operations to designate a signal (pixel intensity over time) as heat plume or not.

Since one goal is to keep cost down, the methods herein will use only one band. IR cameras used by fire fighters (for example, the FX 160 by Infrared Cameras Inc.) detect in long-

wave because it cuts through smoke. Therefore the only logical band to use is the CMWIR, which does show a stronger smoke signal. Furthermore, the LWIR is far more prone to light blooming, which drastically obscures the signal of the heat plume. Therefore, the only useful band available is CMWIR, and **all processes in this thesis will use CMWIR.**

Figure 1 shows a typical frame with active fire and heat plume in it. The red rectangle defines the area of interest that the majority of the methods will operate on. Focusing on a small region reduces computation time and storage requirements, facilitating faster prototyping. The area of interest includes the fire and heat area, and challenging areas: foliage near and long ranges, people walking, and cars driving by.

**Figure 1 – Typical Frame in Scene Showing Region of Interest, Containing Active Fire
(pine_cones channel, frame 2000)**

1.6 Document Organization and Notes to the Reader

Chapter 2 will discuss data acquisition, which describes the data collection mission and the video stabilization. Chapter 3 will discuss the features considered here-in, including their derivation and an analysis of merit. In some cases, experiments were performed that will be presented. Chapter 4 will introduce intensity maps that later algorithms will use. Chapter 5 will develop classifiers, which combine features into decisions on heat plume presence, using different methods. These methods will be defined and analyzed in a similar fashion as the features to study and improve their quality as fire alarms. The methods will also be developed and tuned in response to the analysis. Chapter 6 will conclude with a comparison and summary of the methods tested, suggest future avenues of inquiry, and offer lessons learned. Figure 2 shows a top-level block diagram showing the data flow throughout this thesis.

Figure 2 – Top-Level Block Diagram

1.6.1 Implementation Notes

All primary research was performed in Matlab. Though this document focuses more on the theory, principles, thoughts, results, and observations, this text will refer to function names and code snippets to guide the reader who aspires to reproduce the work described herein. Where appropriate, the document will contain tables of functions with brief descriptions. The appendices contain the code that produced the results shown herein. The full code, including all referenced functions, should be attached to this document. The table of function descriptions will adhere to the format demonstrated in Table 1.

Table 1 – Generic Format for Function Description Tables within This Document

Function / Script Name	Description Overview	
	Function Input	Function Output
script1	A script has no inputs nor outputs, only a sequence, or batch, of commands, hence it will not have two descriptive columns	
script2	This is a nondescript script.	
functionRed	A function may be described in terms of its inputs and outputs.	A code file may be identified as a function by having these two columns.
functionBlue	Functions may have multiple inputs and outputs.	The output description makes the function's purpose evident.
anotherScript	Some deem this script redundant, but it is well commented.	

All raw and derived data will be stored in an organized fashion by band, then channel, then by category, as in the following example:

- Band: CMWIR
 - Channel: oats1
 - Category: features | classification | training
 - SMA_seq30
 - 510.mtx
 - 520.mtx
 - 530.mtx
 - ...

The raw frames are stored in .mtx format, which contains dimension and data type information, making it hassle-free to read from and write to.

The deepest folder (SMA_seq30, a feature) contains a sequence of raw frames. This method of storing data ensures scalability, and facilitates intuitive manipulation of more than 100,000 files, in more than 120 folders.

1.6.2 Video Demonstration

This thesis will be archived with accompanying video demonstrations associated with the classifiers in Chapter 5. If the demo video was the source of a figure, then the video name will be referenced in the figure caption.

1.6.3 Clip Art

All images and clip art in this document are either original or taken from public domain sources.

2 DATA ACQUISITION

Raytheon Vision Systems in Goleta, California sponsors Cal Poly's efforts into forest fire detection, and one way they contribute is by offering the use of their site and equipment. All data used in this thesis was collected from a mission to Goleta. The raw data was then pre-processed in preparation for use in the algorithms developed in Chapters 0 and 4.

2.1 *The Goleta Mission*

On June 18, 2011, a team embarked on a data collection mission to Goleta, California, to Raytheon's Remote Vision Systems site. For the purpose of the mission, the RVS site consisted of a control room, a tower with a set of cameras mounted on top just outside the control room, and a parking lot with a Santa Maria style barbecue pit. The camera tower elevated the cameras to approximately 20 m high, and stood about 800 m distant from the barbecue pit. Figure 3 shows the location, courtesy of Google Maps.

2.1.1 Setup

At the control room, cables relayed the data from the cameras on the tower to computers, where the team used software to capture and record the data to hard drives. Three cameras took data in five bands. One camera took RGB video; one un-cooled camera took long-wave infrared (UCLWIR), and one camera with an in-built cooling system took both long-wave and mid-wave infrared video (CLWIR, CMWIR, respectively). This thesis doesn't consider visible nor short-wave, so those will not be mentioned further. Table below shows individual camera specifications, and Table 3 shows common specifications.

Figure 3 - Data Collection Setup Locations-of-Interest

Table 2 – Individual Camera Specifications

	Focal Length	Aperture	Pixel size
Uncooled LWIR	75 mm	F1	25 μm
Cooled LWIR	100 mm	F2	20 μm
Cooled MWIR	100 mm	F3	20 μm

Table 3 – Common Camera Specifications

Resolution	Nominal Sample Rate	Format
640 x 480	30 fps	14-bit little-endian raw

At the barbecue pit, the team had brought several varieties of fuel, for the purpose of collecting a wider range of data. Perhaps research on the video can discriminate between different fuels, or perhaps one fuel would give a stronger signal. The following fuels were gathered and burned in this mission:

- Charcoal
- Grass and wild oats
- Pine needles
- Pine cones
- Palm leaves
- Thistles
- Wet leaves
- Damp and dry leaves
- Wild rosemary
- Apple wood

2.1.2 Procedure

One person at each site had a dedicated communications role by cell phone, to facilitate coordination of efforts. The communicator also served as the dedicated note-taker on the sequence and timing of events. Since the mission was expected to last a few hours, it was divided into sections in which one fuel was burned, and the video take saved in separate files. One operator per computer remotely controlled the cameras and saved the data according to an established naming convention.

The fuel burn order was planned in advance. For each take section, the control room communicator would log the time and fuel type, direct the computer operators to begin recording, then direct the barbecue pit team to add the fuel to the pit. Throughout the burn, both the control room note-taker and the barbecue site note-taker recorded visual observations of the burn from their perspective. A typical take lasted approximately 10 minutes.

2.2 Raw Data

The data format is 14-bit little-endian, saved as the most significant bits of 16-bit words, where the unused 2 LSBs were assigned to zero. The image pixels are stored in x-y order, one

pixel after the other in a left-to-right row, then one column after another in top-to-bottom columns, then one frame after another through time. Each video is saved to disk as a 1-dimensional bit stream in this fashion. Figure 4 illustrates the data word format.

Figure 4 – 14-Bit Little-Endian Raw Data Saved in 16-Bit Word

The cooled camera that captured CMWIR and CLWIR data passed data to a buffer that concatenated frames in the x-dimension. Each channel updated at 30 fps, staggered with each other, so that the buffer updated at 60 Hz. At each update, the buffer sent its data back to the control room computers via Ethernet (See Figure 5). The computers received and recorded the video frames at the same rate the buffer sent them. Therefore, each cooled infrared video file contains redundant data. The UCLWIR data path had no such complications as the single camera sent its data stream back to the control room, which saved the single stream to its raw data file.

Figure 5 – Cooled Infrared Data Path

Table 4 shows a subset of the raw data files that this thesis will use. The cooled data file names have the convention:

(date)_(time)_LW-MW_(fuel name).raw

The un-cooled (UCLWIR) file names have the convention:

(date)_(time)_(fuel name).raw

Note by inspection of the file names that both long-wave and mid-wave data are stored together. Each file contains 8000 frames, so the file size of the cooled LW-MW file is:

$$\left(640 \cdot 480 \frac{\text{pixel}}{\text{frame}}\right) \cdot \left(2 \frac{\text{bytes}}{\text{pixel}}\right) \cdot \left(2 \frac{\text{frame}}{\text{file}}\right) \cdot \left(2 \frac{\text{written frame}}{\text{captured frame}}\right) = 19,660,800,000 \text{ bytes}$$

The file size of the UCLWIR is:

$$\left(640 \cdot 480 \frac{\text{pixel}}{\text{frame}}\right) \cdot \left(2 \frac{\text{bytes}}{\text{pixel}}\right) \cdot \left(1 \frac{\text{frame}}{\text{file}}\right) \cdot \left(1 \frac{\text{written frame}}{\text{captured frame}}\right) = 4,915,200,000 \text{ bytes}$$

Table 4 – Raw Data Files Used

Raw Data File	Size (bytes)	Source
2011-06-18_102454_LW-MW-14bit_oats1.raw	19,660,800,000	Cooled
2011-06-18_102646_oats1.raw	4,915,200,000	Uncooled
2011-06-18_105906_LW-MW-14bit_pine_cones.raw	19,660,800,000	Cooled
2011-06-18_110100_pine_cones.raw	4,915,200,000	Uncooled

Note: For the remainder of this paper, if a video channel is referenced but not specified as stabilized or pre-stabilized, assume that it is stabilized (Explained in 2.4).

2.3 Data Extraction and Manipulation

The large raw data files (Table 4) were separated into 8000 files containing one raw frame each (Figure 6). This process performed the following operations:

- The 16-bit words were right shifted by 2 bits to place the LSB of the 14-bit information word into the LSB position of the 16-bit recorded word. This moves the 2-bit zero padding to the 2 MSBs instead of the 2 LSBs.
- Convert (x, y) order into (r, c) order (explained below).
- For the concatenated long-wave and mid-wave file,
 - Separate the two channels into different files
 - Discard every other frame from each channel in a staggered pattern (fixCooledIndicex.m).

Figure 6 – Raw Data File Frame-Wise Separated

The cameras recorded raw frames in (x, y) order into the data stream (left-to-right, top-to-bottom), but Matlab interprets the stream in (r, c) order (top-to-bottom, left-to-right). To simplify operations throughout the project, the (x, y)-ordered frames from the raw video were converted to (r, c)-ordered frames before saving them to the raw frame files. The ordering matters because files are 1-dimensional data streams, so the reading function must know the order to correctly

load that 1-dimensional data into 2-dimensional imagery. Figure 7 shows a diagram of the data order from the camera to the raw video file to the raw frame files.

Figure 7 – Frames Converted from (x, y) Order to (r, c) Order

In Figure 7 step (b), the function (`vid2frame.m` or `vid2frame_lwmw.m` from Figure 6) reads the raw video file by columns, yet the camera wrote the data by rows, hence the image becomes transposed: the top row becomes the left column. The figure illustrates this transposition by showing “row1”, “row2”, etc., *rotated*. After a corrective transpose in step (c), the image would display in correct orientation. The columns, designated “col1”, “col2”, etc., are vertically oriented, again showing that the image would display correctly. Step (d) represents the reversible process of writing to and reading from a file in (r, c) order: top-to-bottom, left-to-right.

Now the raw video information is separated into frames, allowing easy access to any frame. Several functions were developed to facilitate data reading and writing, and visualization.

Table 5 – Data Acquisition and Manipulation Function Descriptions

Function / Script Name	Description Overview	
	Function Input	Function Output
vid2frame¹, vid2frame_lwmw²	Script that converts raw video files into separate files containing one frame each, and saves them in hierarchical folders.	
fixCooledIndices	Corrects redundant frames generated by <code>vid2frame_lwmw</code> . Deletes even frame files, then renames odd frame files to be contiguous.	
readframes²	Location of raw video data (already separated into one frame per file), frame dimension, desired frame indices to read.	Matrix of frames, matrix of frame indices.
slideshow	Calls <code>readframes</code> and displays the resulting video matrix in a figure, displaying frames at an adjustable fixed rate, or advanced by keystrokes, to allow examination of the video data.	
raw2bmp	Path of raw input image, and path to bmp output image.	Imports specified raw image and saves it as bmp. No function output.
saveMtx	A matrix, save path, data type (optional).	No output. Writes the matrix to file, preserving dimensionality and type.
loadMtx	Path to a file in a format consistent with <code>saveMtx</code> , data type (optional).	Returns the matrix in the same dimensions it was written as.
mtx2vid	Matrix of frames, save path.	No output. Generates an AVI video of the input frames at the specified save path.

¹ Written by Tim Davenport

² Original by Tim Davenport, modified

2.4 Digital Video Stabilization by Point Feature Matching

When viewed with the tools established in Section 2.3, it became apparent that the video contains motion jitter. The tower, upon which the cameras were fixed, moved slightly as the wind stimulated its high-frequency vibration modes, introducing the jitter. Motion jitter corrupts the temporal signature of each pixel, making the temporal signature of the heat plume more difficult to identify, warranting a video stabilization operation.

Feature matching methods commonly consist of feature registration and matching between frames [8]. Point Feature Matching (PFM) stabilization spatially aligns a frame with another frame by registering and comparing salient points (e.g. corner pixels) between the frames [7]. Since the camera does not move much, all frames appear very similar to the first frame, used as a stable reference, so corner detection produces comparable sets of pixels. The Feature Accelerated Segment Test (FAST) criterion is used to identify corner pixels in both the reference frame and the test frame [10]. Correspondence between reference frame and test frame corner pixel pairs is assigned by choosing the least sum of square differences (SSD) between the 9-by-9 neighborhoods centered about each corner pair. The Random Sampling and Consensus (RANSAC) method throws out the correspondence outliers by assuming a subset of correspondences as inliers, computing a linear geometric transform that fits those inliers, then including all remaining correspondences that closely agree with the transform, as inliers. The linear geometric transform is re-computed for this expanded set of inliers, then the transform is evaluated on how well the transformed test frame matches the reference frame. RANSAC is done 10 times with a different random subset of initial correspondences, and the best fit transform is used to transform the test frame to the reference frame [11], vastly reducing the jitter. To ensure a stable image, every frame is stabilized against the first frame of the video, else accumulated error in the transform causes the view to migrate.

The PFM process is as follows.

1. Collect corner points from a pair of frames using the FAST (Features from Accelerated Segment Test) algorithm. See Figure 8.

(a) Reference Frame

(b) Test Frame

Figure 8 – Corner Points Detected By FAST Algorithm

2. Identify correspondences between corner points. See Figure 9. The yellow lines mark the assigned correspondences based on the minimum SSD. In this case, every visible line marks an incorrect correspondence, but all or most correct pairs correspond as well, and are marked with a 1-pixel yellow line.

Figure 9 – Correspondences Between Corner Points

3. Use RANSAC method to eliminate correspondence outliers and select a well-fitting transform. Figure 10 shows the result with transform applied. Note the absence of outliers and the well-overlapping edge pixels between reference and test frames.

Figure 10 – Inlier Matches From 10 RANSAC Trials

In this manner, all frames of a raw video align to the first frame. The functions in Table 6 perform the stabilization operation.

Table 6 – Video Stabilization Function Descriptions

Function / Script Name	Description Overview	
	Function Input	Function Output
stabilizeVidPF	A frame matrix, ostensibly with motion jitter.	A frame matrix of equal size, motion stabilized.
stabilizeVidPFraw	Script that performs video stabilization upon a specified channel of individual raw frames. Specify with <code>sourceName</code> variable. Writes individual raw frames to a parallel folder named as the source folder + “_PFstab”.	

To measure the effectiveness of the video stabilization, consider the variance images (described in section 3.1.1) shown in Figure 11.

(a) Before Stabilization

(b) After Stabilization

**Figure 11 – Variance Frames Before and After Stabilization
(pine_cones channel, frames 2000 through 2200)**

The first shows variance before stabilization, and the second shows variance after stabilization, for the same time range (frame 2000 to 2200, step 2), and the same intensity range. High variance magnitudes associated with light-dark interfaces significantly reduce without the motion jitter, while the legitimate movement in the scene due to the heat appears uncompromised. Jitter-related noise corrupts every signal in the scene, and more so in areas of high contrast. To demonstrate, consider a perfectly stationary high-intensity pixel adjacent to a perfectly stationary low-intensity pixel. The variance of both pixels over time evaluates to zero. Now add motion jitter with magnitude of 1 pixel, such that the dark and light pixels periodically invade each others' space for short durations. The variance for both pixels will artificially evaluate high. If these two pixels were the same intensity, the distorted variance would evaluate to zero, equivalent to the true variance. Infer from this thought experiment that movement metrics suffer distortion in proportion to the contrast within a locality defined by the magnitude of the jitter, a conclusion supported by Figure 11. Some jitter remains, presumably due to spatial resolution constraints of the cameras.

Note: For the remainder of this paper, if a video channel is not specified as stabilized or pre-stabilized, assume that it is stabilized.

2.5 Initial Data Examination

Before delving into the features, and algorithms, let's visualize the data. Figure 12 shows a frame (2392) of the pine_cones video, before stabilization. 14-bit data can express a range of $[0, 2^{14} - 1] = [0, 16383]$. This frame has a full-scale range (FSR) from [4801, 12215].

(a) Full-Scale Dynamic Range (4801 – 12215)

(b) Histogram

Figure 12 – Frame 2392 of pine_cones (not stabilized)

Figure 13 – Close-Up of Barbecue Pit with Intensity Values Shown

Figure 14 – Mean and Standard Deviation Per-Pixel of Barbecue Pit

For the majority of this document, only a sub-range region of interest of the full frame will be operated on, to save memory requirements and computation time. The region of interest spans a wide range of distance from the camera, including the barbecue pit, foreground foliage, mid-ground foliage, distant foliage, a stationary uniform grassy field, and a stretch of road in view to catch traffic activity. See Figure 1.

2.6 Challenges

2.6.1 Decaying Frame Rate

The frame rate dropped as a recording progressed. The capture software reported the frame rate of the incoming video stream, but the video data itself had no time stamp on it. The frame rate would start at 30 fps, then drop through the course of a recording, as low as 18 fps. It would take about 10 minutes for the frame rate to drop that low, and it stayed relatively constant for the first few minutes of the video. This problem became progressively worse throughout the 3 hours of recording, but did not affect the first few recordings. This thesis focuses on one CMWIR video that was taken very early in the set, and has been shown not to suffer a significant frame rate degradation. The CMWIR video was shown not to degrade fps by comparing noticeable moving features (for example, a puff of rising smoke, a person walking, a car driving, a bird flying) between the CMWIR video and the visible video, which has a time stamp that proves its constant frame rate.

2.6.2 Light Bloom

Light bloom distorts the heat plume. Pixels bleed into their neighbors in proportion to the bleeding pixel's intensity. Since the flame in the scene has a very high intensity, it bleeds into its surroundings and extends well into the heat plume. It has been found that both the flame's intensity and its variation are very high (Section 2.5) compared with the heat plume: flame has a typical intensity of 12,000 and variance that saturates the unsigned 16-bit integer that represents it

(implying that the variance of flame is greater than $2^{16} = 65,536$, which far exceeds anything else in the scene), while heat plume doesn't have a typical intensity (as it brightens the natural background intensity), and has a typical variance of 300. Hence the light bloom causes the exceedingly high variance of the flame to bleed into the variance measurement of the heat plume. One of the assumptions was that the flame would not be visible. This is a flaw that should be rectified in further studies.

3 FEATURES

A “feature,” in this thesis refers to a piece of information local to a pixel coordinate at a given time index. A frame or image of these per-pixel features will also be termed a “feature” or “feature frame,” such that context will make it clear. An eclectic combination of features theoretically identifies a unique signature of a heat plume. Since this thesis focuses on temporal signature, the features considered result from operations through time, per pixel. Let a video frame group spanning contiguous frames of dimension R-by-C and length T, starting at time t_1 and ending at time $t_f = t_1 + T - 1$, be represented as a 3-dimensional matrix,

$$\mathbf{G} = \mathbf{G}_{t_f} = \left[\begin{bmatrix} G_{1,1,1} & \cdots & G_{1,C,1} \\ \vdots & \ddots & \vdots \\ G_{R,1,1} & \cdots & G_{R,C,1} \end{bmatrix} \cdots \begin{bmatrix} G_{1,1,T} & \cdots & G_{1,C,T} \\ \vdots & \ddots & \vdots \\ G_{R,1,T} & \cdots & G_{R,C,T} \end{bmatrix} \right] \quad \text{Equation 1}$$

The cells of a 2-dimensional feature matrix is found with:

$$f_{r,c}^{feature\ identifier} = FeatureFunction\{(G_{r,c,t})|_{t=[1,T]}\} \quad \text{Equation 2}$$

or, in compact form,

$$\mathbf{F}_{t_f}^{feature\ identifier} = \mathcal{F}(\mathbf{G}_{t_f}) \quad \text{Equation 3}$$

for general set-input, single output function *FeatureFunction*. The input to *FeatureFunction* is the set of all time values for the fixed, generic row r and column c .

Throughout this document, feature frame variables will be expressed as a capital letter with the feature identifier (a short-form string indicating the feature’s formal name) in its superscript. If the variable represents the entire frame matrix, it will be in boldface as in Equation 3, and its subscript refers to the absolute time index t_f of the last frame within $\mathbf{G}_{t_f}$. If the variable represents a cell within the matrix, it will be plain-face and its subscripts will identify its position within the matrix, as in Equation 2. Figure 15 illustrates how each pixel of feature frame $\mathbf{F}$ relates to the time-set of the same pixel of the frame group $\mathbf{G}$.

Figure 15 – Relationship between Frame Group and Feature Frame

The following sections will present the rationale behind each feature, provide a definition in terms consistent with convention of this thesis and then briefly argue the feature's merit.

3.1 Statistical Features

3.1.1 Variance

3.1.1.1 Rationale

Variance over time represents information about movement, a defining characteristic of a heat plume. Variance is a commutative figure, so it does not give any information about frequency, only a magnitude of change within the time frame in which it is applied. Many events will register movement in addition to heat plume, such as foliage, cars, people, and birds, but each of these move in different patterns, so time variance carries useful information.

3.1.1.2 Definition

The variance feature frame is the variance over time of a frame group $\mathbf{G}$, per pixel. The *FeatureFunction* $\mathcal{F} = \text{var}(\{. \})$, and the variance frame is described by the following equations.

$$F_{r,c}^{var} = \text{var}(G_{r,c,t} |_{t=[1,T]})$$

In detail:

$$= \frac{1}{t_{len}} \sum_{t=1}^T (G_{r,c,t} - \mu_{r,c})^2$$

where:

$$\mu_{r,c} = \frac{1}{T} \sum_{t=1}^T G_{r,c,t}$$

Equation 4

In short:

$$\mathbf{F}^{var} = var(\mathbf{G})$$

or:

$$\mathbf{F}_{t_f}^{var} = var(\mathbf{G}_{t_f})$$

3.1.1.3 Analysis

Figure 16 shows four sub-frames, sampled at a uniform difference of 30 frames apart (approximately 1 second at 30 fps). Each frame represents the variance of the past 30 frames of original data, so variance frame 3030 is the pixel-wise variance of the range [3001, 3030], represented as $\mathbf{G}_{3030}$. A variance image shows the presence of the heat plume, as well as other areas, like foliage, and light-dark interfaces due to motion jitter that video stabilization (Section 2.4) could not completely correct. But the heat plume signal is strong in the variance image, and varies more with time than the other background noise sources, making variance a useful feature.

Figure 16 – Variance Feature Frames Sample
(Stabilized oats1 channel, frame indices shown)

Section 5.2.2 digs deeper into the variance feature with an experiment.

Table 7 – Variance Feature Function Descriptions

Function / Script Name	Description Overview	
	Function Input	Function Output
FeatureExtraction_Var	Script that extracts variance frames from a given video channel, given time range, and given region of interest.	

3.1.2 Variance Set Statistics (VSS)

3.1.2.1 Rationale

The variance frames, when seen side-by-side (Figure 16), show the progression of a heat plume. Out of the whole scene, the heat plume changes shape the most drastically. Where the heat plume passes, the maximum of a variance will be highly affected, where the mean will be less affected. Contrast the heat plume with stationary noise in the foreground, where the mean and the max will not differ as much. Therefore, a combination of the mean and maximum variance data should give information that can discriminate between heat plume and other background elements.

3.1.2.2 Definition

Variance set statistics refers to statistical operations on a set of uniformly time-separated variance frames. For a set of size SN and a constant time step Δt :

$$\begin{aligned}
 \mathbf{S}_{t_f} &= \left[\begin{bmatrix} S_{1,1,1} & \cdots & S_{1,C,1} \\ \vdots & \ddots & \vdots \\ S_{R,1,1} & \cdots & S_{R,C,1} \end{bmatrix} \cdots \begin{bmatrix} S_{1,1,T} & \cdots & S_{1,C,T} \\ \vdots & \ddots & \vdots \\ S_{R,1,T} & \cdots & S_{R,C,T} \end{bmatrix} \right] \\
 &= [\mathbf{F}_1^{var} \quad \mathbf{F}_2^{var} \quad \cdots \quad \mathbf{F}_{SN}^{var}] \\
 &= \left[\begin{bmatrix} (F_{t_f-SN+1}^{var})_{1,1} & \cdots & (F_{t_f-SN+1}^{var})_{1,C} \\ \vdots & \ddots & \vdots \\ (F_{t_f-SN+1}^{var})_{R,1} & \cdots & (F_{t_f-SN+1}^{var})_{R,C} \end{bmatrix} \cdots \begin{bmatrix} (F_{t_f}^{var})_{1,1} & \cdots & (F_{t_f}^{var})_{1,C} \\ \vdots & \ddots & \vdots \\ (F_{t_f}^{var})_{R,1} & \cdots & (F_{t_f}^{var})_{R,C} \end{bmatrix} \right]
 \end{aligned}$$

$$\mathbf{F}_{t+1}^{var} = var(\mathbf{G}_{t+\Delta t})$$

The set $\mathbf{S}$ is represented as a matrix for simplicity, though order does not matter, as of a set. The time index of $\mathbf{F}_{SN}^{var}$ corresponds to t_f for time identification purposes. That is, the variance set and the derived variance set statistic frames will be indexed at the time corresponding to the last frame in the set at index SN. Variance set statistics used in this thesis are mean and max, which are computed per-pixel over the entire frame set:

$$\begin{aligned} varMean_{r,c}(\mathbf{S}_{t_f}) &= mean\{S_{r,c,1}, S_{r,c,2}, \dots, S_{r,c,T}\} \\ &\rightarrow \mathbf{varMean}_{t_f} \end{aligned} \quad \text{Equation 5}$$

$$\begin{aligned} varMax_{r,c}(\mathbf{S}_{t_f}) &= max\{S_{r,c,1}, S_{r,c,2}, \dots, S_{r,c,T}\} \\ &\rightarrow \mathbf{varMax}_{t_f} \end{aligned} \quad \text{Equation 6}$$

The feature frames $\mathbf{varMean}_{t_f}$ and $\mathbf{varMax}_{t_f}$ are matrices whose elements are defined by Equation 5 and Equation 6, respectively. Recall that the subscripts on $\mathbf{varMean}$, $\mathbf{varMax}$, $\mathbf{S}$, and $\mathbf{G}$ refer to the final time index represented by the frame group $\mathbf{G}_{t_f}$. Figure 17 illustrates how $\mathbf{varMean}_{t_f}$ and $\mathbf{varMax}_{t_f}$ are calculated.

Figure 17 – Variance Set Statistics Visual Aid

3.1.2.3 Analysis

To test these features, variance samples were taken from the pine_cones video (pine_cones_PFstab), from pixels near the heat plume and other high- and low-movement areas for comparison, and various statistics were calculated. Figure 18 shows the locations of the masks used to select these regions, and Table 8 shows the statistics and names of the regions, with data from oats1 video. Table 9 shows more statistics from the pre-stabilized pine_cones video. The masks were created by thresholding a variance frame over 200 frames, to identify regions of greatest movement posing the greatest challenge to heat plume detection. The data are from sequences of length 30, spanning a range of 220 frames. The number of samples from each mask is directly proportional to the mask's area, hence the heat region has the fewest samples.

Figure 18 – Mask Locations for Data Sampling

- (a) Heat plume
- (b) Near foliage
- (c) Mid-ground foliage 1
- (d) Mid-ground foliage 2
- (e) Grassy field
- (f) Near noise
- (g) Distant noise

Table 8 – Variance Set Statistics Defined for Figure 18 Masks (Statistics from oats1 video, frames . Standard deviation shown for convenience)

STANDARD DEVIATIONS OF SEQUENCES					
Min	Mean	Median	Max	Samples	
1.89	4.8	4.5	10.2	348	(a)Heat Plume
1.87	3.5	3.3	12.2	828	(b)Near Foliage
1.57	3.9	3.0	46.4	714	(c)Mid-Ground Foliage
1.61	3.0	2.9	5.4	582	(d)Mid-Ground Foliage2
1.92	3.8	3.4	12.6	714	(e)Grassy Field
1.61	7.2	4.2	98.3	3438	(f)Near Noise
1.03	3.9	3.1	19.8	2802	(g)Distant Noise

Table 9 – More Variance Set Statistics (From pre-stabilized pine_cones video, frames 2000-2200.)

STANDARD DEVIATIONS OF SEQUENCES					
Min	Mean	Max	GeoMean	Samples	
2.51	11.06	47.95	9.74	642	Heat Plume
2.55	14.04	77.95	10.12	840	Near Foliage
2.02	13.51	119.29	6.68	666	Mid-Ground Foliage
1.43	4.42	17.08	4.25	864	Grassy Field

From the numbers, the samples appear different, especially in the pre-stabilized pine_cones video. When varMean and varMax frames are opened and their histograms examined, thresholds can be found that bound the heat plume area, with different content. Table 10 shows a few snapshots of the mean and max features at different thresholds around the barbecue pit.

Table 10 – Variance Statistics Threshold Snapshots

Feature Name	Low Threshold	Middle Threshold	High Threshold
varMax_seq30_set20:	threshold = 500	threshold = 1200	threshold = 2500
varMean_seq30_set20:	threshold = 50	threshold = 100	threshold = 500

The varMean feature contains much movement from heat and other background areas, where the varMax feature is more focused around the fire, because the fire varies wildly. Section 5.3 will develop these features into a classifier.

Figure 19 shows time-sequences of pixels from three regions shown in Figure 18, namely the grassy field (e), foreground foliage (b), and the heat plume (a). Grass has little time variation and little ensemble variation among pixel means; foliage has much greater variation in both time and ensemble; smoke has a high ensemble variation, as its background covers a variety of shades, and a *medium* time variation, as the smoke only gently brightens the natural background pixel shade as the heat waves travel in the breeze. The high ensemble variation in the heat comes from

the background behind the heat, and not the heat itself. The best marker for a variance-only classifier would be a window of standard deviation that matches this smoke.

Figure 19 – Time Sequences of Pixels by Region. Top/Red: Figure 18(c). Middle/Green: Figure 18(b). Bottom/Blue: Figure 18(e)

3.1.3 Simple Moving Average (SMA)

3.1.3.1 Rationale

A moving average represents behavior on a longer time-scale. Every frame of a moving average represents information from the present and the past. Representing past information in the present necessarily contributes to identifying a temporal signature.

3.1.3.2 Definition

The simple moving average was already partially seen in Equation 5 from the variance feature frame derivation.

$$F_{r,c}^{SMA} = \text{mean} \left(G_{r,c,t} \Big|_{t=[1,T]} \right) \\ \rightarrow \mathbf{F}_{t_f}^{SMA}$$

Consistent with the convention so-far developed, the subscript t_f of the SMA-feature frame matrix $\mathbf{F}_{t_f}^{SMA}$ refers to the time of the last frame of $\mathbf{G}$.

3.1.3.3 Merit

SMA shows a general trend over its time range T , mitigates fast changes as low-pass filter. Reduces background noise due to camera intensity resolution.

3.1.4 Exponentially Weighted Moving Average (EWMA or EMA)

3.1.4.1 Rationale

Like SMA, EWMA represents information over past time in the current frame, but instead of representing a range of time uniformly, it does so exponentially, weighting recent information more heavily than older information. It will reduce noise while responding more quickly to changes in the signal. Its frequency response is smooth, where the SMA has prominent side lobes (Figure 20). Furthermore, the EWMA can be expressed recursively, an infinite impulse

response (IIR) filter, hence it can be computed in a progressive manner far more efficiently.

Figure 21 shows the similarity of the time domain response of the SMA and EWMA filters.

Figure 20 – Comparison of Frequency Response Magnitude of SMA and EWMA
(SMA length = 20, EWMA p-value = 0.1)

Figure 21 – Comparison of SMA and EWMA on Step Function
(SMA length = 20, EWMA p-value = 0.1)

The SMA filter had length 20, and the EWMA filter's p-value was 0.1.

It can be shown that the EWMA-subtracted signal is proportional to the moving difference (discrete derivative).

3.1.4.2 Definition

Unlike other features, the EWMA is not defined for a range of time frames, $\mathbf{G}$. Instead it is defined recursively as a linear combination of its previous value, and the current observation.

Per pixel:
$$(F_{r,c}^{EWMA})_t = p \cdot X_{r,c} + (1 - p) \cdot (F_{r,c}^{EWMA})_{t-1}$$

Per frame:
$$\mathbf{F}_t^{EWMA} = p \cdot \mathbf{X} + (1 - p) \cdot \mathbf{F}_{t-1}^{EWMA}$$

The parameter p determines its sharpness or range, analogously to how T determined the sharpness or range of the SMA. A larger p means the current observation weights more than the past observation, so the filter allows higher-frequency content.

3.1.5 Dual-Range Moving Average Difference (DRMAD)

3.1.5.1 Rationale

The scene contains much noise, and most of the noise comes from predictable sources, such as foliage and contrasting interfaces in the presence of jitter. These sources have high variance, but they do not migrate from their locality. A pixel measurement can be seen as a sum of signal and predictable noise [14]. Or, expressed in terms of frames:

$$\mathbf{f} = \mathbf{s} + \mathbf{n}$$

Then:

$$\mathbf{s} = \mathbf{f} - \mathbf{n}$$

Equation 7

where $\mathbf{f}$ is the measurement, $\mathbf{s}$ is the ideally detected heat plume signal, and $\mathbf{n}$ is a noise prediction.

A moving average shows a general trend, which would include intensity trends. Treating a long-range moving average as a noise predictor, and subtracting it from the moving signal will cancel out constant elements of the scene and show only the moving elements. A short-term moving average will reduce random measurement noise, creating a smoother image, more comparable to the long-range moving average, clarifying the output.

3.1.5.2 Definition

The DRMAD will be defined in terms of the EWMA, because of its smooth frequency response and quick computation time.

Per pixel:

$$(F_{r,c}^{DRMAD})_t = (F_{r,c}^{EWMA_{short}})_t - (F_{r,c}^{EWMA_{long}})_t$$

Per frame:

$$\mathbf{F}_t^{DRMAD} = \mathbf{F}_t^{EWMA_{short}} - \mathbf{F}_t^{EWMA_{long}}$$

Equation 8

The “short” and “long” subscripts indicate a larger p -value and smaller p -value, respectively, where $p \leq 0.1$. For simplicity, a DRMAD will be referred to in terms of its p -values in short form:

$$\text{EWMA}(p_{short}) - (p_{long})$$

For example:

EWMA0.07-0.02 refers to EMWA of $p = 0.07$ less EWMA of $p = 0.02$, of a given input channel.

3.1.5.3 Merit

Figure 22 compares multiple DRMADs based on EWMA. The heat plume has relatively high strength compared with the background. There are still weaker signals in the background, especially in the high-contrast interfaces, but not as obvious as the heat plume. Since DRMAD is a difference, it will have positive and negative numbers. For display purposes, a linear mapping is applied such that zero maps to mid-grey, and the absolute largest magnitude maps to 1.

Figure 22 – Comparison of Dual Range Exponentially Weighted Moving Average Difference (DRMAD) pairs (oats1 stabilized channel, e.g. lower left pane is EWMA of p-value = 0.1 less EWMA of p-value = 0.02)

3.2 Principal Component Analysis (PCA)

3.2.1 Rationale

Principal Component Analysis (also known as the Karhunen-Loeve transform, or KLT) transforms the dimensions of input samples into new dimensions such that the variance is maximized along the first basis vector in PC-space, and the subsequent orthogonal basis vectors

point in the direction of the next greatest variance [17]. In this way, most of the variance lies within the first few dimensions. PCA has the notable property of de-correlation. To wit, every dimension of a given data in PC-space has no correlation with any other PC-space dimension. Equivalently, the covariance matrix becomes non-zero only in the main diagonal. PCA can then be used to express data in a unique way that reveals movement information. For the purpose of uncovering movement over time, PCA will be performed over the time dimension, or, as it is known in literature, “multi-temporal PCA.” The first-order principle component is a measure of **persistence**, and the deeper orders accompany **growth**.

3.2.2 Derivation

In general, PCA generates a Principal Component Transform (PCT) $\mathbf{W}$, which maps data in input space to data in PC-space:

$$\mathbf{Y} = \mathbf{X} \cdot \mathbf{W} \quad \text{Equation 9}$$

Where $\mathbf{X}$ and $\mathbf{Y}$ are (m, n) matrices, and $\mathbf{W}$ is a (n, n) matrix. *(Note: In popular literature, X and Y and W are represented as the transpose of what they are represented as here, which only complicates the derivation and application, and increases computation time, solely for the sake of representing the transform as a traditionally pre-multiplied matrix.)*

PCA applies to any one dimension of an initial given data set, and does not discriminate between the other dimensions (this will be explained shortly). For the purpose of extracting temporal information, PCA will be performed along the time dimension, and the pixel locations will have no bearing on the Principal Component Transform (PCT); row and column will be temporarily grouped together, preserving the order. Let the columns of $\mathbf{X}$ be the rows and columns of $\mathbf{G}$, reshaped into $(R \cdot C, 1)$ column vectors, for each time $t \in [1, T]$. Then $\mathbf{X}$ will be dimension $(M = R \cdot C, N = T)$.

$$\mathbf{G}_{R,C,T} \leftrightarrow \mathbf{X}_{R \cdot C,T} \quad \text{Equation 10}$$

Similarly:

$$\mathbf{P}_{R,C,T} \leftrightarrow \mathbf{Y}_{R \cdot C,T}$$

This re-dimensioning is exactly as illustrated in Figure 7 (d). $\mathbf{X}$ and $\mathbf{Y}$ are both simply frame groups where each frame is represented as a column vector with order preserved.

The steps to derive the Principal Component Transform $\mathbf{W}$ are as follows:

1. Compute the covariance matrix, $\mathbf{C}_X$, of the input data set $\mathbf{X}$.

$$\mathbf{C}_X = \frac{1}{R \cdot C} \mathbf{X} \cdot \mathbf{X}^T$$

2. Compute the N Eigenvectors $\mathbf{V}_i$ of the covariance matrix $\mathbf{C}_X$, arranged in decreasing order of associated Eigenvalue, λ_i .
3. Let the columns of $\mathbf{W}$ be the Eigenvectors $\mathbf{V}_i$.

$$\mathbf{W} = [\mathbf{V}_1 \ \mathbf{V}_2 \ \dots \ \mathbf{V}_N]$$

Equation 11

The PCT transforms the observations $\mathbf{X}$ from input space to observations $\mathbf{Y}$ in PC-space, such that the covariance matrix in PC-space $\mathbf{C}_Y$ is a diagonal matrix, where the diagonals are the Eigenvalues λ_i of $\mathbf{C}_X$.

$$\mathbf{C}_Y = \text{diag}(\boldsymbol{\lambda}) = \begin{bmatrix} \lambda_1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \lambda_N \end{bmatrix}$$

The zeros on the non-diagonals of $\mathbf{C}_X$ agrees with the earlier statement that the dimensions in PC-space have no correlation with each other.

To view the output $\mathbf{Y}$, it must be re-ordered to recover the spatial relationship between pixels. Again, refer to Figure 7 (d) to see the relationship between $\mathbf{Y}$ (R·C, T) and $\mathbf{P}$ (R, C, T) (Equation 10). The frames within $\mathbf{P}$ are referred to as Principle Component Images (PCI).

3.2.3 Method

For a frame group $\mathbf{G}$ that windows through a video sequence, its frames are selected at a constant frame interval Δt . The process is as follows:

1. Assign the initial frame group $\mathbf{G}$

2. Compute the PCT, $\mathbf{W}$ (Equation 11) on initial $\mathbf{G}$
3. Loop through the video, progressively windowing $\mathbf{G}_t$. For each $\mathbf{G}_t$,
 - a. Map $\mathbf{G}_t$ to $\mathbf{X}_t$ (Equation 10)
 - b. Transform $\mathbf{X}_t$ to $\mathbf{Y}_t$ using the same $\mathbf{W}$ from step 2 (Equation 11)
 - c. Map $\mathbf{Y}_t$ to $\mathbf{P}_t$

This procedure assumes a stationary field of view, so that the principal component vectors (columns of $\mathbf{W}$) map sets of input pixels to principal component space for any frame group. Furthermore, if thresholds can be found that enclose heat plume motion, those thresholds can apply to the entire video.

Figure 23 shows an example of PCA on 6 frames from a DRMAD channel (EWMA0.07 – 0.02). Each frame is independently auto-linear intensity mapped to show content.

Figure 23 – Example of PCA (b) on Input Frames (a) from oats1 DRMAD (EWMA0.07-0.02_PCA6_autolinear, non-uniform linear map per PC)

3.3 Feature Function Summary

3.3.1 Feature Extraction

Table 11 includes all functions referenced in Section 2.6, to summarize in one place for the reader's convenience, as well as other functions used directly or indirectly.

Table 11 – Feature Extraction Function Descriptions

Function / Script Name	Description Overview	
	Function Input	Function Output
FeatureExtraction_EWMA	Source name, p-parameter of EWMA filter.	Creates a new folder in the associated Features folder containing the EWMA of the input data.
FeatureExtraction_SMA	Source name, SMA length.	Creates a new folder in the associated Features folder containing the EWMA of the input data.
FeatureExtraction_VarStats	Source name, sequence length, set size.	Creates new folders in the associated Features folder containing mean, median, and maximum of the moving variance set.
FeatureExtraction_Var	Script that extracts variance frames from a given video channel, given time range, and given region of interest.	
extractTrainingData	Video channel path, save path, mask path, frame range and step, sequence length.	Collects time-sequences from specified video channel over specified frame range, of specified sequence length, beneath specified mask, and writes them to specified path.
extractTrainingData Batch	Script that calls extractTrainingData in a configurable batch. One convenient launching point for data extraction. Prints report on how many sequences were collected from each source.	
TimeDomainAnalysis	Configurable script that reads the sequence data files that extractTrainingData saves, and calculates the statistics on them. Has the optional functionality to plot histograms, create exponential histogram bins, and save them (not used in this section).	
computePCT	Input frames (R-C-by-T)	Returns the Principal Component Transform, W.

3.3.2 Feature Processing

The Feature Processing family of functions converts features into other features by applying per-frame operations, such as median filtering. Each one creates a new folder in the Features folder of a given video channel, and populates it with frames resulting from the specific process applied to a given source folder.

Table 12 – Feature Processing Function Descriptions

Function / Script Name	Description Overview	
	Function Input	Function Output
FeatureProcessing_MeanSub	Path to two raw data channels, output path, frame range, negMethod (what to do when difference < 0. 'retain', 'reflect', 'saturate')	No output. Performs synchronous frame-wise subtraction and writes the difference to specified output channel folder
FeatureProcessing_PCA	Path to input and output feature folders, PCA parameters, intensity pre-mapping specification.	No output. Performs PCA on the input and saves in output feature folder with a nested folder for each PC image.
FeatureProcessing_Simple	Path to input and output feature folders and a function handle (may be a Matlab inline function)	Applies the handled function to each frame, and saves it in a new feature folder.

4 INTENSITY MAPPING

Some features benefit from intensity mapping either because the range of interest lies within a small range of the data type, or because the data spans both positive and negative values, which can't be plotted. A nonlinear mapping can increase contrast in an image, making the information content more observable to the human observer [15].

The mapping equations presented here may be used by algorithms in Chapter 5, especially in PCA (Section 5.5). This chapter presents the mappings as a reference, so that increased brevity may follow.

4.1 Linear

A linear map may be completely described by a mapping of two points x_1 and x_2 to another two points y_1 and y_2 , respectively. Or, equivalently, of one specific range to another specific range, such that $y = m \cdot x + b$. Reference any elementary algebra text.

$$m = \frac{y_2 - y_1}{x_2 - x_1}$$

$$b = y_1 - m \cdot x_1 = y_2 - m \cdot x_2$$

All that remains is to select the values of x_1 , x_2 , y_1 , y_2 , to derive the mapping parameters, m and b , to perform the mapping that will be denoted as $[x_1, x_2] \rightarrow [y_1, y_2]$.

4.1.1 Autolinear

A mapping is chosen such that $x = 0$ always maps to $y = 0.5$, to ensure a mid-grey representation of zero. The other (x, y) pair is selected based upon the min and max of the input set. The largest magnitude in x is mapped to $y = \pm 1$, preserving sign. To wit,

$$x_1 = 0 \rightarrow y_1 = 0.5$$

$$x_2 = |x|_{max} \rightarrow y_2 = \text{sgn}(x_m), \quad \text{where } m \text{ is taken from } |x|_{max}$$

4.1.2 Min-Max

Min-Max maps the full dynamic range to fit within the full displayable dynamic range:

$$[\min(x), \max(x)] \rightarrow [0, 1]$$

4.1.3 Z-Score

From statistics, the z-score is the normalized representation of a value, having zero-mean and unity variance. And input value is mean-subtracted, then divided by the input set's standard deviation, as thus denoted:

$$y = \frac{x - \text{mean}(x)}{\sigma_x}$$

4.2 Nonlinear

4.2.1 Gamma Mapping (Power Law)

The power law, also known as gamma correction, or gamma mapping, is a nonlinear mapping that may be tuned to place emphasis on smaller values or larger values within the input range. Gamma correction used in this thesis is parameterized by two values: γ determines the shape (emphasis) and x_{sat} determines the width. x_{sat} may be chosen as a percentile, such that values greater than that percentile will be mapped to 1. Equation 12 defines the gamma map, and Figure 24 shows an example of a uniform random distribution of 1000 points between 1 and 100. Both the transfer function and the input and output histograms are shown. In this example, $\gamma = 0.5$, and $x_{max} = 98$, or the 98th percentile.

$$y = \begin{cases} -1; & x < x_{sat} \\ \frac{\text{sgn}(x) \cdot |x|^\gamma}{x_{sat}^\gamma}; & -x_{sat} \leq x \leq x_{sat} \\ 1; & x > x_{sat} \end{cases} \quad \text{Equation 12}$$

(a) Transfer Function

(a) Example Input Distribution (b) Corresponding Output Distribution ($\gamma=0.5$, $x_{max} = 98$)

Figure 24 – Gamma Mapping Example Transfer Function and Histograms

4.3 Composite

4.3.1 Z-Gamma

In Section 5.5, both the linear z-score and the nonlinear gamma mapping will be combined, in that order. The composite z-score and gamma mapping mapping will be referred to as “z-gamma”, or, in the code, as `zgamma`.

4.3.2 ZA-Gamma

Same as Z-Gamma, except that the gamma mapping acts on the magnitude of the Z-score.

4.4 Intensity Mapping Function Summary

Table 13 – Intensity Mapping Function Descriptions

Function / Script Name	Description Overview	
	Function Input	Function Output
linearx4m	Mode 1: Linear mapping parameters.	Mode 1: x4mStruct that fully specifies the mapping.
	Mode 2: x4mStruct and array of intensities.	Mode 2: Data mapped according to x4mStruct.
linearx4mlim	Input range and output range	Linear mapping parameters that enforce the specified range.
nonlinMap	Mode 1: Nonlinear mapping parameters.	Mode 1: x4mStruct that fully specifies the mapping.
	Mode 2: x4mStruct and array of intensities.	Mode 2: Data mapped according to x4mStruct.

5 CLASSIFIERS

Classification systems combine one or more feature frames to produce a classification frame. A classification frame is a binary image, the pixels of which correspond to the same pixels as in a feature image, but represent a decision on whether the pixel represents heat or not heat. The systems described here have some merit on their own at the onset, then will be analyzed, tuned, expanded, and improved. Common metrics will evaluate classifiers on their performance, and guide the line of inquiry in gainful directions.

5.1 Metrics

A standardized test will apply uniformly for all classifiers under study. For many cases, the testing will apply repeatedly to compare different classification parameters, such as a window size or a time constant. Error rate serves as primary metric, and computation time the secondary.

5.1.1 Error Rate

The primary metric for judging the effectiveness of a detection system is its error rate. Error rate is defined as:

$$e = \frac{tp}{tp + fp}$$

where tp represents true positives, and fp false positives. In literature, this is known as “precision.” The measure of truth is whether a positive falls within a prescribed heat region. This measure only approximates the real truth. It would require more accurate knowledge of truth (that is, the exact location and boundary) of the heat plume at all times) to count true negatives (tn) and false negatives (fn), so they will be ignored.

5.1.2 Categorized Detection Count (CDC)

In addition to an error percentage, the positives will be assigned to groups including heat region and common problem areas: pedestrian region, car region, and noise region. Counting these groups gives more information on the ability of each system to reject different types of noise. Figure 25(a) shows these masks as white, enclosed by the colored bands to identify them. (b) shows the heat mask and the non-heat mask. These masks were created by opening a frame such as variance in MS Paint, and hand-drawing the region around it. The heat mask was fine tuned by subtracting (in Matlab) a horizontal line where interface noise lived.

Figure 25 – Movement Category Masks

Error counters will count the sum of heat-assigned pixels that fall within the specified masks over the standardized frame range of video: 510 – 5000.

5.1.3 Computation Time

The code is structured to run one operation at a time though a full video in a completely scalable fashion. The code doesn't have a direct computation time, as each but this metric will estimate the frame rate supported by the algorithm by dividing the number of standardized frames ($5000 - 510 = 4490$) by the total computational time, resulting in a frame rate (fps).

5.2 Variance Corridor / Bayesian Classifier

5.2.1 Rationale

The rationale for the variance corridor is simply that the motion of the heat plume may reside within a specific range of variances that notch thresholding can reveal.

The rationale for the Bayesian classifier is that every type of motion might be characterized by its time-variance. In a general sense, Bayesian classification relies on a-priori knowledge, and often describes Gaussian data. The data considered here aren't Gaussian distributed, but the concept doesn't differ.

5.2.2 Experiment

Recall from Section 3.1.2.3 that sequences of length 30 were extracted over a range of 220 frames, beneath the masks shown in Figure 18, resulting in hundreds and thousands of variance samples per mask. These variances were statistically described by Table 8.

Now consider Figure 26, in which the variances are binned with exponential centers. The hypothesis: that a pixel may be classified to one of the seven classes shown in Figure 26 by the following method:

1. Compute its variance value over a sequence of 30, just as the histogram data.
2. Determining which bin it falls into.
3. Identify which class has the largest corresponding bin (Nearest neighbor), and assign the pixel to that class.

Figure 26 – Exponentially Binned Variance Histogram Per Masked Region (exponentially indexed abscissa: 10^x)

- (a) Heat plume (a.k.a. smoke plume)
- (b) Near foliage
- (c) Mid-ground foliage 1
- (d) Mid-ground foliage 2
- (e) Grassy field
- (f) Near noise
- (g) Distant noise

From this method, a mapping between variance and class can be established: Table 14 shows the mapping.

Table 14 – Correspondence Between Bin Center and Class with Largest Occurrence

Linear Bin Center	6.3	7.9	10	12	15	20	25	31	39	50	63	79	100
Exponential Bin Center	0.8	0.9	1.0	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	2.0
Class	d	d	e	b	a	a	a	a	a	a	f	f	f

The result of the Bayesian variance classifier is simply a *variance corridor* in the range of **14.2 < var < 56.6** (thresholds bisect adjacent linear bin centers). Figure 27 shows the result. It actually appears to select *not* smoke near the heat plume.

Figure 27 – Result of Variance Corridor / Bayesian Variance Classification (oats1, frame 1799)

Figure 28 – Variance within Heat Plume of Figure 27

(a) Variance image with an edge added to the heat plume area

(b) Blow-up of heat plume area (ignore the edge pixels, identified by intensity ~10,000)

Figure 28 shows that the heat plume actually resides in an approximate variance range of [100, 500], far from the range that this implementation of a Bayesian classifier.

5.2.3 Conclusion

Bayesian classification based solely on variance detects motion indiscriminately, passing far more than just the heat plume, but this exploration did reveal where the heat plume lives: in the range [100, 500]. This knowledge will prove useful in Section 5.4 as a filter component.

Since this classification system fails so completely, metrics are considered superfluous.

5.3 Variance Set Statistics – Mean and Max Thresholding (MMT)

By inspection of a feature frame while sliding its dynamic range, a range of values can be found wherein the heat plume is present. Any one feature is unlikely to perfectly identify the heat

plume, non-inclusive of other background content, but combining thresholds of multiple features can provide more accurate classification.

5.3.1 Rationale

Recall from exploration of the variance set statistics in Section 3.1.2.3 that the mean and max statistics appeared to discriminate between classes (heat plume, foliage, etc). Inspection of the numbers alone justifies this classification experiment. An intuitive justification: The mean of the variance set represents how much a pixel varies long-term, a measure of **persistence** relative to the set size (a defining parameter), while the max represents the greatest or fastest change, which should be high at the onset of **growth** (when a heat plume begins to pass through a pixel). Heat plume tends to be sporadic, varying noticeably (between 100 and 500) where it touches, but not always touching the same location. Hence the typical VSS mean would be less than [100, 500] while the typical VSS max would be near the top of [100, 500]. The hypothesis is that other entities within the scene sufficiently differ to distinguish them from the heat plume.

5.3.2 Experiment

Frames of the same time index were opened in varMean and varMax (oats1, stabilized, sequence length 30, set size 20, frame 3140) to investigate the values in the heat plume. Figure 29 shows the two frames (in the region-of-interest already shown in Figure 1) contrast adjusted for clarity to the same range of [0, 800]. Note that varMax is sharper and brighter than varMean, as expected. The heat plume in varMax shows up very strong and large. The border of the trees with the hot building wall (refer back to Figure 1 if necessary) also shows up very strong. This will prove challenging to discriminate from heat plume. Figure 30 shows a zoomed-in view of the heat plume, also contrast adjusted for clarity, and it shows the pixel intensities. The background intensity near the barbecue pit generally hovers between 40 and 100, where the heat plume varies wildly between 100 and beyond saturation at 65535, consistent with findings in Section 5.2.2.

(a) varMean

(b) varMax

Figure 29 – varMean and varMax from oats1, Frame 3140 (Contrast adjusted for clarity to the same range: [0, 800])

47	72	52	52	83	84	92	123	179	509	933	613
114	135	139	111	109	170	211	207	251	681	1121	1008
193	304	428	411	259	248	374	426	479	1004	2157	1785
249	463	781	959	672	386	495	766	944	1646	3768	3240
281	509	930	1192	1351	855	686	987	1596	2956	6609	5984
340	563	1047	1672	2407	2087	1354	1331	2642	5751	12488	11784
338	525	867	1571	2728	3376	2855	2628	4903	11915	25961	26867
253	369	607	1030	1947	3523	5102	5611	10911	29566	60787	64768
154	294	585	1106	1902	4433	12199	19683	28249	65535	65535	65535

Figure 30 – varMean in the Heat Plume, Frame 3140

The precise variance threshold of where heat plume starts and ends is subjective. Figure 31 shows varMean at several threshold values to give an idea of where its histogram is distributed.

(a) varMean > 20

(b) varMean > 50

(c) varMean > 100

(d) varMean > 500

Figure 31 – varMean at Various Thresholds

Three sets of thresholds were selected subjectively. The Loose thresholds show more heat plume signal while letting in much background noise as well. The Tight thresholds focus more around the observed ranges of heat plume, so reject more noise, yet also detect a fewer true heat pixels. Config 3 was based on early explorations. The same process was repeated for varMax, and the threshold values selected to represent the range of heat plume are shown in Table 15. See Figure 32 for realizations of these thresholds.

Table 15 – Variance Set Statistics Thresholds (sequence length 30, set size 20)

	Loose	Tight	Config 3
varMean	[40, 700]	[10, 100]	[60, 150]
varMax	[60, 5000]	[100, 600]	[500, 1500]

Figure 32 – Intersection of Thresholded VSS Mean and Max for Different Configurations (threshold values)

Hardly any true signal survives the Tight and Config3 configurations, so the focus will rest with the loose configuration. To clean up the noisy information, temporal signature expectations can be applied. Recall the **growth** property of the heat plume (by its association with fire, the originator of these characteristic properties). The static background noise has movement that migrates very little. These can be eliminated by discounting the pixels that stay asserted for N consecutive time samples. The “VSL-isAllN” signals in Figure 33 mean “varStats_Loose AND NOT isAllN”, where the isAllN frame’s pixels are true if the corresponding varStats_loose pixels are true for the past N frames (the varStats_loose video has time resolution of 3 fps). They are also median filtered with 3x3 and 5x5 neighborhoods for comparison.

Figure 34 shows the categorized detection count per VSL channel for several filter lengths and median filter sizes.

Figure 33 – Comparison of Filter Lengths on varStats_loose Configuration
(Demo: varStats_loose_isAll123_3fps.avi)

Figure 34 - Categorized Detection Count Per Channel of VSL for Several Filter Configurations

Table 16 – Error Analysis Over Filter Configuration

Channel name:	Good	Bad	E_avg
varStats_loose_-_isAll10_medfilt3	3206	15710	0.727
varStats_loose_-_isAll10_medfilt5	1697	8211	0.482
varStats_loose_-_isAll20_medfilt3	7778	40787	0.827
varStats_loose_-_isAll20_medfilt5	4891	20891	0.750
varStats_loose_-_isAll30_medfilt3	11017	62279	0.842
varStats_loose_-_isAll30_medfilt5	7891	32077	0.785

Table 17 – Computation Time for MMT

Process	Time (s)
Variance Set Statistics calculation	550 s
VarStats_Loose classification	25 s
isAll computation	25 s
Binary subtraction and median filtering	41 s
Total Time:	640 s
Capable Frame Rate: 4490 frames / 640 s = 7.0 fps	

5.3.3 Conclusion

Simply taking the intersection of the thresholded mean and max variance set statistics did not effectively differentiate between heat plume and the interface noise and the moving vehicles. The Loose configuration had a strong heat plume signal as well as pervasive noise, while the Tight configuration selected little of both, and the Config 3 barely selected heat at its most intense. The method required a noise rejection stage before it could offer any use. Implementing the “isAll” filter removed the static noise, vastly cutting down on tree and interface noise.

The best configuration involved subtracting a shorter filter (length 10), then median filtering with a 5x5 neighborhood.

5.4 Variance Set Statistics – Mean by Median (MBM) Quotient

5.4.1 Rationale

Intuitively, the quotient of mean by median will detect outlier changes, which describes the heat plume when it wanders through a pixel irregularly (an example of the **growth** property). The simple reason is that the mean is more sensitive to outliers than the median.

This section will cursorily explore other quotient features aimed at reducing unwanted background noise. The DRMAD (introduced in Section 3.1.5) still has some noise in it, which could be reduced if it were scaled down in proportion to the known movement. The DRMAD as well as the original measurement will be divided by the standard deviation per pixel.

5.4.2 Experiment

Figure 35 shows the operations and results. The original measurement (denoted “src” in the figure), even when divided by the standard deviation, does not offer a way to differentiate between the heat plume and the noise, which still is prominent. The DRMAD/standard deviation quotient yields much noise with no clear indicator of the heat plume. However, the VSS max/mean quotient shows a very clear signal, as does the max/mean quotient. The max/mean quotient corroborates the concept of the VSS max less mean, developed in Section 5.3.

Figure 35 – Comparison of Feature Quotients

The VSS parameters (sequence length and set size) are varied in an attempt to identify optimal values based on a calculated error rate (defined in Section 5.1). The error calculation requires a classification (binary) image, so the feature images of Figure 36 will be thresholded, then median filtered to reduce noise. Figure 37 shows the MBM frames after a threshold an empirical threshold (≥ 3) and a 5x5 median filter.

Figure 36 – Comparison of VSS parameters on MBM

Figure 37 – Comparison of VSS Parameters on MBM, Thresholded, and Median Filtered

Table 18 shows the error rates of the thresholded and median filtered MBM frames. Var(XX)(YY) refers to sequence length XX and set size YY. The error rate proves more sensitive to the set size than the sequence length.

Table 18 – Error Rates of Figure 37 Frames

Channel name:	Good	Bad	E_avg
var2015_Mean-by-Med_thmed5	5152	42409	0.794
var2010_Mean-by-Med_thmed5	2980	31555	0.695
var1015_Mean-by-Med_thmed5	4602	39879	0.743
var1010_Mean-by-Med_thmed5	2936	32175	0.680
var3020_Mean-by-Med_thmed5	6365	49999	0.811

5.4.3 Variance Augmented Mean-By-Median Quotient (VAMBM)

The birds, cars, and pedestrians still show up in MBM alone, but when intersected with the 30-length variance (referred to as “var30” in the pane captions) thresholded above 100, the birds disappear, while the heat plume remains, as was found in Section 3.1.1.3. Figure 38 shows this operation.

Figure 38 – Comparison of VSS Parameters for VAMBM Data (variance length 30)

Let the intersection of MBM with var30 be referred to as the **MBM_var30** data, or VAMBM classification. Figure 39 shows the categorized detection count. The “Noise” refers to

foliage and interface noise. The abscissa labels refer to MBM_var30 series' but are shortened for display purposes.

Figure 39 – Categorized Detection Count Per Channel of MBM_var30 (VAMBM) for Several VSS Configurations

Table 19 – Error Rate of MBM_var30 Over VSS Configurations

Channel name:	Heat	Not	E_avg
MBM2015_var30	3815	21289	0.739
MBM2010_var30	2299	17211	0.650
MBM1015_var30	3814	21308	0.675
MBM1010_var30	2530	19355	0.624
MBM3020_var30	4217	23031	0.766

Table 20 – Computation Time of VAMBM

Process	Time (s)
Variance Set Statistics calculation	550 s
Quotient calculation	185 s
Threshold and median filter	16 s
Dilate and threshold variance, take intersection	28 s
Total Time:	779 s
Capable Frame Rate: 4490 frames / 779 s = 5.7 fps	

5.4.4 Conclusion

MBM effectively filters out the trees by passing outlier movement that the foliage is too stationary to exhibit. Figure 36 shows the MBM before thresholding and filtering and both the foliage and high contrast interfaces are very faint, which is a great start. Furthermore, Figure 39 shows imperceptible noise (foliage and interface), offering quantitative confirmation. When intersected with the variance threshold, the intermittent birds and fast-moving objects are filtered out. This is a great success. However, VAMBM still does pick up pedestrians and vehicles. It would need further supplementation or combination to reduce its false alarm rate.

5.4.5 Demo

This video shows the progression of the classifier. It shows the “isAll” persistence filter process and the median filtering. The ‘=’ characters in the filename denote a comparison of “isAll” parameters (“isAll10” and “isAll20” are shown) and median filter parameters (3x3 and 5x5 median filters are shown)

Demo: varStats_loose_isAll=_medfilt=_3fps.avi

5.5 Principal Component Analysis of Dual-Range Moving Average Difference (PCA-DRMAD)

5.5.1 Rationale

The DRMAD shows promise as a filter that improved heat signal over background noise. Multi-temporal PCA shows movement information. PCA of the DRMAD blends the power of both by finding movement information more characteristic of heat plume. Recall that PC1 can serve as a measure of **persistence**, a primary attribute of heat plume, and that the deeper PC's bear information about motion, an attribute of **growth**.

Foliage and the pedestrian in the scene persistently raise the greatest challenge by their motion's similarity to that of the heat plume. However, PCA offers a much richer set of information about movement than VSS features. Maybe thresholds can be found within each PC image that bound heat. Furthermore, maybe they can be automatically determined, by considering that the first 1000 frames contain only foliage and a pedestrian, and very little heat, thus "setting the bar" that measures the heat plume.

5.5.2 Experiment

1. DRMAD was computed for the ranges shown in

Table 21. Refer to Section 3.1.5, the experiments of which furnished the data re-used in this experiment.

Table 21 – PCA-DRMAD Difference Ranges (Cases)

Difference Case	Short-Range EWMA p-Parameter	Long-Range EWMA p-Parameter
1	0.10	0.02
2	0.07	0.02
3	0.07	0.01
4	0.07	0.008
5	0.05	0.02
6	0.05	0.01
7	0.05	0.008

2. PCA was performed, as presented in Section 3.2, with Autolinear mapping with 1% outlier rejection, calibrated at frame 3000, which has a prominent plume.

3. The maximum and minimum were found over the first 1000 frames, for each of the PC images individually.

4. The PC images were thresholded, as found in Step 3. See Figure 40.

5. Error Analysis was performed (Section 5.1.1). See Figure 41 for the categorized detection count, and Table 22 for the associated channel names and total error rate. Note that there were other minor sources of error beyond the main categories, hence the Non-Heat count in the table will not exactly equal the sum of the non-heat categories in the figure, but they will be comparable.

(a)

(b)

**Figure 40 – PCA-DRMAD with Automatic Threshold
(Demo: EWMA0.05-0.01_PCA6_auto-th.avi)**

Figure 41 – CDC Comparing Auto-Thresholded PC Images (Difference Case 1)

Table 22 - Error Analysis for PCA-DRMAD (Difference Case 1)

Channel name:	Heat	Not	E_avg
EWMA0.07-0.02_PCA6_autolinear_auto-th\1	304	43	0.026
EWMA0.07-0.02_PCA6_autolinear_auto-th\2	450	116	0.071
EWMA0.07-0.02_PCA6_autolinear_auto-th\3	479	197	0.070
EWMA0.07-0.02_PCA6_autolinear_auto-th\4	469	231	0.069
EWMA0.07-0.02_PCA6_autolinear_auto-th\5	523	217	0.099
EWMA0.07-0.02_PCA6_autolinear_auto-th\6	382	144	0.057

PCA-DRMAD filters out every leading challenge category in PC1, detecting only 43 non-heat pixels throughout the entire video's test range (frames 510 to 5000), while retaining the heat plume signal. The deeper PC's also detect much heat plume, but also detect increasing proportions of non-heat, especially pedestrian.. However, inspection of Figure 40 shows that in frame 2700, the heat-related activity appears localized to the same space across all PC images.

Viewing the video corroborates this observation. This spatial correlation can aid in the classification system.

5.5.3 Principle Component Image Combination

Since the auto-thresholded PC1 was able to filter out most unwanted noise sources, it will be used as a necessary condition. That is, for a pixel to count as heat plume, it must be near PC1. Since PC1 has a small signal, it will offer benefit of doubt by dilating by radius 3, because the maximum distance from the heat plume in PC1 to the furthest point of heat plume in a higher-order PC was observed to be approximately 3 (future work could tune or adapt this fixed parameter). The only remaining requirement is that one other auto-thresholded PC image vote for the pixel. Put simply, a pixel will be classified as a heat plume pixel if it is a member of the dilated PC1 image and at least one other PC image.

The test is performed on all seven difference cases in

Table 21. Finally, an error analysis is performed to compare each of the resultant classifiers, same as before. Figure 42 shows the comparison based on the difficulty categories presented in Section 5.1.1. Figure 43 shows the error rate through time index. Table 23 shows the total true positives and false positives and error rate for each channel, corresponding to those in Figure 42. Again, the names in Table 23 correspond to the data channels referred to in the code, for the reader who attempts to reproduce the work.

Figure 42 – CDC Comparing Classifiers for All PCA-DRMAD Difference Cases

Figure 43 – Comparison of Classifiers for All PCA-DRMAD Difference Configurations

Table 23 – Error Analysis for All PCA-DRMAD Difference Configurations

Case	Channel name:	Heat	Not	E_avg
1	EWMA0.1-0.02_PCA6_autolinear_auto-th_cl	871	15	0.013
2	EWMA0.07-0.02_PCA6_autolinear_auto-th_cl	931	17	0.016
3	EWMA0.07-0.01_PCA6_autolinear_auto-th_cl	918	11	0.011
4	EWMA0.07-0.008_PCA6_autolinear_auto-th_cl	944	10	0.009
5	EWMA0.05-0.02_PCA6_autolinear_auto-th_cl	950	23	0.013
6	EWMA0.05-0.01_PCA6_autolinear_auto-th_cl	937	9	0.009
7	EWMA0.05-0.008_PCA6_autolinear_auto-th_cl	928	15	0.013

Inspection of Figure 42 shows that every PCA-DRMAD difference case works well, and “the best one” isn’t obvious. However, looking at the average error rates in Table 23 shows a clear winner in case 6. It has the third highest true positive rate, and the least false positive rate, which arguably carries more merit, as a decent detector may detect a fire before much time passes, but false positives make each alarm less meaningful.

Table 24 – Computation Time of PCA-DRMAD Classifier

Process	Time (s)
Compute DRMAD	

Compute EWMA	326
EWMA Subtraction	26
Perform PCA	102
Threshold PCA	68
Total Time:	522 s
Capable Frame Rate:	4490 frames / 522 s = 8.6 fps

5.5.4 Demo

This video shows the original (stabilized) frames and the PCA-DRMAD classified frames side-by-side. Note it is case 2, which didn't have the optimal error rate, but the difference isn't discernable to the keen observer, so this suffices as a demo.

Demo: EWMA0.07-0.02_PCA6_autolinear_auto-th_c1.avi

5.6 Support Vector Machine (SVM)

5.6.1 Introduction

A SVM trains from a set of observations belonging to a known binary class, then it classifies new observations based upon its trained state [21]. The training is done by transforming the training observations into higher-dimension space in which the two classes become linearly separable. When the separating hyper-plane transforms back into input space, it becomes a curve that bounds the classes. In this case, the SVM uses a radial basis function (RBF) kernel.

5.6.2 Training

SVM needs a set of truth data to train from. That is, it needs a training set representative of heat plume movement, which means the heat plume's location must be exactly known to train it. The challenge is that the heat plume constantly moves. To solve this problem, a mask can be drawn around the approximate area of the heat plume, including all approximate area where heat touches, and then set a threshold on the variance video, and apply a binary intersection. After these operations are done, the output video sequence looks like the clip shown in Figure 44.

Figure 44 – Train_var30 Mask, “Heat Mask” (frames 3030 – 3230, step 10)

The SVM also needs negative training data. For this purpose, a mask was created that selects everything but the fire and heat area. Pixels were selected at random from this mask to collect signal sequences from as negative training data, as the non-heat mask area far exceeds the heat region mask in area. Every pixel within the heat mask was used to collect underlying sequences for positive training data. These methods resulted in an approximately proportionate sizes between positive and negative training sets, totaling about 44,000 training samples.

There were two sets of signals used for SVM training data.

- 1) One set was the PCA set (Section 3.2); that is, a single training sample was a 6-dimensional vector taken from one pixel of the PCA set, where the dimensions corresponded to the PC images. The PC images were unmapped.
- 2) The other was also from the PC images, but in an effort to incorporate more time-related information as well as more meaningful information, the training data consisted of the first 3 PC images at time t_f , in conjunction with the first 3 PC images at time $t_f - 10$ (that is, the previous time index considered, as the output time resolution is divided by 10, to be 3 fps).

When training off the first data set, a 5-fold stratified cross-validation method was performed, wherein the data set is divided into 5 sets, and 4 are used for training while the remaining set is used for validation. The process is repeated for a different set of 4 and 1 until all combinations have been tried. This process trained the SVM to have **5.4% error rate**.

5.6.3 Results

Unfortunately, the SVM was unable to learn the general distinction between heat and non-heat, for both sets of training data. For approximately 44,000 training vectors, there were approximately 11,000 support vectors. Figure 45 shows the results. Both trainings appear homogeneously incorrect. This failure may be due to any of the following reasons:

- The training mask may be faulty.
- The training mask and the matching heat signature may be asynchronous.
- The training mask is defined for individual discrete moments of time to a resolution of 0.33 seconds, yet is used to identify and collect information over 2 seconds. The disparity may be too great.

Figure 45 – Support Vector Machine Output

5.7 Classification Function Summary

Function / Script Name	Description Overview	
	Function Input	Function Output
Classification_BayesVar	Imports saved histogram data from TimeDomainAnalysis as a-priori knowledge to classify variance features.	
Process_VarStats	Directs the entire process of producing, analyzing and displaying MMT from feature extraction to processing to classification to post-processing. Calls FeatureExtraction_VarStats and Classification_VarStats.	
Process_NoiseResist	Used to investigate methods to isolate heat plume movement pattern. Ultimately it discovers VAMBM, which it fully implements, analyzes, and displays.	
Process_DRMAD_PCA	Directs the process of producing, analyzing, and displaying PCA-DRMAD, assuming the EWMA features have already been extracted (FeatureExtraction_EWMA). Calls Process_EMASub, FeatureProcessing_PCA, ErrorAnalysis.	
Process_EMASub	Computes several EWMA DRMADs, permuting several EWMA parameters: e.g. 0.1, 0.07, 0.05, 0.02, 0.01, 0.008. This data supplies Process_NoiseResist.	
Classification_VarStats	Source and output path, frame interval. Output AVI path.	Implements thresholding and intersection of varMean and varMax, to produce “loose”, “tight”, and “config3”. Creates video of results.
Classification_Training	Script that creates the training mask (Figure 44) from a manual mask intersected with thresholded variance.	
Classification_SVM	Source channel, path of training data (produced from ExtractTrainingData_PCA)	Confusion matrix of the support vector machine’s classified output.
ExtractTrainingData_PCA	Source channel, moving mask path (modeled as a classification),	Sets of affirmative and negative training data, collected from source channel beneath the moving mask.
ErrorAnalysis	A set of classifications under test, frame range.	Outputs error rates for each classification, and plots bar graph of what they truly classified by category.

6 CONCLUSION

This thesis has covered the search for and study of features (frames thereof) that represent information about heat plume's characteristic behaviors of persistence and growth. It has discussed how these features were combined to harness the unique information that each feature offered towards emphasizing the distinction between heat plume and not. Classifiers were designed and tested to justify their final parameters, and to compare the relative quality of the methods, side-by-side.

6.1 Feature Conclusions

The features were chosen because they all represented different aspects of time-domain information. While tuning the more successful features in pursuit of error minimization, some lessons emerge. The VSS classifiers suffered less error when the set size was reduced from 20 to 15 to 10, demonstrating that heat plume information demands finer measurement. A shortcoming of the VSS methods is that a small set size compromises the statistics calculated over the set, making it a tool of a broader scope, perhaps less suited to this application than PCA-DRMAD. By its nature, a dual-range moving average difference allows for finer control than VSS because the parameter of the filter can freely vary, where the VSS parameters suffer more dramatically if they aren't within a conducive range. Hence DRMAD more easily enhanced the signal. Furthermore, DRMAD optimized the error rate when its p-parameters were $p_{long}=0.05$ and $p_{short} = 0.01$, which corresponds to a particular frequency range, implying that frequency is relevant, which VSS cannot directly interact with: variance is not sensitive to order or frequency content. By the same token, PCA also does not consider frequency content directly, rather it considers varying degrees of how much change occurs within its time samples. This is still an order of magnitude finer than VSS, and precise frequencies aren't important when the heat plume itself exhibits much chaotic behavior.

6.2 Comparison of Detection Methods

Table 25 gives an overview of the sensitivity of each classifier to each leading challenge category. Every error rating should be regarded as a preliminary figure, with the potential to decrease with judicious further filtering and combining.

Table 25 – Classifier Sensitivity – Categorized Detection Count

	Heat	Noise*	Cars	Pedestrian	Avg Error
Ideal	>> 0	0	0	0	0
Variance Corridor	N/A	N/A	N/A	N/A	N/A
MMT	1700	0	6600	722	48.2%
VAMBM	2530	0	12800	5700	62.4%
PCA-DRMAD	937	0	0	5	0.9%
SVM	N/A	N/A	N/A	N/A	N/A

*Noise refers to interface noise

Table 26 – Comparison of Classifier Computation Time

Method	Computation Time	Frame Rate*
Variance Corridor	N/A	N/A
MMT	640 s	6.0 fps
VAMBM	779 s	5.7 fps
PCA-DRMAD	522 s	8.6 fps

*Frame rate is a superficial feature based on the prototype implementation. The principal source of delay is USB 3.0 HDD access time.

In as much as “we are what we eat,” a classifier’s output needs quality features to process. It follows from the Feature Conclusions that PCA-DRMAD enjoys the most advantage from a resolution and detail standpoint. Its average error rate (Precision) of 0.9% certainly heralds its own success and merit.

6.3 Future Work

- Reduce false positives in VSS feature classifiers, both MMT and VAMBM, by filtering out low-persistence behavior (cars).
- Increase the sensitivity of PCA-DRMAD Classifier without reducing the error rate.
 - When calibrating the automatic threshold, mask out the known fire region, to eliminate any unwarranted bias.
- Variance Set Statistics do not include any frequency information. Temporal frequency domain features may lead to more information than variance alone can offer.
 - Investigate common DSP notch filters such as Wiener, keeping in mind that DRMAD worked best within the frequency range corresponding to $p_{long}=0.05$ and $p_{short} = 0.01$.
- Diagnose why SVM on PCA of DRMAD data failed, and fix it.
- Vary the PCA parameters on DRMAD:
 - Principal component count
 - Period between time samples
- Try PCA on VSS features.

6.4 Lessons Learned

- Plan ahead for data collection missions. Consider the needs of those using the data, survey the available tools, and make use of them.
- Spend time at the beginning of a coding project to develop the tools so that every stage of the prototyping process isn't belabored.

7 BIBLIOGRAPHY

- [1] National Interagency Fire Center. <www.nifc.gov>. May 2012.
- [2] Tyco Fire and Security.
<<http://www.tycofireandsecurity.com/Capabilities/firedetection>> May 22, 2012.
- [3] Beam Detection, Westminster International, Ltd. <http://www.wi-ltd.com/fire/Fire_Detection_Systems/Beam_Detectors> May 22, 2012.
- [4] Wang J, Song W, Wang W, Zhang Y. "A new algorithm for Forest fire smoke detection based on MODIS data in Heilongjiang province", Hefei University of Technology, 2011.
- [5] Zhang D, Han S, Zhao J, Zhang Z, Qu C, Ke Y, Chen X. "Image Based Forest Fire Detection Using Dynamic Characteristics With Artificial Neural Networks." *International Joint Conference on Artificial Intelligence, 2009.*
- [6] Ho C, Kuo T. "Real-Time Video-Based Fire Smoke Detection System." *IEEE/ASME International Conference on Advanced Intelligent Mechatronics, 2009.*
- [7] Mathworks, Computer Vision System Toolbox.
<<http://www.mathworks.com/products/computer-vision/>> May 22, 2012
- [8] Lee K Y, Chuang Y Y, Chen B Y, Ouhyoung M. "Video Stabilization using Robust Feature Trajectories." National Taiwan University, 2009.
- [9] Tordoff B, Murray D W. "Guided sampling and consensus for motion estimation." *European Conference on Computer Vision, 2002.*
- [10] Rosten E, Drummond T. "Machine learning for high-speed corner detection." *European Conference on Computer Vision, May 2006.*
- [11] Forsyth D A, Ponce J. Computer Vision, a modern approach. Prentice Hall, 2003.
- [12] FLIR, "Seeing through fog and rain with a thermal imaging camera."
<http://www.metrum.co.uk/images/AS_FOG.pdf>, 2012.
- [13] Bosch, Gomez, Vergara, Moragues. "Infrared image processing and its application to forest fire surveillance." *IEEE Conference on Advanced Video and Signal Based Surveillance, pp. 283. (2007).*
- [14] Vergara L, Bernabeu P. Automatic Signal Detection applied to fire control by infrared digital signal processing. Signal Processing. Volume 80, pp. 659-669, 2000.
- [15] Gonzalez R C, Woods R E. Digital Image Processing, 3rd Ed. Prentice Hall, 2008.
- [16] Fukunaga, Keinosuke. Introduction to Statistical Pattern Recognition. Elsevier, 1990.
- [17] Shlens J. A Tutorial on Principal Component Analysis.

- [18] PHYS.ORG, New forest fire detection system prototype installed at Lake Tahoe. <<http://phys.org/news179400560.html>>, Dec 7, 2009.
- [19] Li Z, Kaufman Y, Ichoku C, Fraser R, Trishchenko A, Giglio L, Jin J, Yu X, "A Review of AVHRR-based Active Forest Fire Detection Algorithms: Principles, Limitations, and Recommendations.
- [20] Kaufman Y J, Kleidman R G, King M D. "SCAR-B Fires in the Tropics: properties and their remote sensing from EOS-MODIS." J. Geophys. Res., 103:31,955-31,969, 1998.
- [21] Haykin S. "Neural Networks and Learning Machines, 3ed." Prentice Hall, 2009.

8 GLOSSARY

Term / Acronym	Description
CLWIR	Cooled Long-Wave Infrared.
CMWIR	Cooled Mid-Wave Infrared.
DRMAD	Dual-Range Moving Average Difference
EMA/EWMA	Exponential / Exponentially-Weighted Moving Average
PCA	Principal Component Analysis
PF	Point Feature
RANSAC	Random Sample Consensus
SMA	Simple Moving Average
SVM	Support Vector Machine
UCLWIR	Uncooled Long-Wave Infrared.
VAMBM	Variance-Augmented Mean-by-Median Quotient
VSL	Variance (Set) Statistics, Loose threshold and intersection configuration
VSS	Variance Set Statistics

APPENDIX I – CLASSIFICATION CODE

These functions are primarily responsible for all the algorithms and the output seen in this thesis. The entirety of the code is not included in this appendix, in the interest of space (clutter), however the full code should accompany this document as an attachment. The following functions are included herein. The lower levels in the list indicate that the function is called by the higher level function or script.

- Classification_BayesVar
- Process_VarStats.m
 - FeatureExtraction_VarStats
 - Classification_VarStats
- Process_NoiseResist.m
 - FeatureExtraction_VarStats
 - FeatureProcessing_Simple
- Process_DRMAD_PCA.m
 - Process_EMASub.m
- Classification_SVM
 - ExtractTrainingData_PCA.m

Classification_BayesVar.m

```
%%-----%
% Author:    Daniel Kohler
% Date:      4-3-2012
% Description:
%   Imports saved histogram data from TimeDomainAnalysis.m, uses it as a
%   priori knowledge to classify variance features, as extracted by
%   FeatureExtraction_VarStats.m
%-----%
%% Configuration

% Data paths
sourcePath = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR';
sourceName = 'pine_cones_PFstab';
featureName = 'var_seq30';
binPath = 'TDA_config5_expBin0.8-0.1-2.mat';

% Test Configuration (inspect feature folder for applicable range)
FRAME_FIRST = 1629;
FRAME_LAST = 2399;
FRAME_INTERVAL = 10;

outputMtx = 1;
outputAVI = 1;

%% Preparation
featurePath = [sourcePath '\' sourceName '\features\' featureName '\'];
classifiedPath = [sourcePath '\' sourceName '\classification\BayesVar\'];
warning('OFF', 'MATLAB:MKDIR:DirectoryExists');
mkdir(classifiedPath);
warning('ON', 'MATLAB:MKDIR:DirectoryExists');

% Bayesian data - exponentially-distributed histogram bins
binData = load(binPath);
%       bins: {1x7 cell}
%       names: {1x7 cell}
%       binCentersExp: [1x13 double]
%       binCenters: [1x13 double]

% Create look-up table matching bin with best fitting histogram
histCount = length(binData.bins);
binCount = length(binData.binCenters);
bin2histLUT = zeros(binCount, 1);
for binIndex = 1 : binCount
    bestFit = 0;
    for histIndex = 1 : histCount
        if binData.bins{histIndex}(binIndex) > bestFit
            bestFit = binData.bins{histIndex}(binIndex);
            bin2histLUT(binIndex) = histIndex;
        end
    end
end
binEdges = center2edge(binData.binCenters);

%Prepare video for write
fps = 25/FRAME_INTERVAL;          %num2str will go to 5 decimals... not too bad
if outputAVI
    outVidPath = [sourcePath '\' sourceName '\classification\' ...
        sourceName '_BayesVar_' num2str(fps) 'fps'];
    rawMovObj = VideoWriter(outVidPath);
    rawMovObj.FrameRate = fps;
    open(rawMovObj);
end
```

```

end

hWB = waitbar(0, 'Bayesian Histogram Classification');
tic

%Get frame dimensions
feature = loadMtx([featurePath num2str(FRAME_FIRST) '.mtx']);
[nrows ncols] = size(feature);

%% Classification loop
for i = FRAME_FIRST : FRAME_INTERVAL : FRAME_LAST
    %Load feature frame
    disp(['Loading feature frame ' num2str(i)])
    feature = loadMtx([featurePath num2str(i) '.mtx']);
    %Loop through each pixel
    for c = 1 : ncols
        for r = 1 : nrows
            %disp(['Reading [r c] = [' num2str(r) ' ' num2str(c) ']]')
            %Assign this pixel to a bin
            %thisPxBin = assignToBin(binEdges, feature(r, c)); %39.5 sec
            thisPxBin = find(histc(feature(r,c)-.001, binEdges)); %39.5

            %If best fit was smoke, then light it!
            isSmoke(r, c) = (bin2histLUT(thisPxBin) == 1);
        end
    end

    %Output frame to mtx
    if outputMtx
        saveMtx(isSmoke, [classifiedPath num2str(i) '.mtx']);
    end

    %Output frame to video
    if outputAVI
        writeVideo(rawMovObj, uint8(isSmoke).*255);
    end

    imshow(isSmoke)
    pause(0.01)
    waitbar((i-FRAME_FIRST+1)/(FRAME_LAST-FRAME_FIRST) , hWB);
end
toc
close(rawMovObj);
disp(['Result written to: ' outVidPath]);
close(hWB);

```

Process_VarStats.m

```
%%-----%
% Author      :   Daniel Kohler
% Date       :   5/30/12
%
% Description:
%   This script calls functions and implements operations that produce the
%   Variance Set Statistics Loose (VSL) Mean and Max Thresholding (MMT).
% Pre-conditions:
%   - A raw video file has been separated into frames (vid2frame.m,
%     vid2frame_lwmw.m)
%   - Optionally, video stabilization has been performed
%     (stabilizeVidPFraw.m)
%-----%

function Process_VarStats

%This function is meant to command all the calculations required to
%reproduce the output of the time-domain analysis of VarStat
%classification, assuming PFstabilization has already been performed.

clear;

%% General Variable Declarations
sourcePath = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\';
sourceName = 'oats1_PFstab';

%Region of Interest
ROI_rowmin = 175;
ROI_rowmax = 450;
ROI_colmin = 250;
ROI_colmax = 400;

%% Feature_Extraction_VarStats

featurePath = [sourcePath sourceName '\features\'];

FRAME_FIRST = 1;
FRAME_LAST = 5000;
SEQ_STEP = 10;    %(output time resolution)

VSSconfig = 3;
switch(VSSconfig)
    case 1      %Done in 115 s
        SEQ_LEN = 20;
        SET_SIZE = 15;
    case 2      %Done in 339 s
        SEQ_LEN = 20;
        SET_SIZE = 10;
    case 3      %Done in 71 s
        SEQ_LEN = 10;
        SET_SIZE = 15;
    case 4      %Done in 70 s
        SEQ_LEN = 10;
        SET_SIZE = 10;
    case 5      %Done in 522 s
        SEQ_LEN = 30;
        SET_SIZE = 20;
end

%These times are consistent. I'm baffled at the discrepancy of computation
%times, and can't see a pattern or reason for case 2 to be so long.
%Case 3 and 4: SET_SIZE doesn't weight much on computation time.
```



```

    %Maybe it has to do with how fragmented that sector is on the hard
    %drive.

%First output will be at index:
% (SET_SIZE-1) * SEQ_STEP + FRAME_FIRST + SEQ_LEN - 1;

disp('EntireProcess_VarStats calling FeatureExtraction_VarStats...');
FeatureExtraction_VarStats(sourcePath, sourceName, ...
    FRAME_FIRST, FRAME_LAST, SEQ_LEN, SEQ_STEP, SET_SIZE, ...
    ROI_rowmin, ROI_rowmax, ROI_colmin, ROI_colmax);
%}

%% Classification_VarStats
% Oprate on the raw PF-stabilized frames.

FRAME_FIRST      = (SET_SIZE-1) * SEQ_STEP + FRAME_FIRST + SEQ_LEN - 1;
FRAME_FIRST      = 220;
FRAME_LAST       = 5000;
FRAME_INTERVAL    = 10;

thresholdConfig = 1;      %Loose

VSSconfig = 5;
switch(VSSconfig)
    case 1          %Done in 41 s
        meanName    = 'varMean_seq20_set15';
        maxName     = 'varMax_seq20_set15';
    case 2          %Done in 13 s
        meanName    = 'varMean_seq20_set10';
        maxName     = 'varMax_seq20_set10';
    case 3
        meanName    = 'varMean_seq10_set15';
        maxName     = 'varMax_seq10_set15';
    case 4
        meanName    = 'varMean_seq10_set10';
        maxName     = 'varMax_seq10_set10';
    case 5          %Done in 26.5 s
        meanName    = 'varMean_seq30_set20';
        maxName     = 'varMax_seq30_set20';
end

% Output enable
outputMtx = 1;          %a .mtx file per frame
outputAVI = 0;          %an .avi video of all frames

disp('EntireProcess_VarStats calling Classification_Features_VarStats...');
Classification_VarStats(sourcePath, sourceName, ...
    FRAME_FIRST, FRAME_LAST, FRAME_INTERVAL, meanName, maxName,
    thresholdConfig, ...
    outputMtx, outputAVI);

%% Classification Post-Processing (26 s for 5000)
% Generate isAll 10, 20, 30 for noise reduction

FRAME_FIRST      = 220;      %Same as previous
FRAME_LAST       = 5000;     %Same as previous
FRAME_INTERVAL    = 10;      %Same as previous
SEQ_LEN          = 30;       %Numbers of samples per sequences
SEQ_STEP         = 10;       %Counts between sets (sample groups)
%NOTE: The first output will be at frame:
% FRAME_FIRST + (SEQ_LEN-1) * FRAME_INTERVAL;

workPath = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\';

```

```

inPath = 'oats1_PFstab\classification\varStats_loose\';
outPath = ['oats1_PFstab\classification\varStats_loose_isAll' num2str(SEQ_LEN)
'\'];

warning('OFF', 'MATLAB:MKDIR:DirectoryExists');
mkdir([workPath outPath]);
warning('ON', 'MATLAB:MKDIR:DirectoryExists');

WBh = waitbar(0, 'Progress');

frame_group_first = FRAME_FIRST;
frame_group_last = frame_group_first + (SEQ_LEN-1) * FRAME_INTERVAL;
while(frame_group_last <= FRAME_LAST)

    t1 = tic;

    frameMat = [];
    for j = frame_group_first : FRAME_INTERVAL : frame_group_last
        frameMat = cat(3, frameMat, loadMtx([workPath inPath num2str(j)
'.mtx']));
    end
    frameMean = mean(frameMat, 3);
    saveName = [workPath outPath num2str(frame_group_last) ...
        '.mtx'];

    saveMtx(frameMean==1, saveName);
%oats1_PFstab\classification\varStats_loose

    progress = (frame_group_first-FRAME_FIRST)/(FRAME_LAST - FRAME_FIRST -
FRAME_INTERVAL*SEQ_LEN);
    waitbar(progress , WBh, ['Generating isAll: finished i = '
num2str(frame_group_last) ' in ' num2str(toc(t1)) 's.']);

    %Identify next frame group
    frame_group_first = frame_group_first + SEQ_STEP;
    frame_group_last = frame_group_first + (SEQ_LEN-1) * FRAME_INTERVAL;
end % i (frame groups)

disp(['Generated isAll data in ' num2str(toc(tic)) ' s']);
close(WBh);
halleluja;
%}

%% Classification Post-Processing (41 s for 5000)
% Binary mean-subtract with median filter (FeatureProcessing_MeanSub)
% Noise Reduction. X = S + N (measurement = signal + noise)

disp('EntireProcess_VarStats performing binary subtraction and median
filtering...');
tic = tic;

FRAME_FIRST    = 510;
FRAME_LAST     = 5000;
SEQ_STEP       = 10;

sourcePath = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\';
in1Path = 'oats1_PFstab\classification\varStats_loose\';
in2Path = 'oats1_PFstab\classification\varStats_loose_isAll30\';
outPath1 = 'oats1_PFstab\classification\varStats_loose_-_isAll30\';
outPath2 = 'oats1_PFstab\classification\varStats_loose_-_isAll30_medfilt3\';
outPath3 = 'oats1_PFstab\classification\varStats_loose_-_isAll30_medfilt5\';

warning('OFF', 'MATLAB:MKDIR:DirectoryExists');

```

```

mkdir([sourcePath outPath1]);
mkdir([sourcePath outPath2]);
mkdir([sourcePath outPath3]);
warning('ON', 'MATLAB:MKDIR:DirectoryExists');

WBh = waitbar(0, 'Progress');

%st = strel('disk', 1);

for i = FRAME_FIRST : SEQ_STEP : FRAME_LAST

    %Load frames
    meas = loadMtx([sourcePath in1Path num2str(i) '.mtx']);
    noise = loadMtx([sourcePath in2Path num2str(i) '.mtx']);

    sig = meas & ~noise;

    %Operate and save output frames
    %Just mean subtract
    saveMtx(sig, [sourcePath outPath1 num2str(i) '.mtx']);
    %Mean subtract and median filter with 3x3 kernel
    saveMtx(medfilt2(sig), [sourcePath outPath2 num2str(i) '.mtx']);
    %Mean subtract and median filter with 5x5 kernel
    saveMtx(medfilt2(sig, [5 5]), [sourcePath outPath3 num2str(i) '.mtx']);

    waitbar((i-FRAME_FIRST)/(FRAME_LAST - FRAME_FIRST), WBh, ...
        ['Binary subtracting and median filtering. ' ...
        num2str(i-FRAME_FIRST) ' of ' ...
        num2str(FRAME_LAST - FRAME_FIRST)]);

end % i (frame groups)

toc(ticTime)
close(WBh)

%% Generate Video

savePath = 'F:\Fire_Data_6-18-
11_MW_LW\CMWIR\oats1_Pfstab\classification\varStats_loose_isAll=_medfilt=_3fps.
avi';
channelPath = {
    'F:\Fire_Data_6-18-
11_MW_LW\CMWIR\oats1_Pfstab\classification\varStats_loose\'
    'F:\Fire_Data_6-18-
11_MW_LW\CMWIR\oats1_Pfstab\classification\varStats_loose_isAll10\'
    'F:\Fire_Data_6-18-
11_MW_LW\CMWIR\oats1_Pfstab\classification\varStats_loose_-_isAll10\'
    'F:\Fire_Data_6-18-
11_MW_LW\CMWIR\oats1_Pfstab\classification\varStats_loose_-_isAll10_medfilt3\'
    'F:\Fire_Data_6-18-
11_MW_LW\CMWIR\oats1_Pfstab\classification\varStats_loose_-_isAll10_medfilt5\'
    'F:\Fire_Data_6-18-
11_MW_LW\CMWIR\oats1_Pfstab\classification\varStats_loose_isAll120\'
    'F:\Fire_Data_6-18-
11_MW_LW\CMWIR\oats1_Pfstab\classification\varStats_loose_-_isAll120\'
    'F:\Fire_Data_6-18-
11_MW_LW\CMWIR\oats1_Pfstab\classification\varStats_loose_-_isAll120_medfilt3\'
    'F:\Fire_Data_6-18-
11_MW_LW\CMWIR\oats1_Pfstab\classification\varStats_loose_-_
_isAll120_medfilt5\'};
frameFirst = 510;
frameStep = 10;
frameLast = 8000;

```

```

fps            = 3;

lbl1txt = ' (1)oats1_PFstab';

lbltxt = { ' (2)varStats_loose'
           ' (3)isAll10'
           ' (4) 2 & ~3'
           ' (5)medfilt3 of 4'
           ' (6)medfilt5 of 4'
           ' (7)isAll20'
           ' (8) 2 & ~7'
           ' (9)medfilt3 of 8'
           ' (10)medfilt5 of 8'};

rejectionP = 0.00;    %Must be zero for binary images mostly
                      %one value, else linear mapping will result
                      %in NaN.

layout = [ 0  2  3  4  5;
           1  6  7  8  9];

MakeVid_Framework(channelPath, lbl1txt, lbltxt, savePath, ...
    frameFirst, frameStep, frameLast, fps, rejectionP, layout);

%% Generate Video 2
%Compare isAll{10 20 30}

savePath      = 'F:\Fire_Data_6-18-
11_MW_LW\CMWIR\oats1_PFstab\classification\varStats_loose_isAll123=_medfilt=_3f
ps.avi';
channelPath   = {
    %'F:\Fire_Data_6-18-
11_MW_LW\CMWIR\oats1_PFstab\classification\varStats_loose\'
    'F:\Fire_Data_6-18-
11_MW_LW\CMWIR\oats1_PFstab\classification\varStats_loose_-_isAll10_medfilt3\'
    'F:\Fire_Data_6-18-
11_MW_LW\CMWIR\oats1_PFstab\classification\varStats_loose_-_isAll20_medfilt3\'
    'F:\Fire_Data_6-18-
11_MW_LW\CMWIR\oats1_PFstab\classification\varStats_loose_-_
_isAll30_medfilt3\'};
frameFirst   = 510;
frameStep    = 10;
frameLast    = 8000;
fps          = 3;

lbl1txt = ' (1)oats1_PFstab';

lbltxt = { ...' (2)varStats_loose'
           ' (3)VSL-isAll10'
           ' (4)VSL-isAll20'
           ' (5)VSL-isAll30'};

rejectionP = 0.00;    %Must be zero for binary images mostly
                      %one value, else linear mapping will result
                      %in NaN.

layout = [0 1 2 3];

MakeVid_Framework(channelPath, lbl1txt, lbltxt, savePath, ...
    frameFirst, frameStep, frameLast, fps, rejectionP, layout);

%% Error Analysis

```

```

clasPath = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\classification\';

channels = {
    'varStats_loose_-_isAll10_medfilt3\'    %E net
    'varStats_loose_-_isAll10_medfilt5\'    %0.727
    'varStats_loose_-_isAll10_medfilt5\'    %0.482
    'varStats_loose_-_isAll20_medfilt3\'    %0.827
    'varStats_loose_-_isAll20_medfilt5\'    %0.750
    'varStats_loose_-_isAll30_medfilt3\'    %0.843
    'varStats_loose_-_isAll30_medfilt5\'}; %0.785

channelLb1 = {
    'VSL-All10_mf3'
    'VSL-All10_mf5'
    'VSL-All20_mf3'
    'VSL-All20_mf5'
    'VSL-All30_mf3'
    'VSL-All30_mf5'};

frameFirst = 510;
frameStep = 10;
frameLast = 5000;

pathY = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\training\heatRegionY2.bmp';
pathN = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\training\nonHeatRegion2.bmp';

doGraph = true;

[E goods bads] = ErrorAnalysis(clasPath, channels, ...
    frameFirst, frameStep, frameLast, doGraph, channelLb1);

%Display
Emeans = mean(E);
goodsT = sum(goods);
badsT = sum(bads);
disp(sprintf('Channel name:           \tGood \tBad \tE_net'))
for i = 1 : length(channels)
    disp(sprintf('%s\b \t%d\t%d\t%0.3f', channels{i}, goodsT(i), badsT(i),
    Emeans(i)))
end

end %Process_VarStats

```

FeatureExtraction_VarStats.m

```

%%-----%
% Author      :   Daniel Kohler
% Date       :   4/1/2012
%
% Description:
%   For given sourcePath and sourceName, region of interest, sequence
%   length and step and set size, this function will variance set
%   statistics. The set is composed of SET_SIZE variance frames taken at
%   SEQ_STEP distance apart (from the start of the sequences, not
%   back-to-front). The variance frames are time-variance over a sequence
%   of SEQ_LEN time samples. The statistics calculated are mean, median,
%   and max. They will be further used outside the scope of this function.
%
% Notes:
%   Broken off from ClassificationFrameworkTime
%-----%
function FeatureExtraction_VarStats(sourcePath, sourceName, ...
    FRAME_FIRST, FRAME_LAST, SEQ_LEN, SEQ_STEP, SET_SIZE, ...
    ROI_rowmin, ROI_rowmax, ROI_colmin, ROI_colmax)

disp('== FeatureExtraction_VarStats has begun ==');
tic;

%% GLOBAL SETTINGS
NCOLS = 640;
NROWS = 480;
FRAME_INTERVAL = 1;

if nargin == 0

    sourcePath = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR';
    sourceName = 'oats1_PFstab';

    % TEST CONFIGURATION
    FRAME_FIRST = 1;
    FRAME_LAST = 8000;
    SEQ_LEN = 30; %WAS 40
    SEQ_STEP = 10; %WAS 20 (output time resolution)
    SET_SIZE = 20; %set = a collection of stats on a whole group

end
if nargin < 8
    %Region of Interest
    ROI_rowmin = 175;
    ROI_rowmax = 450;
    ROI_colmin = 250;
    ROI_colmax = 400;
end

featurePath = [sourcePath '\\' sourceName '\\features\'];
featureName = ... %Output path
    [{'varMean_seq' num2str(SEQ_LEN) '_set' num2str(SET_SIZE)}
    ['varMax_seq' num2str(SEQ_LEN) '_set' num2str(SET_SIZE)}
    ['varMed_seq' num2str(SEQ_LEN) '_set' num2str(SET_SIZE)}}];

ROI_rowlen = ROI_rowmax - ROI_rowmin + 1;
ROI_collen = ROI_colmax - ROI_colmin + 1;

warning('OFF', 'MATLAB:MKDIR:DirectoryExists');
for i = 1 : length(featureName)
    mkdir([featurePath featureName{i}])
end

```

```

end
warning('ON', 'MATLAB:MKDIR:DirectoryExists');

groupCount = floor((FRAME_LAST - FRAME_FIRST - SEQ_LEN + 1) ...
    / SEQ_STEP) + 1;

var_hist = zeros(ROI_rowlen, ROI_collen, SET_SIZE);

WBh = waitbar(0, 'Progress');

for i = 1 : groupCount
    %Load next frame group
    frame_group_first = FRAME_FIRST + SEQ_STEP * (i-1);
    frame_group_last = frame_group_first + SEQ_LEN - 1;

    tic;

    [frameMat] ...
        = readframes(sourcePath, sourceName, ...
            frame_group_first, frame_group_last, FRAME_INTERVAL, ...
            NCOLS, NROWS, ROI_rowmin, ROI_rowlen, ROI_colmin, ROI_collen);

    frameVar = shiftdim(var(shiftdim(frameMat, 2),1));
    var_hist = circshift(var_hist, [0 0 1]);
    var_hist(:,:,1) = frameVar;

    if i >= SET_SIZE %set full, data now valid
        %Save mean
        meanSaveName = [featurePath featureName{1} ...
            '\ ' num2str(frame_group_last) '.mtx'];
        maxSaveName = [featurePath featureName{2} ...
            '\ ' num2str(frame_group_last) '.mtx'];
        medSaveName = [featurePath featureName{3} ...
            '\ ' num2str(frame_group_last) '.mtx'];
        saveMtx(uint16(mean(var_hist, 3)), meanSaveName);
        saveMtx(uint16(max(var_hist, [], 3)), maxSaveName);
        saveMtx(uint16(median(var_hist, 3)), medSaveName);
    end

    waitbar(i/groupCount, WBh, ['FeatureExtraction\_VarStats. Finished ' ...
        'i = ' num2str(i)]);

end % i (frame groups)

%Save .avi
if(0)
    disp(['Saving output video to ' saveName '.avi']);
    mtx2vid(flipdim(isSmoke_hist,3), [saveName '.avi'], 30/SEQ_STEP, false);
end

disp(['FeatureExtraction_VarStats completed in ' num2str(toc(tictime)) 's.']);
close(WBh)
halleluja;

end

```

Classification_VarStats.m

```
%%-----%
% Author      :   Daniel Kohler
% Date       :   4/30/12
%
% Description:
%   Thresholds and combines varMean and varMax to produce a classifier for
%   further filtering.
%-----%

function Classification_VarStats(sourcePath, sourceName, ...
    FRAME_FIRST, FRAME_LAST, FRAME_INTERVAL, meanName, maxName, config, ...
    outputMtx, outputAVI)

disp('== Classification_VarStats has begun ==');
tic;

%% GLOBAL SETTINGS
if nargin == 0

    NCOLS = 640;
    NROWS = 480;

    sourcePath = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\';
    sourceName = 'oats1_PFstab';

    % TEST CONFIGURATION
    FRAME_FIRST = 220;
    FRAME_LAST = 5000;
    FRAME_INTERVAL = 10;

    config = 1;

    % Feature names must match folder names. Create cell array for multiple.
    meanName = 'varMean_seq30_set20';
    maxName = 'varMax_seq30_set20';

    % Output enable
    outputMtx = 1;      %a .mtx file per frame
    outputAVI = 1;      %an .avi video of all frames
end

%% Preparation

switch(config)
case 1 %Loose
    meanThLow = 40;
    meanThHigh = 700;
    maxThLow = 60;
    maxThHigh = 5000;
    % Procedure name - the output folder name
    procedureName = 'varStats_loose';
case 2 %Tight
    meanThLow = 50;
    meanThHigh = 100;
    maxThLow = 100;
    maxThHigh = 600;
    % Procedure name - the output folder name
    procedureName = 'varStats_tight';
case 3
    meanThLow = 60;
    meanThHigh = 150;
```



```

        maxThLow      = 500;
        maxThHigh     = 1500;
        % Procedure name - the output folder name
        procedureName  = 'varStats_config3';
    end

    meanPath          = [sourcePath sourceName '\features\' ...
                        meanName, '\'];
    maxPath            = [sourcePath sourceName '\features\' ...
                        maxName, '\'];
    classifiedPath     = [sourcePath sourceName '\classification\' ...
                        procedureName '\'];

    warning('OFF', 'MATLAB:MKDIR:DirectoryExists');
    mkdir(classifiedPath);
    warning('ON', 'MATLAB:MKDIR:DirectoryExists');

    %Prepare video for write
    fps = 25/FRAME_INTERVAL;          %num2str will go to 5 decimals... not too bad
    if outputAVI
        outVidPath = [sourcePath sourceName '\classification\' ...
                    sourceName '_' procedureName '_' num2str(fps) 'fps.avi'];
        rawMovObj = VideoWriter(outVidPath);
        rawMovObj.FrameRate = fps;
        open(rawMovObj);
    end

    hWB = waitbar(0, [strrep(procedureName, '_', '\_') ' Classification
    Procedure']);

    %Get frame dimensions
    varMean = loadMtx([meanPath num2str(FRAME_FIRST) '.mtx']);
    [nrows ncols] = size(varMean);

    %% Classification loop
    for i = FRAME_FIRST : FRAME_INTERVAL : FRAME_LAST
        %Load feature frame(s)
        %disp(['Loading features for frame ' num2str(i)])
        varMean = loadMtx([meanPath num2str(i) '.mtx']);
        varMax  = loadMtx([maxPath  num2str(i) '.mtx']);

        c = (varMean > meanThLow & varMean < meanThHigh) & ...
            (varMax > maxThLow & varMax < maxThHigh);

        %Output frame to mtx
        if outputMtx
            saveMtx(c, [classifiedPath num2str(i) '.mtx']);
        end

        %Output frame to video
        if outputAVI
            writeVideo(rawMovObj, uint8(c).*255);
        end

        %imshow(c)
        %pause(0.01)
        waitbar((i-FRAME_FIRST+1)/(FRAME_LAST-FRAME_FIRST) , hWB, ...
            ['Classification_VarStats: Completed frame ' num2str(i)]);
    end

    disp(['Classification_VarStats elapsed time is ' num2str(toc(tictime))]);

    if outputAVI

```

```
        close(rawMovObj);  
        disp(['Result written to: ' outVidPath]);  
    end  
  
    halleluja;  
    close(hWB);  
    clear;  
  
end
```

Process_NoiseResist.m

```
%%-----%
% Author      :   Daniel Kohler
% Date       :   5/30/12
%
% Description:
%   This script studies several feature combinations on their ability to
%   reject noise (non-heat movement patterns). Ultimately, VAMBM is
%   discovered and analyzed.
% Pre-conditions:
%   - A raw video file has been separated into frames (vid2frame.m,
%     vid2frame_lwmw.m)
%   - Optionally, video stabilization has been performed
%     (stabilizeVidPFraw.m)
%   - VarStats seq30 set20 have been extracted already
%-----%

function Process_NoiseResist

featurePath = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\';
clasPath = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\classification\';

%% Extract more parameters of varStats
sourcePath = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\';
sourceName = 'oats1_PFstab';

% BATCH CONFIGURATION
SEQ_LENS = [10 20];
SET_SIZES = [10 15];

% TEST CONFIGURATION
FRAME_FIRST = 1;
FRAME_LAST = 8000;
SEQ_STEP = 10;

%Region of Interest
ROI_rowmin = 175;
ROI_rowmax = 450;
ROI_colmin = 250;
ROI_colmax = 400;

for i = 1 : length(SEQ_LENS)
    for j = 1 : length(SET_SIZES)
        disp(['Calling FeatureExtraction_VarStats for seq' num2str(SEQ_LENS(i))
            ', set' num2str(SET_SIZES(j))]);
        FeatureExtraction_VarStats(sourcePath, sourceName, ...
            FRAME_FIRST, FRAME_LAST, SEQ_LENS(i), SEQ_STEP, SET_SIZES(j), ...
            ROI_rowmin, ROI_rowmax, ROI_colmin, ROI_colmax);
    end
end

%% Create std from var

workPath = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\';
inPath = 'oats1_PFstab\features\var_seq60\';
outPath = 'oats1_PFstab\features\std_seq60\';

FRAME_FIRST = 60;
FRAME_LAST = 8000;
FRAME_INTERVAL = 10;
```

```

    fun = inline('uint16(sqrt(double(f)))', 'f');
FeatureProcessing_Simple(workPath, inPath, outPath, ...
    FRAME_FIRST, FRAME_LAST, FRAME_INTERVAL, fun)

%% Quotient Batch A and B (survey)

frameFirst      = 510;
frameLast       = 5000;
frameStep       = 10;

featurePath = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\';
srcPath      = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\src\';
DRMADpath    = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\EWMA0.07_-_EWMA0.02\';

varMax3020Path = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\varMax_seq30_set20\';
varMean3020Path = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\varMean_seq30_set20\';
varMed3020Path = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\varMed_seq30_set20\';

varMax2015Path = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\varMax_seq20_set15\';
varMean2015Path = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\varMean_seq20_set15\';
varMed2015Path = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\varMed_seq20_set15\';

varMax2010Path = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\varMax_seq20_set10\';
varMean2010Path = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\varMean_seq20_set10\';
varMed2010Path = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\varMed_seq20_set10\';

varMax1015Path = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\varMax_seq10_set15\';
varMean1015Path = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\varMean_seq10_set15\';
varMed1015Path = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\varMed_seq10_set15\';

varMax1010Path = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\varMax_seq10_set10\';
varMean1010Path = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\varMean_seq10_set10\';
varMed1010Path = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\varMed_seq10_set10\';

std30Path = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\var_seq30\';
std60Path = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\var_seq60\';

%Configure a list of division trials here.
%A_div_B = { A, B, outName; ... };
A_div_B = {
    varMean2015Path,    varMed2015Path,    'var2015_Mean-by-Med\';
    varMean2010Path,    varMed2010Path,    'var2010_Mean-by-Med\';
    varMean1015Path,    varMed1015Path,    'var1015_Mean-by-Med\';

```

```

        varMean1010Path,    varMed1010Path,    'var1010_Mean-by-Med\';
        varMean3020Path,    varMed3020Path,    'var3020_Mean-by-Med\';
    };

    if(1)
        warning('OFF', 'MATLAB:MKDIR:DirectoryExists');
        for i = 1 : size(A_div_B, 1)
            mkdir([featurePath A_div_B{i, 3}]);
        end
        warning('ON', 'MATLAB:MKDIR:DirectoryExists');

        hWB = waitbar(0, 'Progress');
        tic;
        i = frameFirst;
        while(i <= frameLast)
            istr = num2str(i);
            for j = 1 : size(A_div_B, 1)

                A = single(loadMtx([A_div_B{j, 1} istr '.mtx']));
                B = single(loadMtx([A_div_B{j, 2} istr '.mtx']));
                Q = A ./ B;

                saveMtx(Q, [featurePath A_div_B{j, 3} istr '.mtx']);
            end

            waitbar((i-frameFirst+1)/(frameLast-frameFirst), hWB, [istr '/'
num2str(frameLast)]);
            i = i + frameStep;
        end
        disp(['Finished division in ' num2str(toc) ' s.']);
        close(hWB);

    end

    %% Create video of quotient batch from A_div_B
    %CONFIGURE
    % Must set A_div_B from above to use the following loop
    for i = 1:size(A_div_B, 1)
        sourcePath{i} = [featurePath A_div_B{i, 3}];
        lbltxt{i} = [A_div_B{i, 3}(1:end-1)];
    end
    lbl1txt = 'oats1_PFstab';
    savePath = [featurePath 'Div=.avi'];
    frameFirst = 510;
    frameStep = 10;
    frameLast = 5000;
    fps = 3;
    rejectionP = 0;
    layout = [0 1 2; 3 4 5];

    MakeVid_Framework(sourcePath, lbl1txt, lbltxt, savePath, ...
        frameFirst, frameStep, frameLast, fps, rejectionP, layout)

    %% Threshold and Median filter.

    %Experimental exploration: threshold at >= 3, medfilt 5x5
    %Repeat with 3x3 if have time.
    workPath = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\';
    inPath = {
        'features\var2015_Mean-by-Med\'
        'features\var2010_Mean-by-Med\'
    }

```

```

    'features\var1015_Mean-by-Med\'
    'features\var1010_Mean-by-Med\'
    'features\var3020_Mean-by-Med\'});
outPath = {
    'classification\var2015_Mean-by-Med_thmed5\'
    'classification\var2010_Mean-by-Med_thmed5\'
    'classification\var1015_Mean-by-Med_thmed5\'
    'classification\var1010_Mean-by-Med_thmed5\'
    'classification\var3020_Mean-by-Med_thmed5\'});

FRAME_FIRST      = 510;
FRAME_LAST       = 5000;
FRAME_INTERVAL   = 10;

fun = inline('medfilt2(f >= 3, [5 5])', 'f');

for i = 1 : length(outPath)
    disp(['Process_NoiseResist calling FeatureProcessing_Simple (' num2str(i)
    '/' num2str(length(outPath)) ') ...']);
    FeatureProcessing_Simple(workPath, inPath{i}, outPath{i}, ...
        FRAME_FIRST, FRAME_LAST, FRAME_INTERVAL, fun)
end
%}

%% Create Video for MBM_thmed5
%CONFIGURE
sourcePath = {
    [clasPath 'var2015_Mean-by-Med_thmed5\']
    [clasPath 'var2010_Mean-by-Med_thmed5\']
    [clasPath 'var1015_Mean-by-Med_thmed5\']
    [clasPath 'var1010_Mean-by-Med_thmed5\']
    [clasPath 'var3020_Mean-by-Med_thmed5\'']};
lbltxt = {
    'var2015_MbM_thmed5'
    'var2010_MbM_thmed5'
    'var1015_MbM_thmed5'
    'var1010_MbM_thmed5'
    'var3020_MbM_thmed5'};
lbl1txt = 'oats1_PFstab';
savePath = [featurePath 'MBM=_thmed5.avi'];
frameFirst = 510;
frameStep = 10;
frameLast = 5000;
fps = 3;
rejectionP = 0;
layout = [0 1 2; 3 4 5];

MakeVid_Framework(sourcePath, lbl1txt, lbltxt, savePath, ...
    frameFirst, frameStep, frameLast, fps, rejectionP, layout)

%% Intersect VS_mbm_thmed5 with dilate(var_seq30>100) (VAMBM)
% Ref: MBM=_var30th-d2.avi

    %var_seq30 has some heat/smoke content below 100. The threshold is set
    %high to cut out the birds. Dilation should compensate.

workPath = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\'
varPath = {
    'classification\var_seq30_th100\'};
mbmPath = {
    'classification\var2015_Mean-by-Med_thmed5\'

```

```

        'classification\var2010_Mean-by-Med_thmed5\'
        'classification\var1015_Mean-by-Med_thmed5\'
        'classification\var1010_Mean-by-Med_thmed5\'
        'classification\var3020_Mean-by-Med_thmed5\'}};
outPath = {
    'classification\MBM2015_var30\'
    'classification\MBM2010_var30\'
    'classification\MBM1015_var30\'
    'classification\MBM1010_var30\'
    'classification\MBM3020_var30\'}};

se = strel('disk', 2);

frameFirst      = 510;
frameInt        = 10;
frameLast       = 5000;

for i = 1 : length(outPath)
    pathA        = [workPath mbmPath{i}];
    pathB        = [workPath varPath{1}];
    pathOut      = [workPath outPath{i}];

    warning('OFF', 'MATLAB:MKDIR:DirectoryExists');
    mkdir([pathOut]);
    warning('ON', 'MATLAB:MKDIR:DirectoryExists');

    hWB = waitbar(0, 'Progress');
    tic;

    for j = frameFirst : frameInt : frameLast
        A = loadMtx([pathA num2str(j) '.mtx']);
        B = loadMtx([pathB num2str(j) '.mtx']);

        F = A & imdilate(B, se);

        saveMtx(F, [pathOut num2str(j) '.mtx']);
        waitbar((j-frameFirst+1)/(frameLast-frameFirst), hWB, ['Performing
binary operation (' num2str(i) '/' num2str(length(outPath)) ')']);
    end

    toc;
    close(hWB);

end
%}

%% Evaluate errors of MBM=_var30th-d2

channels = {
    'MBM2015_var30\'    %0.73877    %E net
    'MBM2010_var30\'    %0.64956
    'MBM1015_var30\'    %0.67488
    'MBM1010_var30\'    %0.62426    same best as before
    'MBM3020_var30\'}; %0.76648

channelLb1 = {
    'MBM2015'
    'MBM2010'
    'MBM1015'
    'MBM1010'
    'MBM3020'};

frameFirst      = 510;
frameStep       = 10;

```

```

frameLast    = 5000;

doGraph      = true;

[E goods bads] = ErrorAnalysis(clasPath, channels, ...
    frameFirst, frameStep, frameLast, doGraph, channelLb1)
Emeans = mean(E);
goodsT = sum(goods);
badsT = sum(bads);

%Display
disp(sprintf('Channel name:           \tGood \tBad \tE_net'))
for i = 1 : length(channels)
    disp(sprintf('%s\b \t%d\t%d\t%.3f', channels{i}, goodsT(i), badsT(i),
Emeans(i)))
end
%}

%% Create Video MBM=_var30th-d2.avi

%CONFIGURE
sourcePath = {
    [clasPath 'MBM2015_var30\']
    [clasPath 'MBM2010_var30\']
    [clasPath 'MBM1015_var30\']
    [clasPath 'MBM1010_var30\']
    [clasPath 'MBM3020_var30\']};
lb1txt = {
    'MBM2015_var30'
    'MBM2010_var30'
    'MBM1015_var30'
    'MBM1010_var30'
    'MBM3020_var30'}
lb11txt = 'oats1_PFstab';
savePath = [clasPath 'MBM=_var30th-d2.avi'];
frameFirst = 510;
frameStep = 10;
frameLast = 5000;
fps = 3;
rejectionP = 0;
layout = [0 1 2; 3 4 5];

MakeVid_Framework(sourcePath, lb11txt, lb1txt, savePath, ...
    frameFirst, frameStep, frameLast, fps, rejectionP, layout)

%% Create Video showing constituents of MBM=_var30th-d2

%CONFIGURE
sourcePath = {
    [featurePath 'var_seq30\']
    [clasPath 'var_seq30_th100\']
    [featurePath 'var1010_Mean-by-Med\']
    [clasPath 'var1010_Mean-by-Med_thmed5\']
    [clasPath 'MBM1010_var30\']};
lb1txt = {
    '(2)var30'
    '(3)var30_th100'
    '(4)var1010 mean/med'
    '(5)th,med5 of 4'
    '(6)MBM1010_var30'}
lb11txt = 'oats1_PFstab';
savePath = [clasPath 'MBM1010_var30th-d2_progression.avi'];
frameFirst = 510;

```



```

frameStep          = 10;
frameLast          = 5000;
fps                = 3;
rejectionP         = [ 0.01    0    0.005    0    0];
layout             = [0    1    2;    3    4    5];

MakeVid_Framework(sourcePath, lbl1txt, lbltxt, savePath, ...
    frameFirst, frameStep, frameLast, fps, rejectionP, layout)

%% Evaluate error rate of channels

channels = {
    'var2015_Mean-by-Med_thmed5\'    %E net    %0.794
    'var2010_Mean-by-Med_thmed5\'    %0.695
    'var1015_Mean-by-Med_thmed5\'    %0.743
    'var1010_Mean-by-Med_thmed5\'    %0.680
    'var3020_Mean-by-Med_thmed5\'}; %0.811
channelLbl = {
    'var2015_MBM'
    'var2010_MBM'
    'var1015_MBM'
    'var1010_MBM'
    'var3020_MBM'};

% channels = {
%     'varStats_loose_-_isAll10_medfilt3\'    %E net    %0.
%     'varStats_loose_-_isAll10_medfilt5\'    %0.
%     'varStats_loose_-_isAll20_medfilt3\'    %0.
%     'varStats_loose_-_isAll20_medfilt5\'    %0.
%     'varStats_loose_-_isAll30_medfilt3\'    %0.
%     'varStats_loose_-_isAll30_medfilt5\'}; %0.
% channelLbl = {
%     'VSL-All10_mf3'
%     'VSL-All10_mf5'
%     'VSL-All20_mf3'
%     'VSL-All20_mf5'
%     'VSL-All30_mf3'
%     'VSL-All30_mf5'};

frameFirst = 510;
frameStep = 10;
frameLast = 5000;

pathY = 'F:\Fire_Data_6-18-
11_MW_LW\CMWIR\oats1_PFstab\training\heatRegionY2.bmp';
pathN = 'F:\Fire_Data_6-18-
11_MW_LW\CMWIR\oats1_PFstab\training\nonHeatRegion2.bmp';

doGraph = true;

[E goods bads] = ErrorAnalysis(clasPath, channels, ...
    frameFirst, frameStep, frameLast, doGraph, channelLbl);

%Display
Emeans = mean(E);
goodsT = sum(goods);
badsT = sum(bads);
disp(sprintf('Channel name:           \tGood \tBad \tE_net'))
for i = 1 : length(channels)
    disp(sprintf('%s\b \t%d\t%d\t%0.3f', channels{i}, goodsT(i), badsT(i),
    Emeans(i)))
end

```

FeatureProcessing_Simple

```

%%-----%
% Feature Processing Family of Functions
% Simple implies single-frame operations, such as filtering or
% thresholding.

% Revisions:
%   5-21-12:   included fun, a function handle. Pass in a function,
%              potentially inline. e.g.
%              fun = inline('medfilt2(f, [3 3])', 'f');
%%-----%

function FeatureProcessing_Simple(workPath, inPath, outPath, ...
    FRAME_FIRST, FRAME_LAST, FRAME_INTERVAL, fun)

ticTime = tic;

if nargin == 0

    % DATA LOCATIONS
    workPath = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\';
    inPath = 'oats1_PFstab\classification\varStats_loose\';
    outPath = 'oats1_PFstab\classification\varStats_loose_SMA20\';
    inPath = 'oats1_PFstab\features\var_seq30\';
    inPath = 'oats1_PFstab\features\var1010_Mean-by-Med\';
    outPath = 'oats1_PFstab\features\var1010_Mean-by-Med_thmed3\';

    % TEST CONFIGURATION
    % The following operates on data that was saved in intervals of 10, hence
    % the FRAME_INTERVAL=10. Every number is units consistent with original
    % 30 fps.
    FRAME_FIRST = 510;
    FRAME_LAST = 8000;
    FRAME_INTERVAL = 10;           %Counts between samples.
                                   %Probably want 1 for features,
                                   %10 for classification.
end

warning('OFF', 'MATLAB:MKDIR:DirectoryExists');
mkdir([workPath outPath]);
warning('ON', 'MATLAB:MKDIR:DirectoryExists');

WBh = waitbar(0, 'Progress');

for i = FRAME_FIRST : FRAME_INTERVAL : FRAME_LAST

    t1 = tic;

    f = loadMtx([workPath inPath num2str(i) '.mtx']);

    %Perform single-frame operation on this frame
    if nargin < 7
        % Manual function
        f = medfilt2(f, [3 3]);
    else
        %Execute function that was passed in
        f = fun(f);
    end

    saveName = [workPath outPath num2str(i) '.mtx'];
    saveMtx(f, saveName);

    progress = (i-FRAME_FIRST)/(FRAME_LAST - FRAME_FIRST);

```

```

        waitbar(progress , WBh, ['FeatureProcessing\_Simple: finished i = '
num2str(i) ' in ' num2str(toc(t1)) 's.']);

end % i (frame groups)

disp(['FeatureProcessing_Simple elapsed time is ' num2str(toc(tictime))]);
close(WBh)
halleluja;

end

```

Process_DRMAD_PCA.m

```
%%-----%
% Author:   Daniel Kohler
% Date:     6/20/12
% Description:
%   Orchestrates the calculations that produce the PCA-DRMAD results and
%   analysis.
%-----%

%% GLOBAL SETUP
%Execute this cell first!

fpath = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\';
cpath = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\classification\';

nPC      = 6;                %number of PC's
nPCstr    = num2str(nPC)     %for convenience of repetition
mapMethod = 'autolinear'

    %mapMethod options:
    %   none
    %   autolinear
    %   zgamma
    %   zagamma

channelSelect = 7;
switch(channelSelect)
    case 1      %Done
        longName = 'EWMA0.1__EWMA0.02';
        shortName = 'EWMA0.1-0.02';
    case 2      %Done
        longName = 'EWMA0.07__EWMA0.02';
        shortName = 'EWMA0.07-0.02';
    case 3      %Done
        longName = 'EWMA0.07__EWMA0.01';
        shortName = 'EWMA0.07-0.01';
    case 4
        longName = 'EWMA0.07__EWMA0.008';
        shortName = 'EWMA0.07-0.008';
    case 5
        longName = 'EWMA0.05__EWMA0.02';
        shortName = 'EWMA0.05-0.02';
    case 6
        longName = 'EWMA0.05__EWMA0.01';
        shortName = 'EWMA0.05-0.01';
    case 7
        longName = 'EWMA0.05__EWMA0.008';
        shortName = 'EWMA0.05-0.008';
end

%% Create DRMAD's
%Creates difference combinations of EWMA.
Process_EMASub;

%% Perform PCA
%Examine the features from the commented code within FeatureProcessing_PCA

disp('Performing PCA');
tic;

frameFirst = 510;
frameLast = 5000;
frameStep = 10;
```

```

mapFrame      = 3000;           %presence of heat plume

sourcePath    = [fpath longName '\\'];
savePath      = [fpath shortName '_PCA' nPCstr '_' mapMethod '\\'];

FeatureProcessing_PCA(sourcePath, savePath, ...
    frameFirst, frameLast, frameStep, mapFrame, nPC, mapMethod);

% Find largest thresholds for each channel before frame 1000, as an
% automatic threshold detector. I could use this in other code as well.
frameFirst = frameFirst + frameStep * (nPC-1);
frameLast = 1000; %Fire has not flared up before this frame
maxTh = zeros(1, nPC) + 0.5;
minTh = zeros(1, nPC) + 0.5;
for j = frameFirst : frameStep: frameLast
    m = reshape(loadMtx([savePath num2str(j) '.mtx']), [], nPC);
    maxTh = max([m; maxTh]);
    minTh = min([m; minTh]);
end
minTh, maxTh

%% Threshold the PCA

disp('Thresholding PCA');
tic = tic;

frameFirst = 560;
frameLast = 5000;
frameStep = 10;
sourcePath = [fpath shortName '_PCA' nPCstr '_' mapMethod '\\'];
savePath = [cpath shortName '_PCA' nPCstr '_' mapMethod '_auto-th\\'];

warning('OFF', 'MATLAB:MKDIR:DirectoryExists');
mkdir(savePath);
for i = 1 : nPC
    mkdir([savePath num2str(i) '\\']); %Create subdirectory per PCI
end
warning('ON', 'MATLAB:MKDIR:DirectoryExists');

hWB = waitbar(0, 'Progress');

for i = frameFirst : frameStep : frameLast
    for j = 1 : nPC
        f = loadMtx([sourcePath num2str(j) '\\' num2str(i) '.mtx']);
        g = f > maxTh(j) | f < minTh(j);
        saveMtx(g, [savePath num2str(j) '\\' num2str(i) '.mtx']);
        % imshow(g), pause(0.01)
    end
    waitbar((i-frameFirst)/(frameLast-frameFirst), hWB, 'Thresholding PCA');
end
close(hWB);

toc(tic);
%}

%% Create video of autothreshold

%CONFIGURE
clear sourcePath
for i = 1 : nPC
    istr = num2str(i);

```

```

        sourcePath{2*i-1} = [fpath shortName '_PCA' nPCstr '_' mapMethod '\' istr
        '\'];
        sourcePath{2*i}   = [cpath shortName '_PCA' nPCstr '_' mapMethod '_auto-
        th\' istr '\'];
        lbltxt{2*i-1}     = ['PC' istr];
        lbltxt{2*i}       = ['PC' istr '_th'];
    end
    lbl1txt               = 'oats1_PFstab';
    savePath               = [cpath shortName '_PCA' nPCstr '_auto-th.avi'];
    frameFirst             = 560;
    frameStep              = 10;
    frameLast              = 5000;
    fps                    = 3;
    rejectionP              = [.01 0 .01 0 .01 0 .01 0 .01 0];
    layout                 = [0 1 3 5 7 9 11; 0 2 4 6 8 10 12];

    MakeVid_Framework(sourcePath, lbl1txt, lbltxt, savePath, ...
        frameFirst, frameStep, frameLast, fps, rejectionP, layout)
    %}

%% Error Analysis

disp('Performing error analysis');
tic = tic;

frameFirst = 560;
frameStep  = 10;
frameLast  = 5000;
nPC        = 6;
mapMethod  = 'autolinear';

for i = 1 : nPC;
    istr      = num2str(i);
    channels{i} = [shortName '_PCA' nPCstr '_' mapMethod '_auto-th\' istr];
    barLabels{i} = ['PC' istr];
end

doGraph      = true;

[E heat nonHeat ped car noise] = ErrorAnalysis(...
    cpath, channels, frameFirst, frameStep, frameLast, ...
    doGraph, barLabels);

%Display
Emeans = mean(E);
goodsT  = sum(heat);
badsT   = sum(nonHeat);
disp(sprintf('Channel name:                \tHeat \tNon-heat\tE_ave'))
for i = 1 : length(channels)
    disp(sprintf('%s \t%d\t%d\t%.3f', channels{i}, goodsT(i), badsT(i),
    Emeans(i)))
end

toc(tic);
%}

%% Classify heat plume
% PC1 has a near perfect track record, but doesn't reach as high.
% An expanding heat plume will have persistence towards the fire, and the
% distal region of the heat plume will have much motion (visible in deeper
% PC's), but not much persistence, but will be NEAR the persistence (PC1).
% Hence look for deeper PC's AND dilated PC1.

```

```

tictime = tic;

frameFirst = 560;
frameLast = 2000;
frameStep = 10;

sourcePath = [cpath shortName '_PCA' nPCstr '_' mapMethod '_auto-th\'];
savePath = [cpath shortName '_PCA' nPCstr '_' mapMethod '_auto-th_c1\'];

warning('OFF', 'MATLAB:MKDIR:DirectoryExists');
mkdir(savePath);
warning('ON', 'MATLAB:MKDIR:DirectoryExists');

se = strel('disk', 3);

hWB = waitbar(0, 'Progress');

for i = frameFirst : frameStep : frameLast
    PC1 = loadMtx([sourcePath '1\' num2str(i) '.mtx']);
    PCrest = zeros(size(PC1));
    for j = 2 : nPC
        PCrest = PCrest + loadMtx([sourcePath num2str(j) '\\' num2str(i)
'.mtx']);
    end
    PC1dil = imdilate(PC1, se);
    g = PC1dil & PCrest >= 1;
    %imshow([PC1 PC1dil g]); pause(0.1)
    saveMtx(g, [savePath num2str(i) '.mtx']);
    waitbar((i-frameFirst)/(frameLast-frameFirst), hWB, 'Combining PCA into
Classifier');
end
close(hWB);
toc(tictime);
%}

%% Error Analysis on the 7 DRMA configurations
disp('Performing error analysis');
tictime = tic;

frameFirst = 560;
frameStep = 10;
frameLast = 5000;

channels = {'EWMA0.1-0.02_PCA6_autolinear_auto-th_c1'
'EWMA0.07-0.02_PCA6_autolinear_auto-th_c1'
'EWMA0.07-0.01_PCA6_autolinear_auto-th_c1'
'EWMA0.07-0.008_PCA6_autolinear_auto-th_c1'
'EWMA0.05-0.02_PCA6_autolinear_auto-th_c1'
'EWMA0.05-0.01_PCA6_autolinear_auto-th_c1'
'EWMA0.05-0.008_PCA6_autolinear_auto-th_c1'};

barLabels = {'Case 1'
'Case 2'
'Case 3'
'Case 4'
'Case 5'
'Case 6'
'Case 7'};

doGraph = true;

[E heat nonHeat ped car noise] = ErrorAnalysis(...)

```

```

        cpath, channels, frameFirst, frameStep, frameLast, ...
        doGraph, barLabels);

%Display
Emeans = mean(E);
goodsT = sum(heat);
badsT = sum(nonHeat);
disp(sprintf('Channel name:           \tHeat \tNon-heat\tE_ave'))
for i = 1 : length(channels)
    disp(sprintf('%s \t%d\t%d\t%0.3f', channels{i}, goodsT(i), badsT(i),
Emeans(i)))
end

toc(ticTime);

```


Process_EMASub.m

```
%%-----%
% Author:   Daniel Kohler
% Date:     5/20/12
%-----%

clear

%% Compute the EMA subtractions for combinations in 'ops'
workPath = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\';
FRAME_FIRST = 510; %510
FRAME_LAST = 8000;
SEQ_STEP = 10; % (output time resolution)

negMethod = 'retain';
           %retain, reflect, saturate

%Paths to individual files, including entire name except for index.
% out = in1 - in2
in_ps = {'0.1', '0.07', '0.05', '0.02', '0.01', '0.008'};
ops = [ 1 4;
        2 4;
        2 5;
        2 6;
        3 4;
        3 5;
        3 6];

for i = 1 : size(ops,1)
    in1Path = ['oats1_PFstab\features\EWMA_p' in_ps{ops(i,1)} '\'];
    in2Path = ['oats1_PFstab\features\EWMA_p' in_ps{ops(i,2)} '\'];
    outPath = ['oats1_PFstab\features\EWMA' in_ps{ops(i,1)} '_-EWMA'
in_ps{ops(i,2)} '\'];

    FeatureProcessing_MeanSub(workPath, in1Path, in2Path, outPath, ...
FRAME_FIRST, FRAME_LAST, SEQ_STEP, negMethod)
end

%% Create EMA-sub video

savePath = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\EMA-
sub=_3fps.avi';
sourcePath = {
    'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\EWMA0.1_-
_EWMA0.02\'
    'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\EWMA0.07_-
_EWMA0.02\'
    'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\EWMA0.07_-
_EWMA0.01\'
    'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\EWMA0.07_-
_EWMA0.008\'
    'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\EWMA0.05_-
_EWMA0.02\'
    'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\EWMA0.05_-
_EWMA0.01\'
    'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\EWMA0.05_-
_EWMA0.008\'};

frameFirst = 510; %510, 1860
frameStep = 10;
frameLast = 5000; %3800
fps = 3;
```

```

lbl1txt = ' oats1_PFstab';
lbltxt = {
    ' EWMA 0.1 - 0.02'
    ' EWMA 0.07 - 0.02'
    ' EWMA 0.07 - 0.01'
    ' EWMA 0.07 - 0.008'
    ' EWMA 0.05 - 0.02'
    ' EWMA 0.05 - 0.01'
    ' EWMA 0.05 - 0.008'};

rejectionP = 0; %Must be 0 for binary images mostly
               %one value, else linear mapping will result
               %in NaN.

layout = [0 2 3 4; 1 5 6 7];

MakeVid_Framework(sourcePath, lbl1txt, lbltxt, savePath, ...
    frameFirst, frameStep, frameLast, fps, rejectionP, layout)

%% Compute stdfilt on each EMA-sub
%The output of this will give an idea of the contrast between the heat and
%background, to use as a guide.
sourcePath = {
    'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\EWMA0.1-_EWMA0.02\'
    'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\EWMA0.07-_EWMA0.02\'
    'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\EWMA0.07-_EWMA0.01\'
    'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\EWMA0.07-_EWMA0.008\'
    'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\EWMA0.05-_EWMA0.02\'
    'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\EWMA0.05-_EWMA0.01\'
    'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\EWMA0.05-_EWMA0.008\'};

FRAME_FIRST = 510; %510
FRAME_LAST = 8000;
SEQ_STEP = 10; % (output time resolution)

warning('OFF', 'MATLAB:MKDIR:DirectoryExists');
for i = 1 : length(sourcePath)
    mkdir([sourcePath{i} '_stdfilt\']);
end
warning('ON', 'MATLAB:MKDIR:DirectoryExists');

hWB = waitbar(0, 'Progress');
for i = 1 : length(sourcePath)
    for j = FRAME_FIRST : SEQ_STEP : FRAME_LAST
        f = loadMtx([sourcePath{i} num2str(j) '.mtx']);
        f = stdfilt(f);
        saveMtx(f, [sourcePath{i}(1:end-1) '_stdfilt\' num2str(j) '.mtx']);
        waitbar((j-FRAME_FIRST)/(FRAME_LAST-FRAME_FIRST), hWB, ['Writing video'
            ' num2str(i) ' of ' num2str(length(sourcePath)) ': ...' sourcePath{i}(end-30:end)]);
    end
end
close(hWB);

%% Create video of stdfilt

```

```

savePath      = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\EMA-sub-
stdfilt=_3fps.avi';
sourcePath    = {
    'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\EWMA0.1_-
_EWMA0.02_stdfilt\'
    'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\EWMA0.07_-
_EWMA0.02_stdfilt\'
    'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\EWMA0.07_-
_EWMA0.01_stdfilt\'
    'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\EWMA0.07_-
_EWMA0.008_stdfilt\'
    'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\EWMA0.05_-
_EWMA0.02_stdfilt\'
    'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\EWMA0.05_-
_EWMA0.01_stdfilt\'
    'F:\Fire_Data_6-18-11_MW_LW\CMWIR\oats1_PFstab\features\EWMA0.05_-
_EWMA0.008_stdfilt\'};

frameFirst    = 510;          %510, 1860
frameStep     = 10;
frameLast     = 5000;        %3800
fps           = 3;

lbl1txt = ' oats1_PFstab';
lbltxt = {
    ' EWMA 0.1-0.02 std'
    ' EWMA 0.07-0.02 std'
    ' EWMA 0.07-0.01 std'
    ' EWMA 0.07-0.008 std'
    ' EWMA 0.05-0.02 std'
    ' EWMA 0.05-0.01 std'
    ' EWMA 0.05-0.008 std'};

rejectionP = 0;              %Must be 0 for binary images mostly
                                %one value, else linear mapping will result
                                %in NaN.
layout = [0 2 3 4; 1 5 6 7];

MakeVid_Framework(sourcePath, lbl1txt, lbltxt, savePath, ...
    frameFirst, frameStep, frameLast, fps, rejectionP, layout)

```

Classification_SVM

```
%%-----%
% Author      :   Daniel Kohler
% Date       :   4/30/12
%
% Description:
%   Trains a support vector machine (SVM) to classify heat data from
%   PCA training data previously collected. Iterates through original data,
%   performs PCA on it per group, and passes each pixel through the SVM
%   classifier. The result is then compared with heat and non-heat masks to
%   collect confusion matrix data.
%
% PRE-CONDITIONS:
%   Perform ExtractTrainingData_PCA.m to produce a set of heat and non-heat
%   training data, saved in \training\ folder.
%-----%

function [confusion, confFrame] = Classification_SVM(sourceName, trainYname,
trainNname)

%% GLOBAL DECLARATIONS
NCOLS      = 640;
NROWS      = 480;

%% CONFIGURATION

if nargin == 0
    sourceName = 'oats1_PFstab';
    trainName  = 'nomap';
    trainYname = ['train_var30_PCA6_' trainName '.mtx'];
    trainNname = ['nonheat_PCA6_' trainName '.mtx'];
    saveName   = ['SVM_PCA6_' trainName];
end
workPath     = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR\';
trainYPath   = [workPath sourceName '\training\' trainYname];
trainNPath   = [workPath sourceName '\training\' trainNname];
savePath     = [workPath sourceName '\classification\' saveName '\'];

warning('OFF', 'MATLAB:MKDIR:DirectoryExists');
mkdir(savePath);
warning('ON', 'MATLAB:MKDIR:DirectoryExists');

maskYname    = 'train_var30';
maskNname    = 'nonHeatRegion.bmp';

maskYpath    = [workPath sourceName '\classification\' maskYname '\'];
maskNpath    = [workPath sourceName '\training\' maskNname];
maskN        = imread(maskNpath);

mtxOut = true;

%% SVM TRAINING

%Load training data
trainY = loadMtx(trainYPath)';
classY = repmat(1, [size(trainY,1) 1]);
trainN = loadMtx(trainNPath)';
classN = repmat(0, [size(trainN,1) 1]);

train = [trainY; trainN]; clear trainY trainN;
clas  = [classY; classN]; clear classY classN;
```

```

if(0)
    %Test the SVM with 5-fold stratified cross-validation.
    CV = cvpartition(clas, 'Kfold', 5);
    err = zeros(CV.NumTestSets,1);
    for i = 1:CV.NumTestSets
        SVM = svmtrain(train(CV.training(i),:), clas(CV.training(i)), ...
                        'kernel_function', 'rbf', ...
                        'method', 'LS', ...
                        'autoscale', 'false', ...
                        'rbf_sigma', 1);
        cl = svmclassify(SVM, train(CV.test(i),:));
        err(i) = sum( cl ~= clas(CV.test(i)) );
    end
    totalErr = sum(err)/CV.N
    %conMat = confusionmat(train(CV.training
end

if(0)
    %Train SVM using Least Squares method
    %(default SMO only works on 2D input)
    SVM = svmtrain(train, clas, ...
                    'kernel_function', 'rbf', ...
                    'method', 'LS', ...
                    'autoscale', 'false', ...
                    'rbf_sigma', 1);
    save([savePath 'trainedSVM.mat'], 'SVM');
else
    %Or just load the last trained SVM
    SVM = getfield(load([savePath 'trainedSVM.mat']), 'SVM');
end

%% CLASSIFICATION
mapMethod      = 'nomap';

frameFirst     = 1860;
frameLast      = 3800;
frameStep      = 10;
groupStep      = 30;
nPC            = 6;          %number of PC's

%Region of Interest
rowmin = 175;
rowmax = 450;
rowlen = rowmax - rowmin + 1;
colmin = 250;
colmax = 400;
collen = colmax - colmin + 1;

frame_group_first = frameFirst - (nPC-1) * frameStep;
frame_group_last  = frameFirst;

%Prepare Principle Component Transform
orig = readframes(workPath, sourceName, ...
                  frame_group_first, frame_group_last, frameStep, ...
                  NCOLS, NROWS, rowmin, rowlen, colmin, collen);
T = computePCT(orig);

tic
hWB = waitbar(0, 'Progress');

%Prepare confusion matrix
i=1;

```

```

confFrame = zeros(frameLast - frameFirst - frameStep * (nPC-1) - 1, 1);
%indices
confusion = zeros(2, 2, frameLast - frameFirst - frameStep * (nPC-1) - 1);
%conf mtx

while(frame_group_last <= frameLast)
    t1 = tic;

    orig = readframes(workPath, sourceName, ...
        frame_group_first, frame_group_last, frameStep, ...
        NCOLS, NROWS, rowmin, rowlen, colmin, collen);

    pca = reshape(orig, [], nPC) * T;    %(R*C)-by-T matrix.

    maskY = loadMtx([maskYpath num2str(frame_group_last) '.mtx']);

    %Memory restrictions! Matlab uses ~4.2GB RAM for 16000 samples
    %Divide the training set into chunks of about 5000 samples
    %CV.test(j) returns 1 stratum instead of the other N-1
    CV = cvpartition(size(pca,1), 'Kfold', floor(size(pca,1)/5000));
    classifiedFrame = [];
    for j = 1 : CV.NumTestSets
        classifiedFrame = [classifiedFrame; svmclassify(SVM, pca(CV.test(j),
:))];
    end

    %confusion variables
    tp = sum((classifiedFrame(:) == 1) & maskY(:));
    tn = sum((classifiedFrame(:) == 0) & maskN(:));
    fp = sum((classifiedFrame(:) == 1) & maskN(:));
    fn = sum((classifiedFrame(:) == 0) & maskY(:));

    confusion(:,:,i) = [tn fp; fn tp];
    %      0   1   classified
    %      0   tn   fp
    %      1   fn   tp
    % true
    confFrame(i) = frame_group_last;
    i = i + 1;

    %Show output
    imshow(reshape(classifiedFrame, rowlen, collen));
    pause(0.01);

    %save mtx
    if mtxOut
        saveMtx(reshape(classifiedFrame, rowlen, collen), [savePath
num2str(frame_group_last) '.mtx']);
    end

    frame_group_first = frame_group_first + groupStep;
    frame_group_last = frame_group_first + (nPC-1) * frameStep;

    waitbar((frame_group_first - frameFirst)/(frameLast-frameFirst-frameStep *
(nPC-1) - 1), hWB, ['Completed frame ' num2str(frame_group_last) ' in '
num2str(toc(t1)) ' s.']);

end

saveMtx(confusion, [savePath '_confusion.mtx']);
saveMtx(confFrame, [savePath '_confInd.mtx']);

end

```

ExtractTrainingData_PCA.m

```

%%-----%
% function [seqY seqN] = ...
%     ExtractTrainingData_PCA(maskNameY, maskNameN, sourceName, doDelay)
%
% Author:    Daniel Kohler
% Date:      4/30/12
%
% Description:
%
%     Create training data from original frame data, through a moving mask
%     stored as a .mtx series in the same folder. Negative training data comes
%     from a stationary mask, where 20 asserted points are selected at random
%     per frame to represent non-heat data.
%     If doDelay is true then the first 3 features will be the first pc
%     frames, and the second 3 features will be the first 3 previous pc
%     frames.
%
% Output:    If output arguments are specified, then seqY and seqN will be
%             returned.
%             If no output arguments are specified, then seqY and seqN will
%             be written to the sourceName\training folder.
%             Format is nPC-by-trainCount.
%
% PRE-CONDITIONS:
% A mask sequence has been created in \classification\train... describing a
% tight moving area around smoke.
% A static non-smoke mask has been created, that will be used for SVM
% training. It is much more massive than the heat mask, therefore random
% locations will be taken from it to use as negative training data.
%-----%

% 5/21/12: Created masks that may train better. N2 and Y2. Try if time.

function [seqY seqN] = ...
    ExtractTrainingData_PCA(maskNameY, maskNameN, sourceName, doDelay)
%% GLOBAL DECLARATIONS
NCOLS      = 640;
NROWS      = 480;
sourcePath = 'F:\Fire_Data_6-18-11_MW_LW\CMWIR';

if nargin == 0
    sourceName = 'oats1_PFstab';
    maskNameY  = 'train_var30';    %assumed a folder in \classification\
    maskNameN  = 'nonHeatRegion.bmp';
    doDelay    = false;
end

maskYpath = [sourcePath '\\' sourceName '\classification\' maskNameY '\\'];
maskNpath = [sourcePath '\\' sourceName '\training\' maskNameN];

%% TEST CONFIGURATION
MASK_FIRST = 1860;    %first mask frame
MASK_LAST  = 3800;    %last mask frame
MASK_STEP  = 10;      %period between mask time samples
nPC        = 6;       %number of PC's

mapMethod   = 'zgamma';
saveNote    = '_100prctile';
if doDelay, dtxt = '_delay'; else dtxt = ''; end
savePathY   = [sourcePath '\\' sourceName '\training\' maskNameY ...
    '_PCA' num2str(nPC) dtxt '_' mapMethod '.mtx']

```

```

savePathN    = [sourcePath '\\' sourceName '\training\nonheat_PCA' ...
    num2str(nPC) dtxt '_' mapMethod '.mtx']

%Region of Interest
rowmin  = 175;
rowmax  = 450;
rowlen  = rowmax - rowmin + 1;
colmin  = 250;
colmax  = 400;
collen  = colmax - colmin + 1;

maski = MASK_FIRST;
frame_group_first = maski - (nPC-1) * MASK_STEP;
frame_group_last  = maski;

tic
hWB = waitbar(0, 'Progress');

%Prepare Principle Component Transform
orig = readframes(sourcePath, sourceName, ...
    frame_group_first, frame_group_last, MASK_STEP, ...
    NCOLS, NROWS, rowmin, rowlen, colmin, collen);
T = computePCT(orig);

%Prepare transforms
pca = reshape(orig, [], nPC) * T;
switch(mapMethod)
    case 'none'

        case 'zgamma'
            pca = zscore(pca); %compute z-scores
            x4m = nonlinMap(pca, 'gamma', 0.5, 100); %compute gamma mapping
parameters
        case 'zagamma'
            pca = abs(zscore(pca)); %compute z-scores and rectify
            x4m = nonlinMap(pca, 'gamma', 0.5, 100); %compute gamma mapping
parameters
end

maskN = imread(maskNpath);
seqY = [];
seqN = [];
pca_last = [];

while(frame_group_last <= MASK_LAST)

    orig = readframes(sourcePath, sourceName, ...
        frame_group_first, frame_group_last, MASK_STEP, ...
        NCOLS, NROWS, rowmin, rowlen, colmin, collen);

    %Principle component Transform
    %T = computePCT(orig);
    pca = reshape(orig, [], nPC) * T;

    %PC mapping
    switch(mapMethod)
        case 'zgamma'
            pca = zscore(pca); %compute z-scores
            pca = nonlinMap(pca, x4m); %apply gamma mapping
        case 'zagamma'
            pca = abs(zscore(pca)); %compute z-scores
            pca = nonlinMap(pca, x4m); %apply gamma mapping
    end
end

```



```

%Plot histograms
for i = 1 : 6
    subplot(2,3,i), hist(pca(:,i), 100)
    title(['PC' num2str(i)]);
end

%Load masks
maskY = loadMtx([maskYpath num2str(maski) '.mtx']);

%Extract sequences from the heat and nonheat masks
%ABOVE-AVERAGE RISK AREA THAT COULD EXPLAIN THE MALO I'M SEEING
nind = find(maskN); %indices of ones in maskN
ri = randi(numel(nind), 25, 1); %select 25 of these at random
if doDelay
    if ~isempty(pca_last)
        seqY = [seqY [pca(maskY, 1:3)'; pca_last(maskY, 1:3)']];
        seqN = [seqN [pca(nind(ri), 1:3)'; pca_last(nind(ri), 1:3)']];
    end
else
    seqY = [seqY pca(maskY, :)'];
    seqN = [seqN pca(nind(ri), :)'];
end

pca_last = pca;

waitbar((maski-MASK_FIRST+1)/(MASK_LAST-MASK_FIRST), hWB, ['Completed PCA
sequence extraction for frame ' num2str(maski)]);
maski = maski + MASK_STEP;
frame_group_first = maski - (nPC-1) * MASK_STEP;
frame_group_last = maski;
end
toc
close(hWB);
size(seqY);

%Save data to file
saveMtx(seqY, savePathY);
saveMtx(seqN, savePathN);

```

ErrorAnalysis.m

```
%%-----%
% Author      :   Daniel Kohler
% Date       :   4/30/12
%
% Description:
%For a set of classification channels, counts how many pixels fall into
%regions by category (heat, pedestrian, trees and noisy spots, cars).
%Reports percentage error.
%-----%

%5/23/12: removed mask path arguments. Assume constant, for simplicity.

function [E heat nonHeat ped car noise] = ErrorAnalysis(...
    classificationPath, channels, frameFirst, frameStep, frameLast, ...
    doGraph, barLabels)

if nargin < 1

    classificationPath = 'F:\Fire_Data_6-18-
11_MW_LW\CMWIR\oats1_PFstab\classification\';
    channels = {'varStats_loose_-_isAll120_medfilt3'};

    frameFirst = 510;
    frameStep = 10;
    frameLast = 8000;

    doGraph = true;
end
if nargin < 6
    doGraph = false;
end

pathY = 'F:\Fire_Data_6-18-
11_MW_LW\CMWIR\oats1_PFstab\training\heatRegionY2.bmp';
pathN = 'F:\Fire_Data_6-18-
11_MW_LW\CMWIR\oats1_PFstab\training\nonHeatRegion2.bmp';
pathPed = 'F:\Fire_Data_6-18-
11_MW_LW\CMWIR\oats1_PFstab\training\pedRegion.bmp';
pathCar = 'F:\Fire_Data_6-18-
11_MW_LW\CMWIR\oats1_PFstab\training\carRegion.bmp';
pathNoise = 'F:\Fire_Data_6-18-
11_MW_LW\CMWIR\oats1_PFstab\training\noiseRegion.bmp';

%Load masks
clasY = imread(pathY);
clasN = imread(pathN);
clasPed = imread(pathPed);
clasCar = imread(pathCar);
clasNoise = imread(pathNoise);

hWB = waitbar(0, 'Progress');

%Prepare and clear region counters
heat = [];
nonHeat = [];
ped = [];
car = [];
noise = [];

i = 1;
fi = frameFirst;
```

```

while(fi <= frameLast)
    for j = 1 : length(channels)
        f = loadMtx([classificationPath channels{j} '\ ' num2str(fi(i))
'.mtx']);

        heat(i, j) = single(sum(sum(f & clasY)));
        nonHeat(i, j) = single(sum(sum(f & clasN)));
        ped(i, j) = single(sum(sum(f & clasPed)));
        car(i, j) = single(sum(sum(f & clasCar)));
        noise(i, j) = single(sum(sum(f & clasNoise)));
    end

    waitbar((fi(i)-frameFirst+1)/(frameLast-frameFirst), hWB, [num2str(fi(i))
 '/' num2str(frameLast)]);
    fi(i+1) = fi(i) + frameStep;
    i = i + 1;
end
fi = fi(1:end-1); %remove the extra
close(hWB);

E = nonHeat ./ (heat + nonHeat);

disp('Net error rates for trials:');
E(isnan(E)) = 0;
mean(E)

if doGraph
    %Plot error rate over frame index
    if length(channels) == 1

        figure
        hold on
        subplot 211, plot(fi, [heat nonHeat]);
        legend 'True' 'False';
        title('Correct Classification Per Frame');
        ylabel('Count');
        hold off
        subplot 212, plot(fi, E);
        title('Error Rate Per Frame');
        xlabel('Frame Index');
        ylabel('Count');
    else
        figure
        hold on
        subplot 311, plot(fi, heat);
        title('Approximate Correct Classification Per Frame');
        ylabel('Count');
        subplot 312, plot(fi, nonHeat);
        title('Approximate Incorrect Classification Per Frame');
        ylabel('Count');
        hold off
        subplot 313, plot(fi, E);
        title('Error Rate Per Frame');
        xlabel('Frame Index');
        ylabel('Count');
    end

    %Bar plot
    figure
    heatT = sum(heat); %total errors per channel
    pedT = sum(ped);
    carT = sum(car);
    noiseT = sum(noise);
end

```

```

        plotData = [heatT; pedT; carT; noiseT]';
        bar(plotData);
        set(gca, 'XtickLabel', barLabels);
        legend('Heat Pedestrian Car Noise');
        title('Categorized Detection Count Per Channel')
    end

end

```

stabilizeVidPFraw.m

```

%%-----%
%   Author:      Daniel Kohler
%   Date:        3/12/12
%
% POINT FEATURE VIDEO STABILIZATION
% Based on the example given at the following webpage:
% http://www.mathworks.com/products/computer-vision/demos.html?
% file=/products/demos/shipping/vision/videostabilize_pm.html
% THE FOLLOWING IS THE CONTENT OF cvexEstStabilizationTform AND
% cvexTformToSRT
%
% REQUIRES that input be type DOUBLE.
%
%How to interface this with existing efforts?
% 1. Input frameMat, output stabilized frameMat
% 2. Input paths to raw, output parallel stabilized raw
%THIS FILE IMPLEMENTS 2. stabilizeVidPF.m implements 1.
%-----%

function stabilizeVidPFraw
tic;

showProgress = true;

sourcePath = ...
    'F:\Fire_Data_6-18-11_MW_LW\CMWIR';
sourceName = 'oats1';

%VIDEO-SPECIFIC DATA. MUST PROVIDE.
nrows      = 480;
ncols      = 640;
frame_first = 1595;
frame_last  = 2400;      %last index

%CONFIGURATION
maxPts = 150;           %Num corner pts to extract from each frame
ptThresh = 1e-3;        %Corner detection sensitivity
neighborhoodSize = 9     %Odd number, default 9

%% PROCESS ENTIRE VIDEO

if showProgress
    WB = waitbar(0);
end

hGTE = vision.GeometricTransformEstimator;
hGT = vision.GeometricTransformer;
hGTPrj = vision.GeometricTransformer;

hCD = vision.CornerDetector( ...

```

```

        'Method','Local intensity comparison (Rosen & Drummond)', ...
        'MaximumCornerCount', maxPts, ...
        'CornerThreshold', ptThresh, ...
        'NeighborhoodSize', [neighborhoodSize neighborhoodSize]);

% Process all frames in the video

filepath = strcat(sourcePath,'\ ',sourceName,'\ ', ...
                  sourceName,'_',num2str(frame_first), '.raw');
fid      = fopen(filepath, 'r');
movMean  = single(fread(fid, [nrows ncols], 'uint16'));
fclose(fid);

imgB = movMean;
imgBp = imgB;
refFrame = movMean;
correctedMean = imgBp;

for ii = frame_first+1 : frame_last
    % Read in new frame
    filepath = strcat(sourcePath,'\ ',sourceName,'\ ', ...
                      sourceName,'_',num2str(ii), '.raw');
    fid      = fopen(filepath, 'r');
    imgB     = single(fread(fid, [nrows ncols], 'uint16'));
    fclose(fid);

    movMean = movMean + imgB;

    if(1) %Generate pretty graphs for demo purposes.
        pointsA = step(hCD, refFrame);
        pointsB = step(hCD, imgB);

        cvexShowImagePair(imadjust(refFrame/2^14), imadjust(imgB/2^14), ...
                           'Corners in reference frame', 'Corners in next frame', ...
                           'SingleColor', pointsA, pointsB);

        % Extract features for the corners
        blockSize = 9; % Block size.
        [featuresA, pointsA] = extractFeatures(refFrame, pointsA, ...
                                                'BlockSize', blockSize);
        [featuresB, pointsB] = extractFeatures(imgB, pointsB, ...
                                                'BlockSize', blockSize);

        % Match features which were found in the current and the previous
frames
        indexPairs = matchFeatures(featuresA, featuresB, 'Metric', 'SSD');
        pointsA = pointsA(indexPairs(:, 1), :);
        pointsB = pointsB(indexPairs(:, 2), :);
        cvexShowMatches(imadjust(refFrame/2^14), imadjust(imgB/2^14), ...
                         pointsA, pointsB, 'Referece Frame', 'Test Frame');
    end

    H = cvexEstStabilizationTform(refFrame, imgB, hCD, hGT, hGTE);
    imgBp = step(hGTPrj, imgB, H);

    % Display as color composite with last corrected frame
    if showProgress
        waitbar((ii-frame_first)/(frame_last-frame_first), WB, ...
                ['Saving ' sourceName '\_PFstab\_ ' num2str(ii) '.raw']);
    end
    correctedMean = correctedMean + imgBp;

    if(0)

```

```

        filepath      = strcat(sourcePath, '\\', sourceName, '_PFstab\\',      ...
                                sourceName, '_PFstab_', num2str(ii), '.raw');
        fid            = fopen(filepath, 'w');
        fwrite(fid, imgBp, 'uint16');
        fclose(fid);
    end
    %ii = ii+1;

end

correctedMean = imadjust((correctedMean/frame_last)/2^16);
movMean = imadjust((movMean/frame_last)/2^16);
figure(1)
subplot(121), imshow(movMean), title('input movie average');
subplot(122), imshow(correctedMean), title('stabilized movie average');

if showProgress
    close(WB);
end

toc;
end

```