TIME SERIES PROCESSING OF FLIR IMAGERY FOR MTI AND CHANGE DETECTION

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ABSTRACT

This paper addresses the problem of *calibrating* FLIR images of a scene that are acquired at different time points to construct information for Moving Target Indication (MTI) and change detection. A signal model is developed to identify variations and imperfections of a FLIR sensor in time. This model is utilized to compensate for relatively slow variations of a *bias* in the FLIR sensor via a Fourier-based processing. Furthermore, a two-dimensional adaptive filtering method is developed to compensate for variations of Image Point Response (IPR) of a FLIR sensor as well as sub-pixel changes in the relative coordinates of the sensor-target over time. Results with time series FLIR data of a scene with an airborne helicopter and a ground target are provided.

I. INTRODUCTION

A classical problem in surveillance with various types of sensors such as radars, optical or infra-red [1]-[2] involves examining a scene at various time points and fusing the information of these sensors for image registration, or detecting what we refer to as a *change*. For example, in surveillance with spaceborne or airborne optical devices, the user utilizes optical images of a scene at different time points to detect changes in, e.g., the environment or the enemy's arsenal. Forward-looking infra-red (FLIR) devices have also been used to detect changes in a scene to detect moving targets or man-made structures.

A fundamental problem associated with these systems is that the "stationary background" (also referred to as clutter) should exhibit the same behavior (signature) when viewed at different time points. We refer to this scenario as perfectly *calibrated* sensors. Unfortunately, perfectly calibrated sensors do not exist in practice. In the ideal case of perfectly calibrated sensors, the change in two images can be detected by simply subtracting one image from the other. With uncalibrated sensors, the differencing operation is not practical. This is due to the fact that most of these dual sensory systems seek to detect subtle (weak) changes. Unfortunately, the calibration error's power exceeds a change's power in most practical scenarios.

In this paper, we examine the problem of fusing information in uncalibrated time series FLIR imagery for Moving Target Indication (MTI) or change detection. FLIR sensors, similar to optical sensors, rely on an *integration* interval in time to capture the radiating sources in the imaging environment. A longer integration interval yields a better signal to noise and signal to sensor non-linear error ratio. On the other hand, a small interrogation interval is required to capture subtle changes particularly in the FLIR-MTI problems. Due to this, the time series FLIR imagery suffer from a non-linear error that we refer to as horizontal scan bias. In Section II, we provide a signal model for the scan bias error, and present a method for calibrating time series FLIR imagery to compensate for this source of error.

A more common form of mis-calibration in sensory systems (FLIR, optical, radar, etc.) is associated with variations is Image Point Response (IPR) or Point Spread Function (PSF) in time. A simpler version of this issue is referred to as *sub-pixel registration.* Variations of IPR corresponds to a physical phenomenon that is associated with a sensor circuitry system (gain and phase delay) as well as the sensor physical structure. In Section III, we will provide a model for this, and outline a two-dimensional adaptive filtering method to calibrate FLIR imagery for this source of error.

Finally, we present results using a set of time series FLIR imagery in Section IV. This database provides two different types of MTI and change detection problems. One involves detecting an airborne helicopter that rapidly appears in and disappears from the imaging scene. The other example involves a ground targets that exhibits slow IR changes in time. The merits of the methods that are described in Sections II and III will be studied for these two types of targets.

II. HORIZONTAL SCAN BIAS CALIBRATION

We denote the time FLIR imagery that are acquired

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in time via $f(x, y, t)$ where (x, y) is the image plane and t identifies the time domain. A discrete set of measurements of this 3D signal is made, e.g., $f(x_i, y_j, t_k)$. Consider the images that are acquired at two different time points, e.g., $t = t_1$ and $t = t_2$. For notational simplicity, we denote them as

$$f_1(x_i, y_j) = f(x_i, y_j, t_1), \tag{1}$$

and

$$f_2(x_i, y_j) = f(x_i, y_j, t_2). \tag{2}$$

Under the null hypothesis (i.e., there is no moving target or change in the imaging scene), these two images at a *fixed* scan line y_j can be related via

$$f_2(x_i, y_j) = f_1(x_i, y_j) + a_j(x_i), \tag{3}$$

where $a_j(x_i)$ is an unknown slowly-fluctuating (bias) signal. However, in presence of a relative change in the two images (e.g., a moving target), the model becomes

$$f_2(x_i, y_j) = f_1(x_i, y_j) + a_j(x_i) + f_e(x_i, y_j), \tag{4}$$

where $f_e(x_i, y_j)$ identifies the change.

By constructing the simple difference of the two images, i.e.,

$$\begin{aligned} f_d(x_i, y_j) &= f_2(x_i, y_j) - f_1(x_i, y_j) \\ &= a_j(x_i) + f_e(x_i, y_j), \end{aligned} \tag{5}$$

we obtain a statistic that is equal to the change information if there is no bias problem, i.e., $a_j(x_i) = 0$; in practice, this condition cannot be met. In this case, our problem is to first obtain an estimate of the bias signal, calibrate the first image with that estimate, and then construct the difference signal. The procedure to obtain such an estimate is described next.

As we mentioned earlier, the bias signal of a FLIR sensor is a relatively slow-fluctuating signal with respect to the actual target signature (otherwise, the sensor is highly defective and cannot produce useful image information). Meanwhile, a typical change in a time series FLIR imagery that is due to a moving or dynamic target is fairly localized and, thus, rapid. This implies that by a *severe* one-dimensional lowpass filtering of the second image $f_2(x_i, y_j)$ in the x_i domain, the signature of the change will be significantly suppressed. Meanwhile, since the bias signal $a_j(x_i)$ is a slowly-fluctuating (lowpass) function, it is unaffected by lowpass filtering.

Thus, the lowpass filtered signal for $f_2(x_i, y_j)$ can be identified by

$$f_{2LPF}(x_i, y_j) \approx f_{1LPF}(x_i, y_j) + a_j(x_i), \tag{6}$$

where $f_{1LPF}(x_i, y_j)$ is the lowpass filtered version of the first image $f_1(x_i, y_j)$. Thus, an estimate of the bias signal can be constructed using the difference of the lowpass filtered first and second images; that is,

$$\hat{a_j}(x_i) = f_{2LPF}(x_i, y_j) - f_{1LPF}(x_i, y_j). \tag{7}$$

We denote the first image that is calibrated by the estimated bias signal by

$$\hat{f}_1(x_i, y_j) = f_1(x_i, y_j) + \hat{a_j}(x_i). \tag{8}$$

Then, the change in the FLIR image can be detected via the difference of the second image and the above calibrated first image; that is,

$$\begin{aligned} \hat{f}_d(x_i, y_j) &= f_2(x_i, y_j) - \hat{f}_1(x_i, y_j) \\ &\approx f_e(x_i, y_j). \end{aligned} \tag{9}$$

It is crucial to note that the (one-dimensional) lowpass filtering should only be performed in the horizontal domain x_i at a fixed scan line y_j. This is due to the fact that the bias signal is a *highly-fluctuating* function in the y_j domain. Filtering in the scan y_j domain results in further smearing and streaking of the bias signal in the target signature and, thus, is undesirable.

The above horizontal scan bias signal calibration *removes* the biased scan lines in $f_1(x_i, y_j)$, and *artificially adds* the biased scan lines of the other image. The resultant calibrated difference image $\hat{f}_d(x_i, y_j)$ shows a significant reduction in the undesirable scan lines with respect to the uncalibrated difference image $f_d(x_i, y_j)$. However, the outcome can be further improved by a bias signal calibration using the *ensemble* of the entire time series image data. For this, we define the average of the ensemble via

$$f_0(x_i, y_j) = \frac{1}{K} \sum_{k=1}^{K} f(x_i, y_j, t_k). \tag{10}$$

Since the scan bias lines appear in a random order in the y_j domain as t_k varies while the background FLIR signature remains unchanged, this average signal possesses a significantly weaker scan bias signal. Moreover, since any change signature may appear in only a few frames of the time series, the change signatures are also weak compare to the background FLIR signature. Thus, the average image $f_0(x_i, y_j)$ provides a good representation of the background FLIR signature with minimal scan bias signal and change.

In this case, the average image $f_0(x_i, y_j)$ is a suitable candidate to *remove* scan bias signal in every member of the time series image. For this, we exploit the same rational that we used earlier to relate the severely lowpass filtered (one-dimensional in the horizontal x_i domain) versions of the two members. Let $f_{0LPF}(x_i, y_j)$ be the lowpass filtered of the average image, and $f_{kLPF}(x_i, y_j, t_k)$ be the lowpass filtered of the k-th FLIR image. Then, these two can be related via

$$f_{0LPF}(x_i, y_j) \approx f_{kLPF}(x_i, y_j) + a_{kj}(x_i), \tag{11}$$

where $a_{kj}(x_i)$ is the undesirable scan bias signal in the k-th FLIR image. Thus, an estimate of this bias signal can be constructed using the following:

$$\hat{a}_{kj}(x_i) = f_{0LPF}(x_i, y_j) - f_{kLPF}(x_i, y_j). \tag{12}$$

Then, an estimate of the k-th FLIR image without bias scan lines can be obtained from

$$\hat{f}_k(x_i, y_j) = f(x_i, y_j, t_k) \; + \; \hat{a}_{kj}(x_i). \qquad (13)$$

For notational simplicity, we use $f_k(x_i, y_j)$, $k = 1, 2, ..., K$ to identify these bias-calibrated FLIR images in the following discussion.

III. ADAPTIVE IPR CALIBRATION

As we pointed out in the introductory section, almost all sensory systems suffer from variations in IPR when they are used to interrogate the same scene. These are much more subtle sensor variations with a dynamic range that is less than a FLIR sensor bias signal that was described in the previous section. The modeling of IPR variations are examined next.

Consider the FLIR imagery (after bias calibration) that are acquired at two different time points, e.g., $f_1(x_i, y_j)$ and $f_2(x_i, y_j)$. Under the null hypothesis (i.e., no change), in the continuous image domain (x, y) these two images can be related via

$$\begin{aligned} f_2(x, y) &= f_1(x, y) \;\; ** \; h(x, y) \\ &= \int_\eta \int_\beta f_1(x - \eta, y - \beta)\; h(\eta, \beta)\; d\eta\; d\beta, \qquad (14) \end{aligned}$$

where $**$ denotes two-dimensional convolution in the spatial domain, and $h(x, y)$ is an *unknown* (miscalibration) impulse response which depends on the variations of the FLIR sensors in time. Hence, one has to perform a *blind* calibration of the two images. A method for this using a two-dimensional adaptive filtering and its implementation via a signal subspace processing method are described in [4], [5]; this is briefly outlined next.

Adaptive filtering methods have been suggested to solve the above-mentioned blind calibration problem in one-dimensional cases [3]. To apply these adaptive filtering methods in the two-dimensional problems, consider the discrete version of the model in (1):

$$f_2(x_i, y_j) = \sum_{m=-n_x}^{n_x} \sum_{n=-n_y}^{n_y} h_{mn}\; f_1(x_i - m\Delta_x, y_j - n\Delta_y), \qquad (15)$$

where (Δ_x, Δ_y) represent the sensor sample spacing in the (x, y) domain. In the adaptive filtering approach, the second FLIR image $f_2(x_i, y_j)$ is estimated via

$$\hat{f}_2(x_i, y_j) = \sum_{m=-n_x}^{n_x} \sum_{n=-n_y}^{n_y} \hat{h}_{mn}\; f_1(x_i - m\Delta_x, y_j - n\Delta_y); \qquad (16)$$

the estimated coefficients $\hat{h}_{mn}$ are determined based on minimizing the squared error between $f_2(x_i, y_j)$ and $\hat{f}_2(x_i, y_j)$ (the LMS algorithm [3]). Then, the statistic used for MTI or change detection is constructed via

$$\hat{f}_d(x_i, y_j) = f_2(x_i, y_j) - \hat{f}_2(x_i, y_j). \qquad (17)$$

Unfortunately, solving the above-mentioned two-dimensional adaptive filtering problem in a conventional finite-memory computer is a formidable task. An alternative practical method, called *signal subspace processing*, is introduced in [4], [5] to solve this problem. This is achieved via projecting $f_2(x_i, y_j)$ into a set of orthogonal basis functions that span the linear signal subspace of

$$\Psi = \Big[\; f_1(x_i - m\Delta_x, y_j - n\Delta_y); \quad m = -n_x, \ldots, n_x, \;\; n = -n_y, \ldots, n_y \;\Big]$$

The orthogonal basis functions are formed via, e.g., the Gram-Schmidt procedure. The details of this can be found in [4], [5].

IV. RESULTS

We use a FLIR database that is composed of $K = 178$ time frames that are acquired within approximately 12 seconds to study the merits of the methods that were described in Sections II and III. Figure 1a shows the FLIR image that is measured; this image exhibits the bias scan lines. Figure 1b is the bias scan calibrated image.

Figure 1a. M03LW003: Uncalibrated

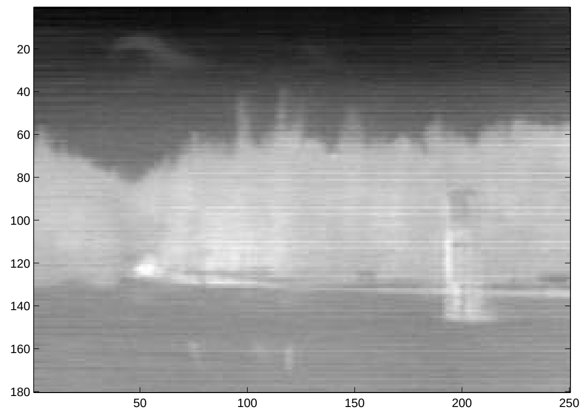
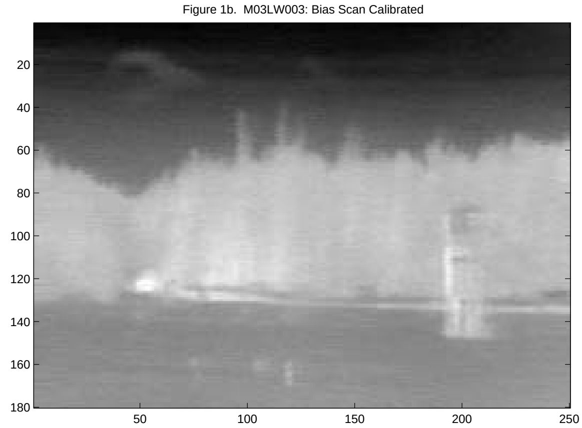


Figure 1b. M03LW003: Bias Scan Calibrated



In this experiment, a helicopter briefly appeared in the imaging scene in the fourth frame of the FLIR time sequence. Figure 2a shows the difference between the third and fourth frames without any calibration. In addition to the helicopter, the scan bias line and variations of the sensor IPR results in formation of erroneous change information. Figure 2b is the signal subspace processing (SSP) difference that is obtained after utilizing the two calibrations that are discussed in Sections II and III; for the SSP difference, the helicopter signature is more prominent than the surrounding clutter signature.

Figure 2a. M03LW003 & M03LW004: Uncalibrated Difference

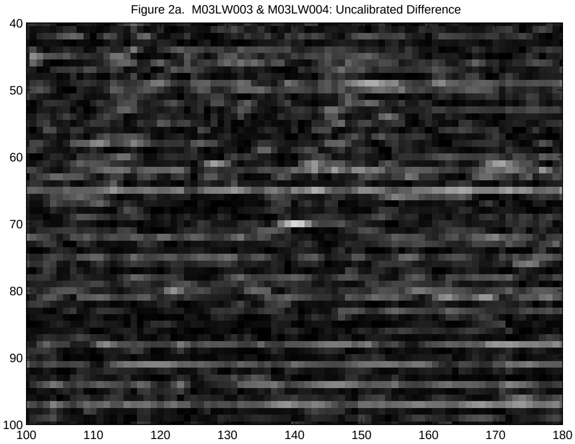
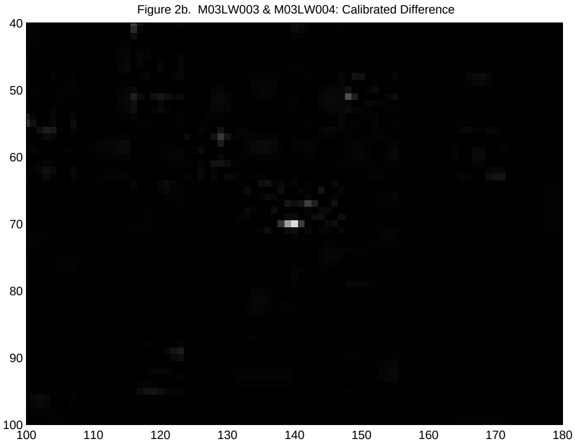
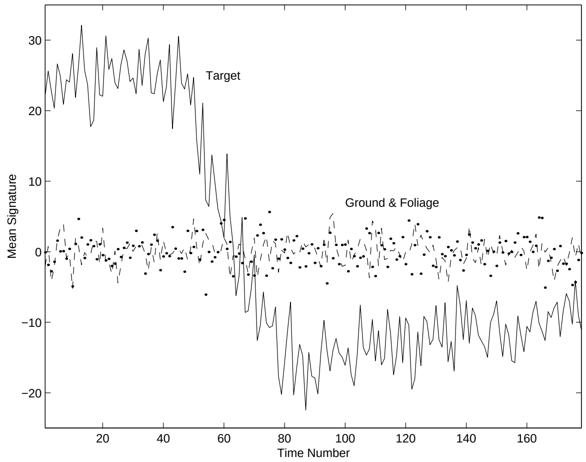


Figure 2b. M03LW003 & M03LW004: Calibrated Difference



The final example involves the information in the entire 178 frames after the bias calibration is performed. The solid line in Figure 3 shows the signature of a target on the ground versus time after its mean value is removed. The dashed and dotted lines, respectively, are the same signatures for ground clutter and foliage. These results indicate that the ground target exhibited *gradual* change in time while the clutter and foliage remian approximately unchanged. This behavior could be exploited to segment the signature of man-made targets whose thermal radiation show gradual variations (e.g., an engine cooling off or warming up) in time. We should point out that the SSP method *compensates* for this form of gradual and subtle change in two *consecutive* time frames. However, by processing frames that are separated further in time, e.g., frames 1 and 178, the change is detectable though it is weak.

Figure 3. Mean Calibrated Sigantures versus Time



V. SUMMARY

This paper presented methods for modeling imperfections in time for a FLIR sensor. Two methods were described to blindly calibrate for bias scan error signal and IPR variations of a FLIR sensor. Results were provided to show the merits of these algorithm for MTI and ground target detection.

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