WHITE PAPER

Discriminant Function Change in ERDAS IMAGINE®

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For ERDAS IMAGINE® 2011, Intergraph has developed a new algorithm for change detection between two co-registered images acquired at different dates. This algorithm, named Discriminant Function Change (DFC), characterizes the natural distribution of spectral clusters in the data space of one image, then uses a discriminant function to measure probability of change of the pixels in the other image. The algorithm's conceptual procedure is explained in the following steps:

1. First, determine which image is to be the base image, i.e. which image will we find change against. We will call this $image_{base}$ for notation purposes. This algorithm is image-order variant, meaning that it will yield different results depending on which image (before or after) is the base. More on this concept will be discussed later.
2. Perform an unsupervised classification on $image_{base}$ into a reasonable number of spectral classes (64 – 128 classes). The DFC user interface allows the uulletser to define the unsupervised parameters. The final result is relatively nsensitive to this parameter.
3. Take the thematic image output from the unsupervised classification of $image_{base}$, notated as $class_{base}$, and use this thematic image as a zonal mask to extract a set of multivariate signatures (mean vector, M and covariance matrix, Cov) from the other image notated as $image_{change.}$
4. For each pixel in $image_{change,}$ compute the Mahalanobis Distance (MD) using the signature corresponding to the class, c to which it is affiliated from the previous step's zonal operation using the formula: MD = $(X\text{-}M_c)T\ (Cov_c^{-1})\ (X\text{-}M_c)$.
5. Since the MD is a Chi^2 distribution (assuming multi-normal data) the MD metric can be converted to a Probability using a Chi^2 lookup table. More discussion on the multi-normal assumption will follow.
6. The Probability metric for each pixel is written to an output image, $image_{Prob.}$ This image is a floating point image with values from 0.0 to 1.0.B

Image Order and Directional Change

The output image, $image_{prob,}$ created by DFC represents the probability that a pixel in $image_{change}$ is statistically different from the spectral cluster to which it belonged in $image_{base.}$ In other words, a pixel in $image_{prob}$ will have a value near 1.0 if it no longer belongs to the same spectral cluster in $image_{change}$ than it did in $image_{base.}$ Conversely, a pixel in $image_{prob}$ will have a value near 0.0 if it belongs to the same spectral clusters in both $image_{base}$ and $image_{change.}$ Consider the panchromatic multi-temporal images in Figures 1a and 1b. These images, collected six years apart, exhibit significant areas of change.

Figure 1a: Before Image (2003)

Figure 1b: After Image (2009)

In the left side of the image, a large building structure has been built and in the right side of the image, a wetlands area has been drained and a subdivision has been built.

The images in Figures 2a and 2b are the resulting output probability of change images from DFC. Figure 2a was computed using the before image as the base image, $\text{image}_{\text{base,}}$ and the after image as the change image, $\text{image}_{\text{change.}}$ Note that Figure 2a contains high probability pixels (shown as very bright) in the new features that have been added between the two image dates, that being primarily the large building structure to the left and the subdivision roads to the right.

Figure 2a: DFC, before image as a base

Figure 2b: DFC, after inage as base

Figure 2b was computed using the after image as the base image, $image_{base,}$ and the before image as the change image, $image_{change.}$ Note that in Figure 2b the primary area of high probability pixels is from the area of wetlands that were drained on the right side of the image. Note also that Figure 2a has no distinguishable high probability pixels for the wetlands area and Figure 2b has no distinguishable high probability pixels for the new building and subdivision roads.

These results demonstrate the image order variance of the DFC algorithm. Since DFC computes spectral clusters defined from $image_{base}$ and then the statistical outliers in $image_{change,}$ it is only sensitive to pixels with new spectral characteristics in $image_{change.}$ So by computing DFC both ways, with the before image and after image as the $image_{base}$ we can separate out positive change from negative change. Positive change shows the new features that are in the after image that are not in the before image, i.e. features that have appeared (Figure 2a). Negative change shows features that are in the before image that are not in the after image, i.e. features that have disappeared (Figure 2b). The DFC user interface allows for the computation of both the Positive Change Image and/or Negative Change Image. It also provides for the Combined Change Image which is an image with the maximum pixel values from both the positive and negative change images.

The Multi-normal Assumption and Outliers

As mentioned in the DFC description, the Mahalanobis Distance discriminant function assumes that the spectral signatures are multi-normal, i.e. Gaussian across all N dimensions. Recall that the DFC process uses the unsupervised classification, $class_{base}$ as a zonal mask to extract a set of signatures from $image_{change.}$ This means that there is no way to guarantee that the signatures of all the classes are multi-normal. However, since the signatures have a pixelwise alignment with spectral clusters computed using an iterative, self-organizing, unsupervised classification process, the signatures of classes with little or no change will exhibit a relatively multi-normal distribution. Consider Figures 3a – 3d which depict the class histograms of some of the DFC-derived signatures. Note that deviation from multi-normality occurs in the signatures of classes where change has occurred.

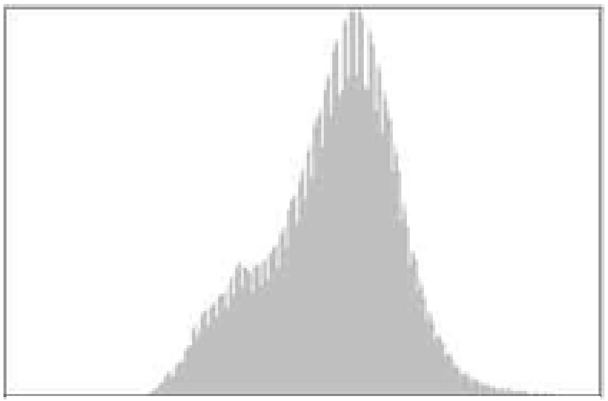

Figure 3a: Little change

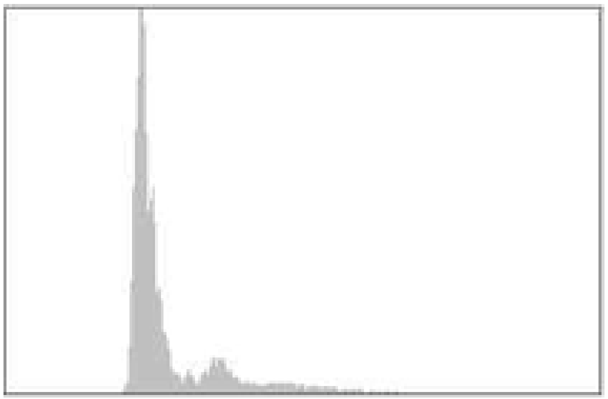

Figure 3b: Small change

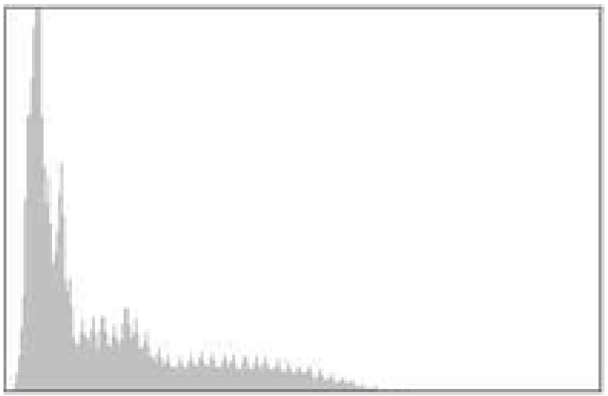

Figure 3c: Moderate change

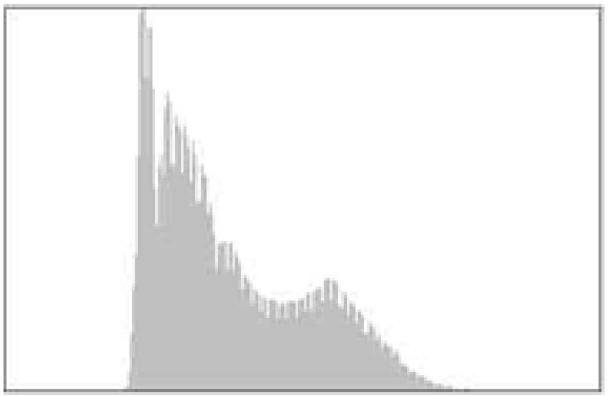

Figure 3d: Large change

This deviation due to change will present as outlier spikes, extended tails, or skewness in the distribution depending on the percent of change pixels that occurred in each class.

This behavior of the DFC-derived signatures leads to the realization of two potential shortcomings of the algorithm. First, consider how the algorithm would behave if the entire (or very large percent) of a spectral class changed. The derived signature for such a class would not show the change as outlying a predominantly unchanged distribution, but rather the change itself would dominate the distribution. If this were to occur, then the DFC results for this class would be inaccurate. However, since the spectral clusters are computed from all the pixels in the image and the spatial arrangement of the pixels are ignored, it reduces the likelihood that any single class distribution will be over dominated by change. So while it is possible for a large feature with unique spectral characteristics relative to the rest of the image to exist, dominate a spectral class and then change (appear or disappear), it is a rare occurrence.

The second shortcoming in the DFC algorithm arises from the fact that unsupervised signatures have naturally occurring outliers. These outliers are usually from pixels with either very unique spectral characteristics and sparse occurrence in the image, or more commonly, from very bright pixels. Because these outliers are naturally occurring and not due to change, they will manifest as false positives in the DFC result. While the first shortcoming of an entire spectral class being dominated by change is rare, false positive errors from naturally occurring outliers is more common and has been dealt with as part of the DFC algorithm.

Outlier Clipping

The advanced tab on the DFC user interface has options for outlier clipping. The options allow for clipping just the high values, just the low values, or both from the images. For setting clipping the clipping thresholds a parameter called Sigma^ is used. Sigma^ is the standard deviation approximation using the Median Absolute Deviation (MAD) statistical technique for outlier identification. The formula for used is: $MAD = \text{median}_i\ (|X_i - \text{median}_j\ (x_j)|)$.

Figure 4a: Before image (2003)

Figure 4b: After image (2009)

Figure 4c: DFC with no clipping

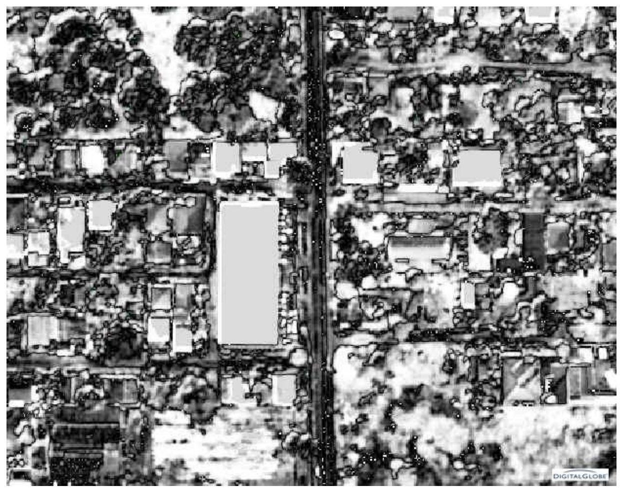

Figure 4d: DFC with clipping at +3.0 Sigma

Figures 4a and 4b are the before and after image which contain some very bright building rooftops. One can see that these rooftops have not changed between the two images collection dates. However, since these pixels are naturally occurring outliers in their class distribution, they are giving a high probability of change showing as very bright pixels in Figure 4c. By setting the option to perform outlier clipping on the high values using the default +3.0 Sigma^, the false positive results have been diminished as shown in Figure 4d. The DFC output values dropped from the range of 0.95 – 0.98 to the range of 0.75 – 0.80. This is significant since most applications will post process the DFC results and set a probability threshold at 0.90 or 0.95 thereby removing the false positives.

Conclusion

Discriminant Function Change (DFC) is a novel ERDAS IMAGINE process for change detection in multi-temporal image pairs. It is computed by selecting one image as the base and then detecting statistical outliers the other image. For this reason, it can separate two different types of change, finding features that are in one image and not the other. Given images collected at different dates the results can be thought as positive change (features that appear) and negative change (features that disappear) between collection dates.

There are two other important properties of the DFC algorithm. First is the property of low sensitivity to differences in illumination between the images. Since it measures Mahalanobis Distance using the classes mean and covariance matrix, if the mean of a class shifts, the MD metric remains unchanged. The second property that is important is that there is no dependence on the images having the same band and wavelength characteristics. The images may have a different number of bands and/or different band/wavelength mappings.

The potential shortcoming of false positives due to entire classes being dominated by change is rare in practice. While false positives due to natural outliers in the unsupervised classes may be prevalent in some data sets, a strategy to reduce these occurrences is implemented as part of the DFC process.

The real potential of the DFC algorithm will lie in its utility in more complex workflows like object-oriented change detection. DFC will provide a robust spectral based probability of change per pixel which can then be thresholded and clumped into raster objects. Or, it can be used in conjunction with image segmentation to compute the zonal mean probability of change per segment and further processed.

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