Early Forest Fire Detection in the Spectral Domain

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A special thanks goes to Raytheon RVS for allowing the use of their multispectral cameras and data acquisition equipment. Without their resources and support, this project would not have been possible.
I. INTRODUCTION

Forest fires are responsible for property damage, crop damage, air pollution, and most importantly, the loss of human life each year in the United States. With a system to detect fires in their infancies, the U.S. can save the annual $900 million spent to fight forest fires, as well as the additional $733 million annual costs in property and crop damage. Currently, there are satellite-based fire detection systems in place, but such systems prove to be inadequate due to their inability to perform constant surveillance of the same geographical area, as well as providing a spatial resolution that cannot detect fires until they have grown considerably in size (e.g. not suitable for early fire detection).

This project proposes a land-based early forest fire detection system which analyzes the infrared and visible spectral signatures of a fire’s plume and body. One visible and three infrared cameras are set up to record the same fire prone area (same field of view). The three different electromagnetic bands available are first spectrally analyzed at a point in time, and the combination of these spectral signatures across the visible and IR bands return a unique signature that is exclusive to a fire. More points in time are spectrally analyzed in the same way, giving a set of unique spectral signatures. These pixel intensities of the signatures in this set are then averaged to filter out the random behavior of a fire and its smoke plume, which results in a spectral signature in which a fire would exhibit. The spectral signature of the landscape can then be obtained and compared to this set, returning the probability that there is a fire in an analyzed area.

It is believed that this method in conjunction with the method of principal component analysis, which analyzes and isolates a fire in the temporal domain, produces a process that is more reliable in detecting early forest fires than any fire detection systems that are currently in use.
II. BACKGROUND, SPECIFICATIONS, & REQUIREMENTS

The data that has been captured for analysis consists of 14-bit cooled mid-wave IR (CMWIR), cooled long-wave infrared (CLWIR), uncooled mid-wave infrared (UCMWIR), and 8-bit visible images. The 14-bit IR images have possible pixel intensity values of 0 to 16384 ($2^{14}$), while the 8-bit visible images have possible pixel intensity values of 0-256 ($2^8$). The cameras were mounted on a tower about 800m away from the site of the fire pit.

The specifications of the four cameras used are shown in Table 1:

<table>
<thead>
<tr>
<th>Camera</th>
<th>Dynamic Range</th>
<th>Resolution</th>
<th>Focal Length (mm)</th>
<th>Pixel Size (μm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Visible</td>
<td>8-bit: 0-255</td>
<td>873x1068</td>
<td>Not known</td>
<td>Not known</td>
</tr>
<tr>
<td>Cooled MWIR</td>
<td>14-bit: 0-16383</td>
<td>640x480</td>
<td>100</td>
<td>20</td>
</tr>
<tr>
<td>Cooled LWIR</td>
<td>14-bit: 0-16383</td>
<td>640x480</td>
<td>100</td>
<td>20</td>
</tr>
<tr>
<td>Uncooled LWIR</td>
<td>14-bit: 0-16383</td>
<td>640x480</td>
<td>75</td>
<td>25</td>
</tr>
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Table 1 - Specifications of cameras used in data capture

From Table 1, it can be seen that there are four variables among the cameras that must be accounted for:

1. **Different dynamic range for visible camera** – While the IR cameras capture data with 14 bits, the visible camera can only capture 8 bits. This means that the visible camera will not be able to display as much detail in its picture compared to IR.

2. **Different resolution for visible camera** – The visible camera displays an area that consists of more pixels, which means that the visible image must be converted to a 640x480 image so that pixels can be compared 1-to-1.

3. **Different focal lengths of cameras** – With three different focal lengths (although the visible focal length size isn’t known, it can be seen that it is different from the others), there are three different “fields of view” (FOV) for the images. This means that the same area of the landscape isn’t captured—one set of frames from a camera effectively sees more (or less) of the area that an equivalent set of frames in time of another camera sees. As a result of this, the frames must be aligned before any comparisons across the bands can be made.

4. **Different pixel sizes** – Different pixel sizes may contribute to some error; for example, the 25μm pixel size of the uncooled LWIR camera will capture more data than a 20μm pixel of the cooled
cameras. Like the issue with different focal lengths, the uncooled data will have to be aligned with the cooled data so that the information being analyzed is the same for each pixel.

With so many key parameters to account for as a result of utilizing different cameras, it is to be expected that the necessary image transformation and alignment will contribute as the main sources of any errors that may occur.

III. DESIGN

The design of the early forest fire detection system is outlined in the block diagram in Figure 1:

As shown in the diagram, the method for fire detection is as follows:

1. Record & gather data from the four cameras.
2. Split video into individual frames. Although data is captured at 30 frames per second, only one frame per second is extracted due to the fact that there are virtually no differences between adjacent frames.
3. Align the images, using the image that shows the least amount of the landscape as the base image. This ensures that all the data shows the same area after alignment is performed.

4. Select frames of interest and visually identify the fire/smoke area. Record pixel intensity values of this area, and then average them to produce a unique signature for the fire/smoke in this image. Repeat for data from other cameras for images at the same point in time.

5. Step through each pixel in the image, comparing it with the unique signature and calculating the probability that the pixel represents smoke/fire. Repeat for data from other cameras for images at the same point in time.

6. Map the probabilities of the four sets of data to a 640x480 image. Combine these images to get a probability across the various electromagnetic bands. Apply thresholding to the image to isolate fire.
IV. EXPERIMENT/METHODOLOGY

The experiment was performed on the images in Figures 2 through 5.

Figure 2 - Visible image of test area
Figure 2A - Visible image zoomed in to identify fire source

Figure 3 - Uncooled long-wave IR image of test area
Figure 4 - Cooled long-wave IR image of test area

Figure 5 - Cooled mid-wave IR image of test area
A. Image Alignment

When comparing the uncooled long-wave image (Figure 3) with the uncooled IR images (Figures 4 and 5), it is apparent that the uncooled image does not share the same field of view. Thus, it is necessary to align the uncooled image as close to the cooled images as possible in order to make accurate comparisons. Since the uncooled image captures more of the area (a wider field of view), it is necessary to use the cooled images as the “base” images, and crop the uncooled image to match the cooled images.

The method used for alignment is simple: identify the common features/landmarks found in both uncooled and cooled and record their pixel positions. These common landmarks are shown in Figures 6 and 7. The red and yellow numbers in both images represent how many pixels on the x and y axes the common landmarks are from the edges of the images.

Figure 6 - Measuring two landmarks in CLWIR image that are common to UCLWIR
Figure 7 - Measuring same two landmarks in this UCLWIR image that are common to CLWIR

It can be seen that in the cooled image, the pixel ranges are as follows:

\[ x_c = 24:595 = 571 \text{ pixels} \]
\[ y_c = 41:301 = 260 \text{ pixels} \]

Similarly, the pixel ranges for the equivalent relative area in the uncooled image are as follows:

\[ x_{uc} = 138:481 = 343 \text{ pixels} \]
\[ y_{uc} = 100:260 = 160 \text{ pixels} \]

The ratio of cooled pixels to uncooled pixels is then:

\[ x_{\text{factor}} = \frac{571}{343} = 1.6647 \]
\[ y_{\text{factor}} = \frac{260}{160} = 1.6250 \]

Knowing these ratios, the next step is to convert cooled pixels to uncooled pixels. This is necessary to find how many pixels the uncooled image must be cropped by to match the cooled image.

Pixels to right edge = \( \frac{45}{1.6647} = 27.0319 \approx 27 \) pixels

Pixels to left edge = \( \frac{24}{1.6647} = 14.4170 \approx 14 \) pixels
Pixels to top edge = 179 / 1.625 = 110.1538 = 110 pixels

Pixels to bottom edge = 41 / 1.625 = 25.2307 = 25 pixels

Finally, the dimensions for the aligned uncooled LWIR image can be calculated:

\[ x_{uc,aligned} = (138 - 14) : (481 + 27) = 124:508 \]

\[ y_{uc,aligned} = (100 - 25) : (440 + 110) = 75:550 \]

This new cropped area is outlined in green in Figure 7. The last step is to apply interpolation to this image to have a resolution of 640x480, the same resolution as the cooled images (the same is done to the visible image). Figure 8 shows the final aligned uncooled long-wave IR image.

![Figure 8 - UCLWIR image after alignment with CLWIR](image)

It is important to note that Figure 8 lacks some sharpness that is present in Figure 7. This is due to two things: the conversion of cooled pixels to uncooled pixels (which consisted of rounding, as there are no fractions of pixels), and resizing the image to 640x480. It is expected that this will contribute to some error in the analysis.
B. Pixel Intensity & Probability Computations

Now that all the images are aligned, their pixel intensity values can be measured, and a spectral signature can be extracted. Figure 9 shows the pixel intensity values for all six wavelengths.

![Spectral Signatures of Fire Area and Smoke Plume](image)

The values are normalized from 0 to 1 (to account for the fact that IR data is 14-bit while visible is only 8-bit), and the bands are mapped on the horizontal axis as follows: 1=Blue, 2=Green, 3=Red, 4=cooled mid-wave, 5=cooled long-wave, 6=uncooled long-wave. The values are connected by lines in the graph to signify the intensity values for the same pixel position across the six bands. The blue data represents the entire image, while the red data represents only the manually selected fire area (see Figure 2A).

Figure 10 shows the averages of the data in Figure 9, with the blue line again representing the entire image and the red line representing the fire area. The red data is the primary focus, as this gives the unique spectral signature of the fire which is used to compare other pixels against.
Knowing the average intensity value of the fire, the probabilities of other pixel values representing fire pixels in the scene can be calculated. This is done by first measuring the maximum and minimum intensity values in the image for a particular band. Then, two assumptions can be made: the average value for that band represents 100% probability, and the intensity value that is farthest away from the average (either the max or min value), represents 0% probability, as there is no other possible value within the image that can be less of a “match” to the average intensity. By knowing the intensity values for 100% and 0% probability, all other probabilities for each intensity value can be calculated.

The cooled mid-wave IR 14-bit data is used to demonstrate, where possible intensity values can range from 0 to 16383:

| CMW max | 11307 |
| CMW mean | 7246.3 |
| CMW min | 175 |

Table 2 - CMW intensity values for computing probability (not normalized)
The first step is to identify which of the extremes is furthest from the mean:

\[
\text{DiffMax} = 11307 - 7246.3 = 4060.7
\]

\[
\text{DiffMin} = 7246.3 - 175 = 7071.3
\]

Since “DiffMin” is the larger of the two values, the minimum CMW value can be labeled as having 0% probability of representing a fire pixel, as there are no other values in the image that deviate further from the mean.

Knowing the values for 0% and 100%, the calculations for figuring the probabilities for the rest of the values is done by “percentage step” process. The percentage step represents how the probability changes from one intensity value to the next. This value is calculated below:

\[
\text{Percentage step} = \frac{100\%}{\text{DiffMin}} = \frac{100\%}{7071.3} = 0.0141\%
\]

(Note that if DiffMax is greater than DiffMin, DiffMax is used in this calculation instead)

Probabilities can now be assigned to each intensity value in the image. For example, a value of 7245—one value lower than the mean—yields a probability of \((100\% - 0.0141\%) = 99.9859\%\). The value of 7244 yields a probability of \([100\% - (2*0.0141\%)] = 99.9718\%\). The value of 2624 yields a probability of \([100\% - (4622*0.0141\%)] = 34.8298\%\). It can be seen that the general equation for processing the probability is:

\[
\text{Probability} = [100\% - (n*\text{Percentage step})]
\]

where \(n = (\text{average intensity} - \text{current pixel intensity})\) if average intensity > current pixel intensity 

or \(n = (\text{current pixel intensity} - \text{average intensity})\) if average intensity < current pixel intensity

The resulting probability values are shown in Figure 11. The peak of the resulting “pyramid” represents a 100% match at that particular intensity (for this example 7246), with probabilities tapering off on both sides of this value.
The same process is applied to the cooled long-wave and uncooled long-wave data. These results are shown in Figures 12 and 13.

**Figure 11 - Probabilities of pixel intensity values representing a fire pixel (cooled mid-wave IR)**

**Figure 12 - Probabilities of pixel intensity values representing a fire pixel (cooled long-wave IR)**
Figure 13 - Probabilities of pixel intensity values representing a fire pixel (uncooled long-wave IR)

After all the probabilities are calculated, they are divided by 100 to return values between 0 and 1, which makes it easier for MATLAB to show. Figures 14, 15, and 16 show probability images for cooled mid-wave, cooled long-wave, and uncooled long-wave IR data, respectively. Areas that are whiter indicate a higher probability of a fire in the image.
Figure 14 - Probability visualization of cooled mid-wave IR data

Figure 15 - Probability visualization of cooled long-wave IR data
The same analysis cannot be performed on the visible image. This is because it is made up of three separate 8-bit bands: blue, green, and red, which are combined to make the visible image shown in Figure 2. Therefore, the data cannot be analyzed separately, as doing so will return variation in the individual grayscale bands, not variation in the actual visible image. Additionally, the fact that the data is only 8-bits cripples the accuracy that is appreciated in the 14-bit images. Lastly, it is expected that the analysis of visible images would return a higher error rate compared to the IR images, as anything in the image that is the same color as the average intensity value of the fire area will falsely return a high probability of representing a fire. While these deficiencies of the visible image prevent it from standing on its own, it is still helpful when combined with the IR images to rid the final probability image of false heat signatures that the IR images label as having high probability of fire (i.e. the rooftops of buildings in Figure 16).
The probability calculation of the visible image begins with treating the pixels of the blue, green, and red bands as 3D points in space. Then, knowing the average pixel intensity values of the fire for each band, a vector representing the probabilities for each pixel of the visible image can be created using the Euclidean Distance formula:

\[
\text{Visual Image Probability} = \sqrt{(\text{current Blue pixel value} - \text{avg blue intensity})^2 + (\text{current Green pixel value} - \text{avg green intensity})^2 + (\text{current Red pixel value} - \text{avg red intensity})^2}
\]

The result is shown in Figure 17.

![Figure 17 - Probability visualization of visible data](image)

As the purpose of this project is to detect a fire utilizing multiple wavelengths of the electromagnetic spectrum, the next step is to combine the probabilities of the IR and visible data. The procedure for doing this is similar for finding the probability for the visual image using the Euclidean Distance formula:
Combined Probability =
\[ \sqrt{(\text{current Blue pixel value} - \text{avg blue intensity})^2 + (\text{current Green pixel value} - \text{avg green intensity})^2 + (\text{current Red pixel value} - \text{avg red intensity})^2 + (\text{current CMW pixel value} - \text{avg CMW intensity})^2 + (\text{current CLW pixel value} - \text{avg CLW intensity})^2 + (\text{current ULW pixel value} - \text{avg ULW intensity})^2} \]

The result of this probability is shown in Figure 18. Notice that the lone “bright” spot in the image is the fire.

![Figure 18 - Probability visualization of combined visible and IR data](image)

C. Image Relaxation & Thresholding

Figure 18 is an adequate representation of the probability of the fire, but it can be improved with the processes of relaxation and thresholding, which results in an binary image that displays pixels as either representing fire, or not at all. Relaxation is the idea that if a given pixel has a high probability of representing a fire, the probabilities that the pixels adjacent to it increase. Thresholding converts the probabilities to either a value of 0 or 1. If the probability is greater than or equal to an acceptable
probability defined by the user, then it is changed to a value of 1 and represents a fire. If it is less, it is changed to a value of 0 and does not represent a fire. The result of these two processes is shown in Figure 19. The acceptable probability used is 50% or greater.
V. CONCLUSION AND RECOMMENDATIONS

Preliminary results of this project are very promising. Recording pixel intensity values and assigning probabilities to each pixel in the images has proven to be an effective method in detecting a fire. More tests are necessary to confirm that this method works under different conditions, such as in a different environment and burn materials. An important thing to note is that the smoke plume of the fire wasn’t as prevalent as it is in Figure 2. There are two likely reasons for this. The first is that the plume did not exhibit a heat signature that was strong enough to differentiate it from the rest of the scene, and thus was not detected very well by the IR cameras. The second reason is that the plume had a visible intensity that was very similar to the items directly behind it, resulting in some loss of the signature in the visible band.

Next, the “percentage step” method used in figuring the probabilities of pixels for the IR images can be prone to errors due to noise. Since the probabilities are calculated using maximum and minimum intensity values, any noise that pushes the minimum or maximum beyond the real minimum or maximum of the images (i.e. noise min value < real min value, or noise max value > real max value) will skew the calculations and return false probability values, especially as the noise grows beyond the intensity range of the image.

Additionally, several improvements can be made so future data acquisition & tests are easier:

- Time-stamp all videos. This will make it easier to align frames from all the different cameras. The images used may not be 100% synchronized, which would skew the results. Time stamps in every image would make this a non-issue.
- Use a visible camera with a higher dynamic range than $2^8$. This will provide data with higher detail and accuracy, and would produce less false probability values (as seen in Figure 17).
- Use cameras with lenses that have the same focal lengths. This will assure that all cameras are capturing data in the same field of view. Working with different fields of view requires that the images be approximated to the desirable FOV, which requires transforming images and results in less reliable data and results.
- Use more bands, especially IR. More bands mean more accurate results, which means a lower error rate in detecting fires.
More tests and analysis. Due to the random nature of a fire, there isn’t a specific spectral signature that would represent all fires. Variables such as the environment in which the fire is occurring, the material(s) that are burning, and even the time of day and climate conditions of the surrounding area can produce signatures that are drastically different from one another.

Lastly, if Figure 19 is examined closely, it can be seen that two pixels at the top center of the image (located at (248, 52) and (250, 52)) are falsely labeled as fire pixels. Combining this method with another promising method, principal component analysis (PCA) in the temporal domain, should theoretically produce a comprehensive fire detection method that has a very low error rate.

VI. BIBLIOGRAPHY

APENDIX A – SENIOR PROJECT ANALYSIS

Project Title: Early Forest Fire Detection in the Spectral Domain
Student’s Name: Dennis Keyes  Student’s Signature: ____________________________
Advisor’s Name: John Saghri  Advisor’s Initials: ______  Date: _________________

• Summary of Functional Requirements
This project aims to create a system that will detect fires in their infancy before they grow out of control and destroy hundreds of acres of land, thousands of homes, and thousands of lives. This is done by capturing video of a landscape via IR and visible cameras and calculating the probability that a fire is occurring in a given area based on an average or typical spectral signature of an actual fire. The data from the two cameras provide comprehensive and unique sets of information that complement each other well for detection purposes.

• Primary Constraints
The biggest constraint in this project was that the camera specifications didn’t match one another. Varying dynamic bit ranges, resolutions, lens focal lengths (field of views), and pixel sizes all demand that images must be transformed and aligned prior to experimentation and analysis, leading to data that is not as accurate as in its original forms.

Additionally, the all data was captured in a controlled setting that does not necessarily represent a real-world environment where a fire would be detected, as fires break out in a variety of settings. This is particularly important for visible data, as the smoke plumes of early/small fires are often semi-transparent and exhibit a signature based on what is behind it.

• Economic
Final for project: $0 (no parts were required)
This is an ongoing project, and thus has no start or end date.
Manufacturers of cameras would be the main profiteers of this project, as well as state and federal governments that would otherwise contribute large amounts of money to fight fires.

• If manufactured on a commercial basis:
This project has not yet reached the manufacturing stage.

• Environmental
The main focus of this project is to improve the environment by preserving land that would otherwise be decimated by fire outbreaks, so it has a potentially large positive impact on the environment. Also, this system has zero emissions and no carbon footprint, and would thus have little to no negative effects on the environment.

• Manufacturability
This part of the project is still in the “proof of concept” phase, and has not yet reached the manufacturing stage. However, since the proposed system uses commercial products that are widely available, manufacturability should be relatively simple, requiring only the calibration of cameras to scan the same area.
• **Sustainability**
  Required maintenance of the IR and visible cameras is minimal, and the project does not require an exorbitant amount of power to perform. Upgrading would be in the form of adding more cameras for extra levels of accuracy, and would not be difficult to do.

• **Ethical**
  There are no ethical concerns regarding this project.

• **Health and Safety**
  There are no health concerns associated with this project.

• **Social and Political**
  This project would benefit society as a whole, as there is a universal acceptance that minimizing fires to save land, money, and (most importantly) lives. The only parties that would receive extra benefit from this project would be the manufacturers of the cameras that are necessary for this project.

• **Development**
  The newest technique that was developed was the method to produce probability values that are assigned to each pixel. Knowing the minimum and maximum values that a pixel could be, it can be assumed that the average pixel value of a fire for that band can be assigned 100% probability, and the pixel value that is farthest from this mean (either the minimum or maximum pixel value) can be assigned 0% probability. Knowing 0% and 100% probabilities, the rest can be deduced based on how many intensity values are found between the 100% and 0% pixels.

  More generally, the idea of having an average spectral signature across multiple bands is something that is not commonly used in detecting fires. While IR and visible spectrums are used, they are rarely combined and analyzed for detection purposes.