Background estimation in multispectral imagery

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Abstract: A machine learning framework is employed for estimating the background spectrum at a pixel of interest using pixel values in an annular neighborhood of that pixel.

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1. Background

To detect whether there is a target or anomaly or anomalous change in a given pixel, an important first step is to estimate the background [1]; that is: to estimate the value of that pixel if a target were not present. For traditional target detection, that estimate is often just the mean value of all the pixels in the image [2–6]. For anomaly detection, oddly enough, the tradition is a little different: one *can* use the global mean, but it is more common to employ a local mean, estimated from an annulus of pixels that surround the pixel of interest [7]. Meanwhile, for anomalous change detection, even more oddly, the tradition is again to use the global mean [8–10]. There is nothing in the mathematics, however, that demands (or even prefers) the choice of local or global mean for any of these three detection tasks.

Two advantages of the global mean are that it is relatively insensitive to the spatial extent of the target (assuming rare targets), and that it is based on large-number statistics. By contrast, an annulus-based local estimator of the background can be contaminated by target pixels if the target is larger than the "hole" in the center of the annulus. For this reason, the annulus often includes a buffer of "guard pixels" immediately surrounding the pixel of interest; these pixels are not included in the estimate of the local mean. But the local estimator has one very important advantage: due to the non-stationarity of the background imagery, the local estimator is often much more accurate. A potential target in a forested area will have an annulus that is composed of forest-y pixels, and so the estimated background will be forest-like; in the same image, another target in a desert area will have a desert-y annulus and the estimated background will be desert-like. A global mean in this scenario would estimate the background as a kind of spectral average of forest and desert, which ultimately would not correspond to a real material.

Despite the long tradition of using a global mean in target detection, *local* background estimation was shown to be useful for small targets [11–13], and more recently, a learning-based framework was introduced [14–17]. Here, the pixel of interest is estimated by a general function (not just the mean) of the pixels in the annulus. Furthermore, this function can be *fit* to the data so as the minimize the estimation error. Because an image typically has many pixels (upwards of millions in common remote sensing applications), and because each pixel/annulus pair provides a training sample, there is ample training data for fitting even potentially complicated functions.

2. Formulation

For a target-free pixel y surrounded by an annulus of pixels $\mathbf{x}$, we estimate $y \approx \hat{y} = f(\mathbf{x})$ for some function f. In particular, we choose f to minimize the average error that $\hat{y}$ makes in approximating y; e.g., $f = \operatorname{argmin}_f \sum_{n=1}^{N} \|y_n - f(\mathbf{x}_n)\|^2$, where the samples are taken from the image: $(\mathbf{x}_1, y_1), \ldots, (\mathbf{x}_N, y_N)$. Note that if the image has D spectral bands and the annulus has K pixels, then $f : \mathbb{R}^{K\times D} \to \mathbb{R}^D$.

3. Target detection

Given a background estimation function f, and therefore a background estimate $\hat{y}_n = f(\mathbf{x}_n)$ for every pixel n, we can rewrite target detection in terms of these estimates. Instead of "subtracting the mean," we subtract the background estimate. Thus, the classic matched filter [2] becomes $t^\top R^{-1}(y - \hat{y})$, where t is the target signature and $R = (1/N)\sum_{n=1}^{N}(y_n - \hat{y}_n)(y_n - \hat{y}_n)^\top$ is the covariance matrix of the residuals.

The matched filter is a widely-used detection algorithm, but it is formally based on the "additive model" – which says that the target signal is *added* to the background signal. There are scenarios where this is appropriate, but a common alternative is the "replacement" model – which says that an opaque sub-pixel target leads to a linear combination of target signal and background; i.e., the target *replaces* part of the background. It is common practice to employ detectors (such as the matched filter) that are optimized for the additive model in situations for which the replacement-model might be more appropriate, and it is often the case that these detectors are still reasonably effective (even if sub-optimal). We have observed, however, that this reasonable effectiveness diminishes when it is a local instead of a global background subtraction [17]. Put another way, the advantage to using local background estimation diminishes when the detector is not well matched to the detection scenario.

4. Decomposing f

Because $f : \mathbb{R}^{K\times D} \to \mathbb{R}^D$ is a function from one high-dimensional space to another high-dimensional space, there are many degrees of freedom in its estimate. Both for reasons of computational efficiency and to avoid overfitting, it can be advantageous to decompose the function into lower-dimensional components. The most straightforward way to do this is with band-by-band estimation. Here, we write $f_d : \mathbb{R}^K \to \mathbb{R}$ for $d = 1,\dots,D$ as the estimator for the d'th band. In this scheme, each f_d function is separately fit to the d'th band (another option is to constrain all f_d functions to be the same). The most natural way to do this is to use the spectral bands, but it has been found empirically that employing principal component bands generally leads to better performance [15]. In addition to these spectral constraints, spatial constraints based on symmetry considerations have also been considered [15].

Most practical efforts to estimate $f(\mathbf{x})$ for multispectral images have been limited to linear functions, and these have been found to be more effective than local means [14–17]. Estimates of the regression function $f(\mathbf{x})$ can in principle call on all of the tools of machine learning, and there is every reason to believe that nonlinear $f(\mathbf{x})$ can be more effective still. This remains, however, a challenge for future research.

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