

**Micro-Forest Fire Detection (MFFD)
LWIR detector and Principle Component Analysis
for Fire Detection**

By

Bryce Du

Senior Project

**Electrical Engineering Department
Cal Poly San Luis Obispo
Raytheon Co.**

Table of Contents

Sections

Acknowledgements.....	4
I. Introduction.....	4
II. The Experiment.....	5
III. PCA Background.....	14
IV. Results of Principle Component Analysis.....	16
V. Conclusion and Future Work.....	21
VI. Bibliography.....	22

Appendices

A. Test Images Before the Smoke.....	23
B. Test Images After the Smoke.....	31
C. Analysis of Senior Project.....	39

List of Figures

Figures

1. 9:36am LWIR and Visible.....	6
2. 9:53am LWIR and Visible.....	7
3. 10:20am LWIR and Visible	8
4. 10:26am LWIR and Visible	9
5. 10:48am LWIR and Visible	10
6. 11:56am LWIR and Visible	11
7. 11:58am LWIR and Visible	12
8. 12:07pm LWIR and Visible	13
9. Basic PCA Example.....	15
10. PCA of 15 Images at 12:06pm.....	16
11. PCA of 15 Images at 12:07pm.....	18
12. PCA 1, 2, 3, 4 Side by side Comparison.....	20

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Introduction

The Mirco-Forest Fire Detection team (MFFD) is working with Raytheon Co. on a ground based fire detection system in Goleta, CA to effectively locate a small fire before it can grow into a multi-million dollar disaster. Because we intend to create a ground based detection system, we are aware of the possibilities of objects within the line of sight of the source. Our goal is to detect the smoke plume from above the source such that Line of Sight of the fire is not required or needed.

We started our research by using a LWIR camera on a test fire approximately 800m away. With the data collected, our team decided to implement the use of Principle Component Analysis (PCA) to isolate the smoke plume. PCA is a method that can collect the principle components in data and present the results in layers. These layers can be used to detect the fire plume as well as the source of the fire. The MFFD team decided to use the PCA on a fixed area over small interval of time to detect the fire. The results reveal a plume of smoke directly above the source of the fire.

The Experiment

On May 08, 2010, the member of the MFFD Team participated in an experiment where we would create a test fire within a barbeque trailer to simulate a small fire. The goal for the MFFD Team is to detect the presence of a fire before it spreads and becomes uncontrollable. The detector we used for the experiment was a LWIR camera with the follow specifications:

640x480 resolution

25u pixels

77mm lens

The camera was places approximately 20 meters in the air

Positioned about 800 meters away.

The MFFD Team decided to use coals as a way to fuel the test fire. We began by using a 1' x 1.5' coal bed at 9:36am seen in Figure 1.

We were able to barely notice the fire in the LWIR but also (in the video recording) the presence of heat leaving the fire through pixel variations directly above the source. The variations are invisible in the screen shots but exist as you watch the video over time.

The team continued on the experiment by increasing the intensity of the fire as well as adding branches and leaves to create smoke. The following figures will provide a timeline of screen shots for the experiment. (Figures 2-8)



Figure 1
May 8, 2010 9:36am
LWIR (top) and Visible (bottom)
1' x 1.5' Coal Bed



Figure 2
May 8, 2010 9:53am
LWIR (top) and Visible (bottom)
1' x 1.5' Coal Bed



Figure 3
May 8, 2010 10:20am
LWIR (top) and Visible (bottom)
2' x 2' Coal Bed with burning debris



Figure 4
May 8, 2010 10:26am
LWIR (top) and Visible (bottom)
2' x 2' Coal Bed with burning Debris



Figure 5
May 8, 2010 10:48am
LWIR (top) and Visible (bottom)
2' x 3' x 1' Pyramid with Debris



Figure 6
May 8, 2010 11:56am
LWIR (top) and Visible (bottom)
8 bags of coal + Debris (Largest Fire)



Figure 7
May 8, 2010 11:58am
LWIR (top) and Visible (bottom)
8 bags of coal + Debris (Largest Fire)



Figure 8
May 8, 2010 12:07pm
LWIR (top) and Visible (bottom)
8 bags of coal + Debris (Largest Fire)

PCA Background

The basis of principle component analysis is to isolate the principle components into layers and review them to analyze the variations in the datasets. A principle component is a set of orthogonal axes that define a projection that will encapsulate the maximum amount of variation in the dataset. Essentially, the first principle component will contain most of the constant background data while the following principle component layers will contain the variations. The Figure 9 has a simple example of a Principle Component Transformation. The amount of datasets you input into the PCA is equal to the number of principle component layers you get out.

The PCA is a great way to isolate the minute variations in the data, so we decided to implement the PCA on a fixed test area over a period of time to isolate the smoke plume above the fire source. As the fire continues to run its course, the pixels of heat will be detected by our camera and stored onto screen shots. These pixels will be invisible to the naked eye however these high intensity pixels exist and can be isolated using the PCA. The screen shots will be collected over a period of time and then used for a PCA. The heat being dissipated above the fire will present itself in the second or third levels of the PCA.

A Simple Example of Principal Component Transformation

Finding the Mean Vector

1	2	2	Band 1
3	2	3	4
4	4	3	4
6	7	5	Band 2

Set of two multispectral images

$$\text{Average band 1} = (1+2+2+3+4+4+5+6) / 9 = 3.444$$

$$\text{Average band 2} = (2+3+4+4+3+4+6+7+5) / 9 = 4.222$$

Mean Vector

$$\begin{bmatrix} u_1 \\ u_2 \end{bmatrix} = \begin{bmatrix} 3.44 \\ 4.22 \end{bmatrix}$$

Finding the Variances

Band 1 with mean removed

1-3.44 = -2.44	2-3.44 = -1.44	2-3.44 = -1.44
3-3.44 = -0.44	4-3.44 = +0.56	4-3.44 = +0.56
4-3.44 = +0.56	5-3.44 = +1.56	6-3.44 = +2.56

Band 2 with mean removed

2-4.22 = -2.22	3-4.22 = -1.22	4-4.22 = -0.22
4-4.22 = -0.22	3-4.22 = -1.22	4-4.22 = -0.22
6-4.22 = +1.78	7-4.22 = +2.78	5-4.22 = +0.78

$$\text{Variance band 1} = [(-2.44)^2 + (-1.44)^2 + (-1.44)^2 + (-0.44)^2 + (+0.56)^2 + (+0.56)^2 + (+1.56)^2 + (+2.56)^2] / 9 = 2.52$$

$$\text{Variance band 2} = [(-2.22)^2 + (-1.22)^2 + (-0.22)^2 + (-0.22)^2 + (-1.22)^2 + (-0.22)^2 + (+1.78)^2 + (+2.78)^2 + (+0.78)^2] / 9 = 2.44$$

(1)

To find the Principal Component Transformation Matrix T

First find the eigenvectors t_i and eigenvalues λ_i from the covariance matrix

$$C t_i = \lambda_i t_i$$

$$\begin{bmatrix} 2.52 & 1.76 \\ 1.76 & 2.44 \end{bmatrix} t_i = \lambda_i t_i$$

$$t_1 = \begin{bmatrix} -0.7154 \\ -0.6987 \end{bmatrix}$$

$$\lambda_1 = 4.25$$

$$t_2 = \begin{bmatrix} 0.6987 \\ -0.7154 \end{bmatrix}$$

$$\lambda_2 = 0.72$$

We now form the transformation T matrix by placing the eigenvectors next to each other based on decreasing values of eigenvalues

$$T = [t_1 : t_2 : \dots : t_n]^T = \begin{bmatrix} -0.7154 & 0.6987 \\ -0.6987 & -0.7154 \end{bmatrix}^T$$

$$T = \begin{bmatrix} -0.7154 & -0.6987 \\ 0.6987 & -0.7154 \end{bmatrix}$$

(3)

Finding the Covariance

Band 1 with mean removed

-2.44	-1.44	-1.44
-0.44	+0.56	+0.56
+0.56	+1.56	+2.56

Band 2 with mean removed

-2.22	-1.22	-0.22
-0.22	-1.22	-0.22
+1.78	+2.78	+0.78

Covariance between band 1 and band 2

$$= [(-2.44) \cdot (-2.22) + (-1.44) \cdot (-1.22) + (-1.44) \cdot (-0.22) + (-0.44) \cdot (-0.22) + (+0.56) \cdot (-1.22) + (+0.56) \cdot (-0.22) + (+0.56) \cdot (+1.78) + (+1.56) \cdot (+2.78) + (+2.56) \cdot (+0.78)] / 9 = 1.76$$

Setting up the Covariance Matrix C

Set of two multispectral images

1	2	2	Band 1
3	2	3	4
4	4	3	4
6	7	5	Band 2

Covariance Matrix

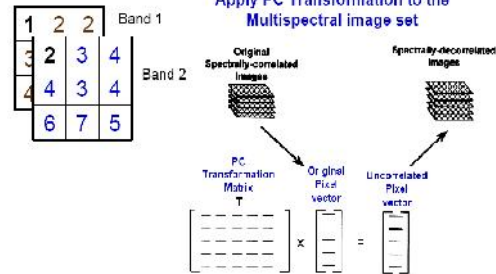
$$C = \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix} = \begin{bmatrix} 2.52 & 1.76 \\ 1.76 & 2.44 \end{bmatrix}$$

Correlation Coefficient Matrix

$$\begin{bmatrix} 1.0 & 0.7 \\ 0.7 & 1.0 \end{bmatrix}$$

(2)

Apply PC Transformation to the Multispectral image set



$$\begin{bmatrix} -0.7154 & -0.6987 \\ 0.6987 & -0.7154 \end{bmatrix} \times \begin{bmatrix} 1 \\ 2 \end{bmatrix} = \begin{bmatrix} -2.11 \\ -0.73 \end{bmatrix}$$

Final Principal Component images

(the floating numbers have to be mapped to integers in the range of 0-255)

Principal Component 1

-2.11	-3.53	-4.22
-4.94	-4.96	-5.68
-7.05	-8.47	-7.79

$$\text{Variance} = \lambda_1 = 4.25$$

Principal Component 2

-0.73	-0.75	-1.46
-0.77	+0.65	-0.07
-1.49	-1.51	+0.61

$$\text{Variance} = \lambda_2 = 0.72$$

PC1 has $[4.25 / (4.25 + 0.72) \times 100] = 85.5\%$ of the energy (information content) of the set of two spectral images

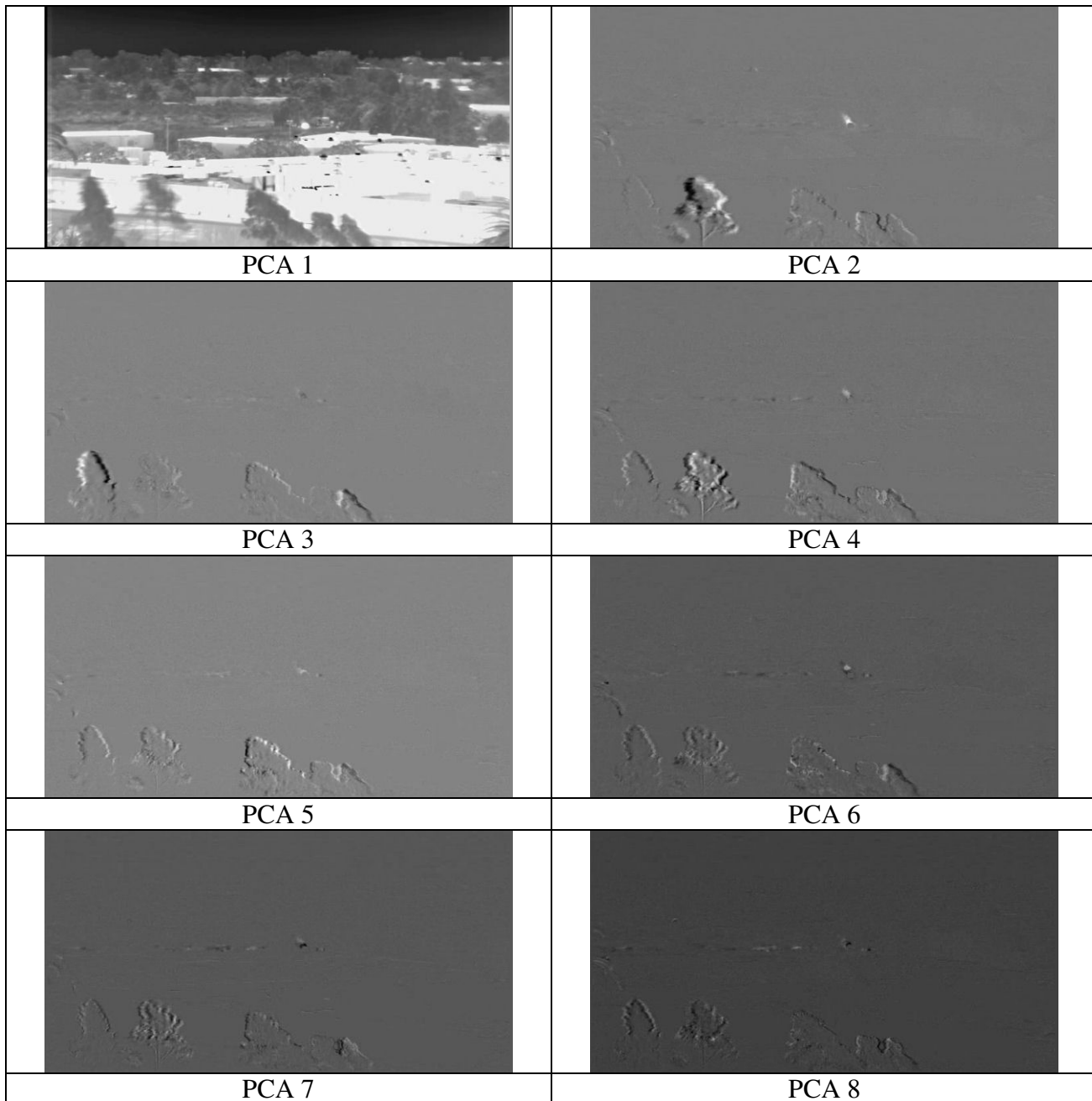
(4)

Figure 9
Basic PCA Example

Results of the Principle Component Analysis

When doing the PCA, I decided to use two different datasets from the experiment; one contained a small fire with negligible smoke while the other contained the largest fire with the most amount of smoke during. I used 15 screen shots taken over a 13 second period and ran it through our PCA program to output the following results.

The input images can be seen in the Appendix. Figure 10 shows the PCA results for a 13 second interval with little or no smoke appearing above the fire source.



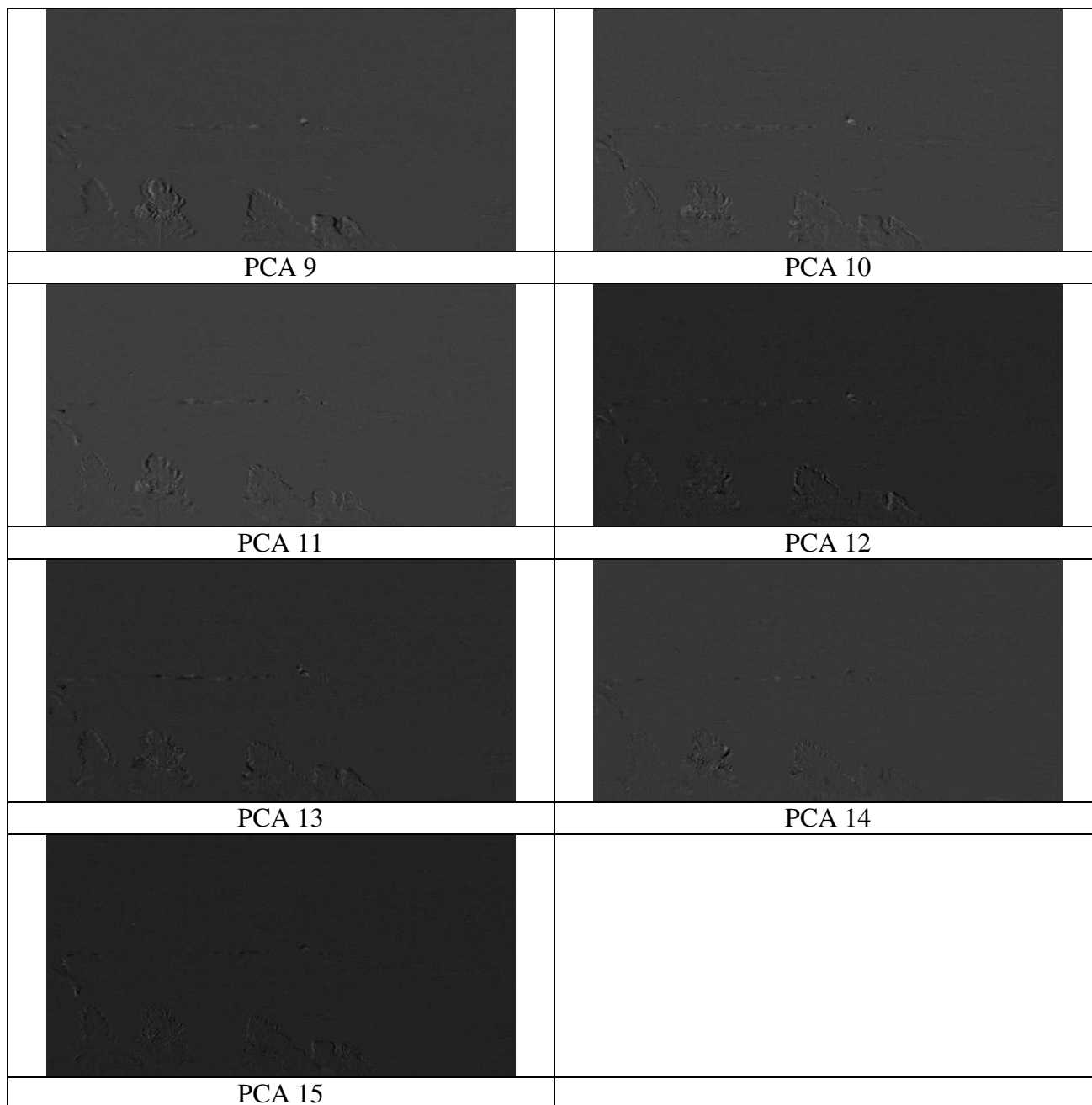
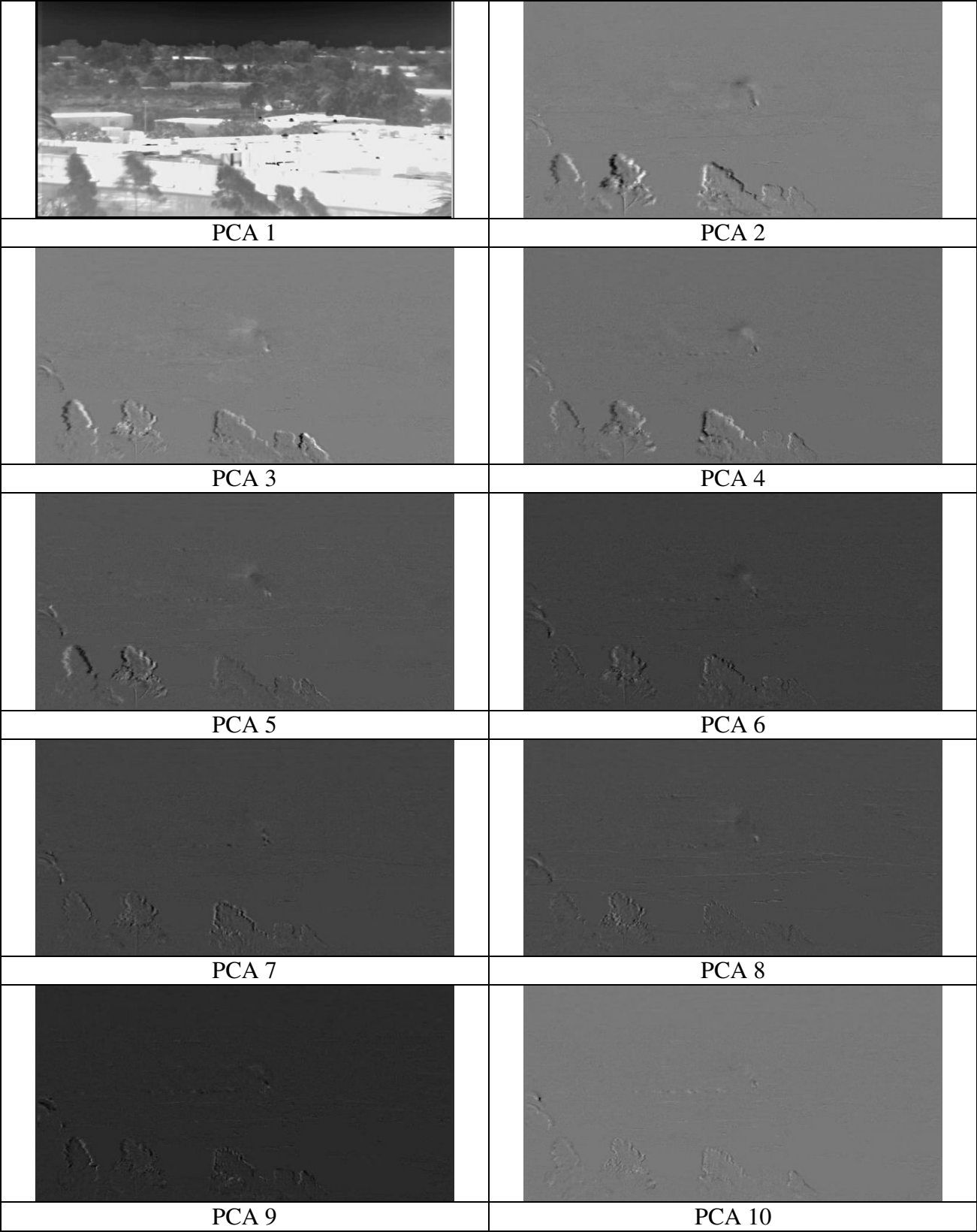


Figure 10
PCA of 15 Images at 12:06pm

The PCA showed evidence of the smoke plume. Although there was no visible plume of smoke during the experiment, the PCA picked up a small signal above the fire. One issue with the PCA results is the existence of the swaying trees. These trees give false positives within the PCA and must be removed and filtered for this method to be successful.

The next set of images in Figure 11 will be a PCA of the area but with a larger fire. This will allow for better results.

Figure 11 is the results with a larger smoke plume. Again, the input images are attached in the Appendix.



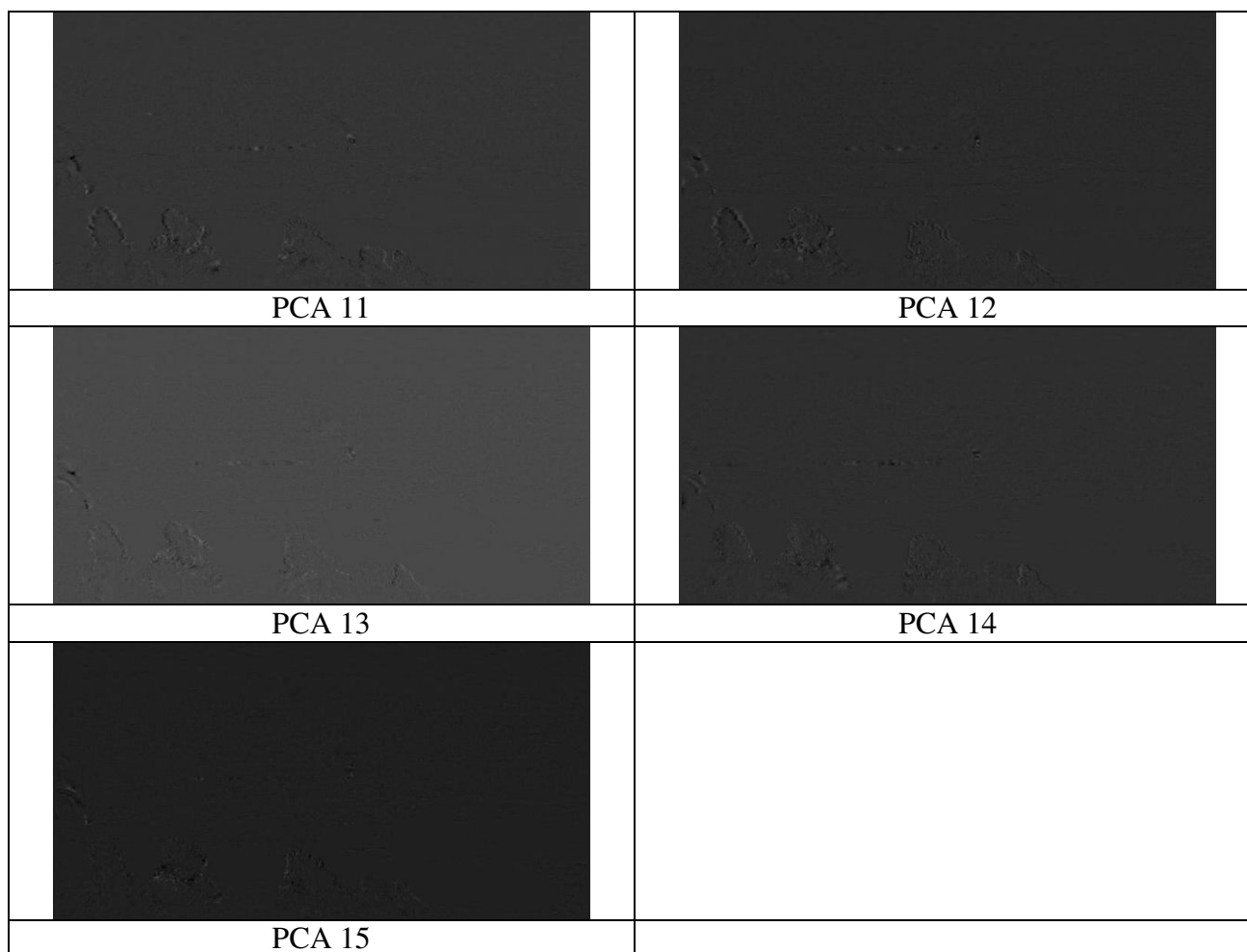


Figure 11
PCA of 15 Images at 12:07pm

Doing the PCA on the images with a larger smoke plume revealed a more noticeable signal within each layer. The trees still appear in these and still require a filter to remove them. However, the result is noticeable during the smaller stages of the fire.

Generally, more than 90% of the variations in the datasets present themselves in the first two or three principle component layers. Figure 12 is a side by side comparison of the two different PCA results.

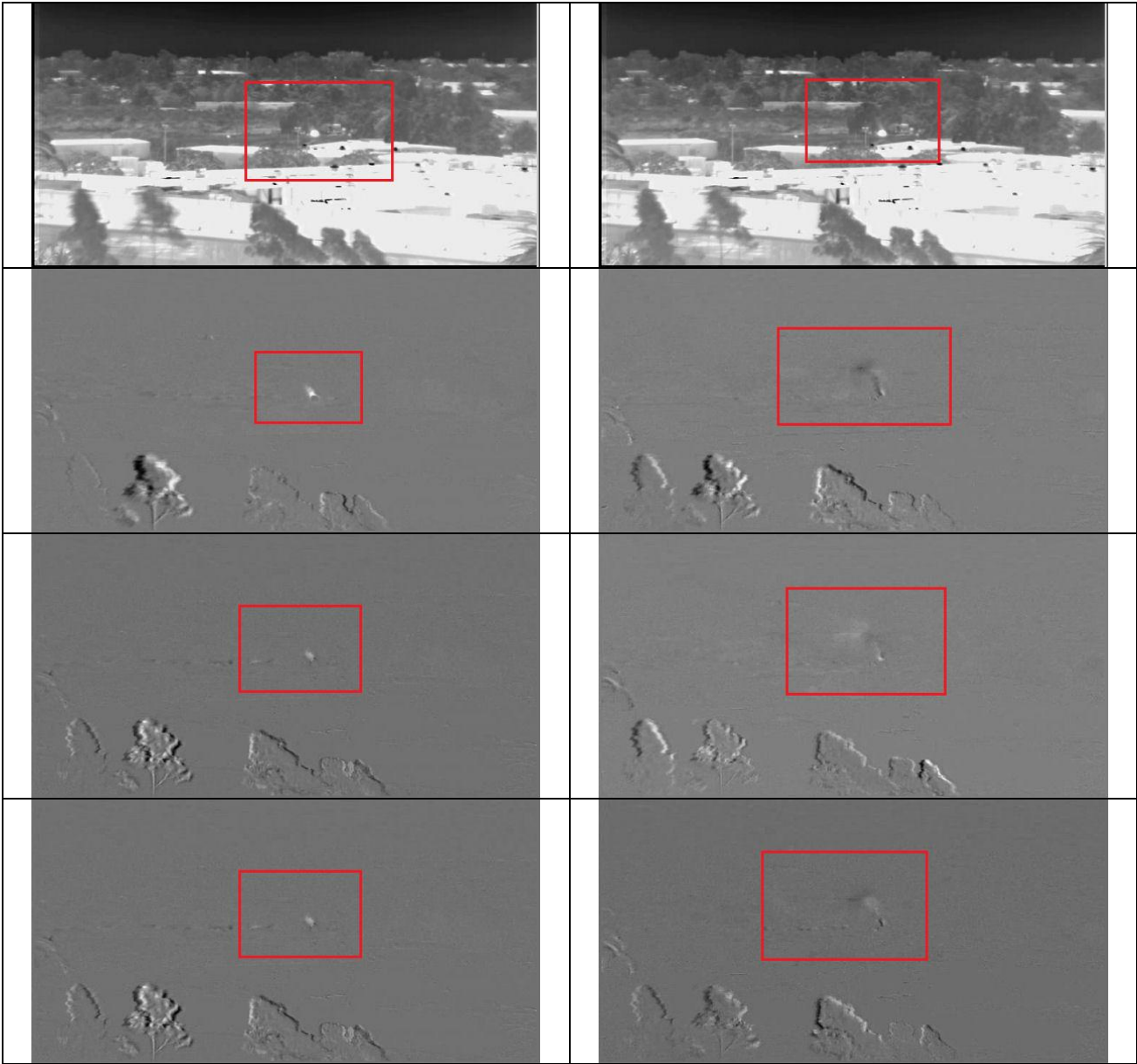


Figure 12
PCA 1, 2, 3, 4
Side by side Comparison
No smoke (Left) and Smoke (Right)

Conclusion and Future Work

With the results we have from the PCA, we can easily detect a fire at the smaller stages before it grows rampant. The PCA reveals a smoke plume directly above the source of the fire which is the information we want to prevent a large fire. Also, the PCA analysis was able to detect the fire by only using data acquired over a 15 second period.

However, the false positives are an issue. The waving of the trees and the passing of the cars appear on the PCA layers. These false positives will require filters to prevent them from appearing for the final product. We know that the frequency of the fire plume will differ from the cars and trees such that a specific low-pass filter can improve results. Also, because the PCA uses the mean of the matrix, Adaptive Principle Component Analysis is a method that segments parts of the matrix and run a PCA on the individual entities. Adaptive PCA would isolate the area of interest and detect the presence of a smoke plume.

During the experiment, we were using a LWIR camera within the 8 – 15 μm range such that this is only finding thermal readings. Forest fires appear much brighter in the 3 – 5 μm range. In the future, the MFFD team plans to use a MWIR camera that will detect the fire better than the LWIR we used in this experiment. In addition to the new detector, the use of an Adaptive PCA would improve the results. The MFFD team plans to continue on the research to find the best ground based fire detection system.

Bibliography

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February 26, 2002

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Spring 2010

Appendix A

Appendix A contains the raw LWIR images used in the PCA of the fire before the smoke plume existed. The raw images are in chronological order and are time stamped.



Appendix A Figure 1
LWIR @ 12:06:40 (top)
LWIR @ 12:06:41 (bottom)



Appendix A Figure 2
LWIR @ 12:06:42 (top)
LWIR @ 12:06:43 (bottom)



Appendix A Figure 3
LWIR @ 12:06:43 (top)
LWIR @ 12:06:44 (bottom)



Appendix A Figure 4
LWIR @ 12:06:45 (top)
LWIR @ 12:06:46 (bottom)



Appendix A Figure 5
LWIR @ 12:06:47 (top)
LWIR @ 12:06:48 (bottom)



Appendix A Figure 6
LWIR @ 12:06:49 (top)
LWIR @ 12:06:50 (bottom)



Appendix A Figure 7
LWIR @ 12:06:51 (top)
LWIR @ 12:06:52 (bottom)



Appendix A Figure 8
LWIR @ 12:06:53 (top)

Appendix B

Appendix B contains the raw LWIR images used in the PCA for the largest smoke plume. These images were captured and used as the inputs for the PCA. The images are in chronological order.



Appendix B Figure 1
LWIR @ 12:07:30 (top)
LWIR @ 12:07:30 (bottom)



Appendix B Figure 2
LWIR @ 12:07:31 (top)
LWIR @ 12:07:32 (bottom)



Appendix B Figure 3
LWIR @ 12:07:33 (top)
LWIR @ 12:07:34 (bottom)



Appendix B Figure 4
LWIR @ 12:07:35 (top)
LWIR @ 12:07:36 (bottom)



Appendix B Figure 5
LWIR @ 12:07:37 (top)
LWIR @ 12:07:38 (bottom)



Appendix B Figure 6
LWIR @ 12:07:39 (top)
LWIR @ 12:07:40 (bottom)



Appendix B Figure 7
LWIR @ 12:07:41 (top)
LWIR @ 12:07:42 (bottom)



Appendix B Figure 8
LWIR @ 12:07:43 (top)

Analysis of Senior Project Form

Appendix C

• Summary of Functional Requirements

The goal for the Micro-Forest Fire Detection team is to create a ground-based fire detection system that uses IR detectors to locate a fire in the early stages before spreading and causing a million dollar disaster. Currently, my senior project is an analysis of the use of Principle Component Analysis in conjunction with a LWIR camera to detect a plume of smoke directly a fire source. The project's intensions are to demonstrate and show that the PCA of a fixed area over a small period of time can be used to detect a fire plume that will locate the source of the fire.

With proof that a PCA over a fixed area can locate a fire, we intend to place IR cameras in strategic locations to overlook a large area such as Santa Barbara County. The ability to locate the smoke plume can remove any line-of-sight issues with the source of the fire.

• Primary Constraints

The detector type is the limiting factor. We require a IR camera that does not requires maintenance, a cooling system, and within the Mid-wave band. We are looking for a detector that can see within the 3-5um waveband however these cameras are very expensive.

Because the cameras the project worked with are extremely expensive, the team used their resources with Raytheon and Cal Poly to be able to run an experiment in Goleta, CA. The experiment used the PS360 which is a multispectral detector with detection ranges within the LWIR, SWIR, and Visible Light but each with different resolution (some ranging from 480x600 and 1280x1080). We used these datasets to run a PCA however the differences in resolution made it impossible. At this point, we decided to attempt something different and run a PCA of a fixed area over a small period of time and review the results. The results showed us a way to isolate the variations in the rising smoke plume.

The Raw 10-bit data from the detectors were compressed into 8-bit .AVI files reducing the accuracy of the data. In addition, we were only working in the 8-15um detector range rather than the 3-5um detector range we initially wanted to work in. Aside from that, the use of the PCA over a period of time still worked effectively in detecting the smoke plume. If applied onto the MWIR detector, we expect even more promising results.

• Economic

No component parts required for the project.

Final costs: \$0

Original development time: Beginning Stages of the project, no set final date.

Actual development time: On-going project, still no final date.

• If manufactured on a commercial basis:

No manufactured device proposed yet. The team is still in search for the best detector type and the best analysis method.

• Environmental

The main purpose of this project is to impact the environment positively. The idea of a ground-based fire detection system began with the purpose to prevent the millions of dollars lost in damages from the forest fires in Santa Barbara County. Because the final product is intended for long-term use and low maintenance, there should be little or no negative effects on the environment until replacement and disposal is required.

• Manufacturability

We are currently not in the manufacturing phase of the project. We are in the process of deciding which IR camera is best suited for our specifications that require little or no maintenance.

• Sustainability

The IR detector will require low maintenance such that maintenance on the completed device will be minimal. Currently, the project team is looking into the best method in improving the detected signal from the PCA while determining the best IR detector for the final device.

• Ethical

This project's purpose is to eliminate the threat of forest fires destroying the homes and causing millions of dollars of damages. This project is only intended to prevent forest fires at the primitive levels.

The final project is intended to be sold to fire prevention organizations.

• Health and Safety

There isn't any health concerns associated with this project.

• Social and Political

The MFFD project is intended to prevent forest fires, providing greater safety to the community, and saving money from lost by these fires.

• Development

The newest idea in this project is the use of the Principle Component Analysis on a fixed area over a period of time. This method's purpose is to isolate the small variations within the image. In this project's case, the small variations are the rising smoke or remnants of heat from the source of the fire.