Two evolutionary algorithms optimize clusters and automate feature selection in multispectral images

George H. Burgin[*a], H. Price Kagey[b], James C.Jafolla[c]

[a]Natural Selection, Inc, 9330 Scranton Rd., San Diego, CA 92121
[b]Lockheed Martin Corp., 4770 Eastgate Mall, San Diego, CA 92121
[c]Surface Optics Corp., 11555 Rancho Bernardo Rd., San Diego, CA 92121

ABSTRACT

Evolutionary computation can increase the speed and accuracy of pattern recognition in multispectral images, for example, in automatic target tracking. We have developed two classes of evolutionary algorithms for exploiting multispectral imagery. The first method treats the clustering process. It determines a cluster of pixels around specified reference pixels so that the entire cluster is increasingly representative of the search object. An initial population (of clusters) evolves into populations of new clusters, with each cluster having an assigned fitness score. This population undergoes iterative mutation and selection. Mutation operators alter both the pixel cluster set cardinality and composition. Several stopping criteria can be applied to terminate the evolution. An advantage of this evolutionary cluster formulation is that the resulting cluster may have an arbitrary shape so that it most nearly fits the search pattern. The second algorithm class automates the selection of features (the center-wavelength and the bandwidth) for each population member. For each pixel in the image and for each population member, the Mahalanobis distance to the reference set is calculated and a decision is made whether or not this pixel belongs to a target. The sum of correct and false decisions defines a Receiver Operating Curve, which is used to measure the fitness of a population member. Based on this fitness, the algorithm decides which population members to use as parents for the next iteration.

Keywords: Multispectral image analysis, evolutionary algorithms, Mahalanobis distance

1. INTRODUCTION

This paper demonstrates two applications of evolutionary algorithms that improve speed and accuracy of the analysis of multispectral images. A parking lot serves as scenario; multispectral images taken under different environmental conditions, such as weather, time of day, viewing angles are analyzed. The objective of the experiments is to identify an object, or multiple objects, called template objects, in one multispectrally captured scene and to subsequently search for and identify, either in the same or in a different multispectral image other objects that are similar to the template object(s).

The science (and art) of classifying multispectral and hyperspectral images has been developed and perfected over several decades. Its origin can often be traced to the analysis of space-based remote sensing. Early applications focused on identifying and specifying properties of the Earth's surface, for such diverse problems as detection of ore deposits or assessing the quality of crops, such as corn. Landgrebe's survey article "Hyperspectral Image Analysis" [1], even though published in 2002, has still much to offer today. Landgrebe was also instrumental in the development of the highly successful software "Multispec" [2] To conclude the appreciation of Landgrebe's contribution to multispectral remote sensing, we refer to his outstanding textbook "Signal Theory in Multispectral Remote Sensing" [3]

Readers interested in specific examples of multiband scene analysis for mineral exploration and other Earth resource applications are referred to MicroImages informative web page [4], "Introduction to hyperspectral imaging". This site offers interesting results of NASA's "Visible/Infrared Imaging Spectrometer (AVIRIS) for the Cuprite, Nevada mining area, and also contains a worthwhile summary of "Spectral Reflectance and Radiance".

* gburgin@natural-selection.com; phone 1 858 455 6449; fax 1 858 455 1560; www.natural-selection.com

Mathematics of Data/Image Pattern Recognition, Compression, Coding, and Encryption X, with Applications,
edited by Gerhard X. Ritter, Mark S. Schmalz, Junior Barrera, Jaakko T. Astola,
Proc. of SPIE Vol. 6700, 67000E, (2007) · 0277-786X/07/$18 · doi: 10.1117/12.732211

The innovative contribution of the current paper consists in the application of two computationally intelligent algorithms for simultaneously solving the clustering problem and the problem of finding efficient reduction of the number of features in multispectral images.

Target identification and recognition have important real-world applications. For example, in counter-terrorist efforts, one might identify a car with a suspicious driver or load. One might later search for the same car (possibly with a changed license plate) in a different location. Other applications might include identification of shipping containers in a port of origin and later identifying the same containers in a destination port.

The paper is organized as follows: Section 2 introduces multispectral images typical for the selected scenario. Technical details of the multispectral imaging system, the embedded processor and the associated software are described. Section 3 explains the essential features of the evolutionary clustering algorithm and the evolutionary feature selection algorithm. In section 4 important properties of distance measures in general and of the "Zero mean differential area" algorithm and the Mahalanobis distance measure in particular are described. Details about the two evolutionary algorithms are summarized in section 5. Section 6 describes some interesting results obtained by applying the two evolutionary algorithms. The paper concludes with recommendations for further research in the fascinating field of multispectral image analysis.

2. METHODOLOGY

2.1 Sample images

Figures 1 and 2 show two different views of a parking lot. The two figures are very similar, a noteworthy difference is the gray "calibration panel", pointed out in figure 1

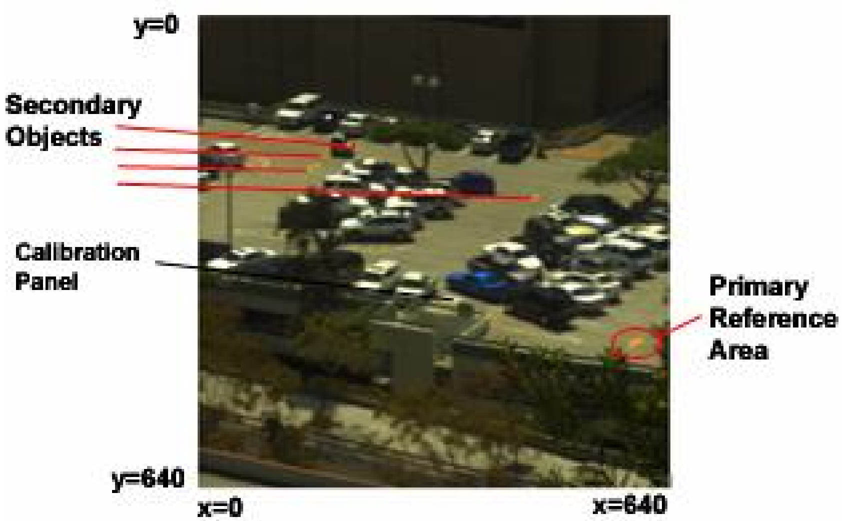

Fig 1. RGB image FV1 (obtained from a multispectral image by a tristimulus transformation)

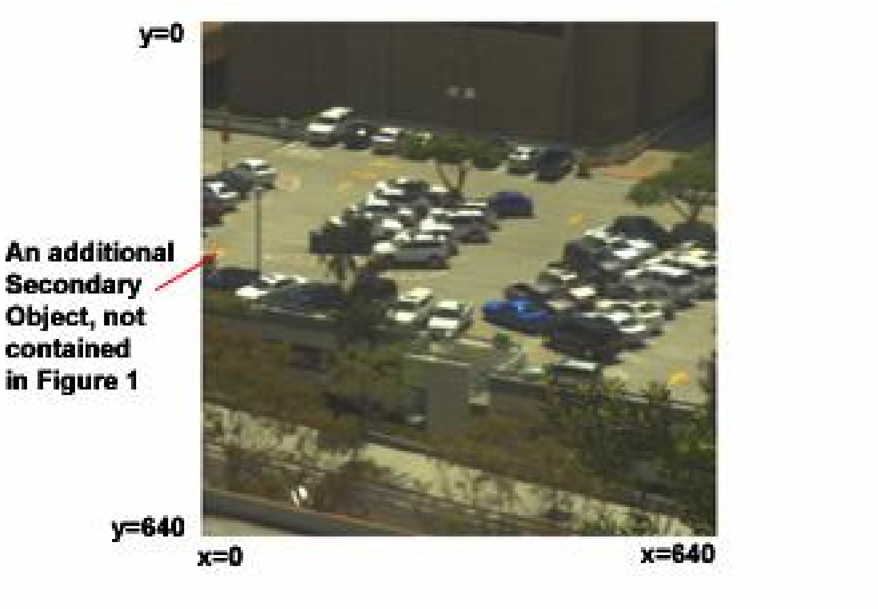

Fig 2. RGB image FV2. Same parking lot as shown in figure 1. This image is used to search for objects similar to the primary reference object shown in figure 1.

2.2 Imaging System

All the results described in this paper were obtained with a camera system manufactured and marketed as commercial off-the-shelf equipment by the Surface Optics Corporation, San Diego (SOC). Salient features of the SOC-700 system are:

Table 1. Specifications of the SOC-700 multispectral imaging system

Spectral Band:	400 … 900 nm (0.4 … 0.9 microns)
Number of Bands	120 Bands with 4 nm resolution
Dynamic range	12 bits
Exposure Time	10 … 10^7 microseconds
Line Rate	Up to 100 lines/second (120 bands)
Pixels per Line	640
Image size	640 x 640 x 120 x 2 bytes (~100 Mbytes)

2.3 Embedded Processor

Standard PCI interfaces connect camera and PC-board. Board performs radiometric calibration atmospheric correction and spectral correlation. A detailed description of the calibration procedure will appear in a forthcoming paper by James Jafolla.. Software can also perform tristimulus conversion of a multispectral image to an RGB image that can be displayed in real time to the operator for target designation and identification.

3. EVOLUTIONARY ALGORITHMS

3.1 Separate algorithms developed by NSI and SOC

The two *evolutionary* algorithms described in this paper (clustering and feature selection) were developed by the principal author of this paper. Independently, Dr. James Jafolla of SOC developed a *genetic* algorithm for an optimal selection of *sequences* of filtering operations. Jafolla's genetic algorithm will be described in a forthcoming paper.

3.2 Clustering algorithm

Here, the problem was to find clusters of pixels that are spectrally similar. What we mean by "spectrally similar" is defined in more detail in section 4, "Distance measures". Quickly identifying suitable clusters of pixels is particularly important in real-time target identification, where we can not expect to have highly trained (PhDs) operators. Ideally, the operator recognizes in an RGB display a potential target. He points the curser to a pixel in the target area (the template centroid pixel) and the evolutionary algorithm then autonomously searches the image for surrounding pixels whose spectral composition is, within a prescribed threshold, similar to the spectrum of the template centroid pixel. Successful target recognition critically depends on this clustering process because the cluster may be used as the "training" area for the pattern recognition algorithm(s). The more uniformly the spectral composition of the training area is defined, the easier it will be for the pattern recognition to find similar areas in either the same image or in some other, related image.

3.3 Feature selection algorithm

The SOC-700 can provide up to 120 different spectral reflectance values for each of the imaged pixels. It is reasonable to ask: Do we really need120 different wavelengths for each pixel? Experience has shown that reducing the number of features (wavelengths) in a pattern recognition problem not only reduces the computational effort to search for similar objects, but it may actually improve the recognition performance. This performance can be measured by the "Receiver Operating Characteristic" (ROC) curve applied to a particular operating problem. Representative ROC curves are given in section 5.

4. DISTANCE MEASURES

4.1 General properties of distance measures

Analysis of multispectral images routinely requires an estimate of the *similarity* between two different spectra. The similarity must be expressed in a quantifiable form. Measured spectra are inherently *noisy*. Estimation of similarity requires comparing two or more noisy, *multidimensional* vectors. This comparison may be considered to be a *filtering* (or a correlation) process. Consider an a priory defined template vector v_T, we now filter all the spectra of each pixel in the image against this template vector. We tacitly assume that all vectors have the same number of components.

If the correlation value between a target vector and the template vector exceeds a predefined value, we declare that the target pixel *matches* the template, else we declare no match. Noise of course affects this decision and it may cause one of the two types of erroneous classification: a) a missed detection or b) a false alarm (declaring a match if in reality the pixel does not match the properties of the template).

Not only the noise (or more accurately, the *signal-to-noise ratio*) affects the ratio of missed detections to false alarms, but equally important the distance metric that is used to determine similarity. Many potentially useful distance measures between vectors are known and could be used. Some well known candidate distance measures include:

- Euclidian distance
- Bhattacharyya distance
- Mahalanobis distance
- Zero mean differential area (ZMDA)

The original objectives of the research reported in this paper were to explore various applications of evolutionary and genetic algorithms in multispectral image analysis. Early results however indicated that different distance measures used for scoring the results obtained with different evolutionary algorithms influenced the fitness function (the quality by which the performance of different evolutionary algorithms were measured), as much, if not more, than the algorithms per se. This dependency of the performance of recognition algorithms (in general, not only evolutionary algorithms) deserves to by studied in greater detail and more systematically.

In the work reported in this paper, attention was focused on two distance measures:

- Zero mean differential area
- Mahalanobis distance

These two distance measures will now be defined.

4.2 Formula for ZMDA distance

Let $L(\lambda_n)$ n= 1 … N represent the spectrum of an arbitrary "target" pixel and $F(\lambda_n)$ the *composite* spectrum of the primary reference area (F for filter) then the ZMDA distance is defined as:

$$C_{ZMDA} = 1 - \sqrt{\sum \left[\frac{L(\lambda_n) - \langle L(\lambda_n) \rangle}{\sqrt{\sum \left(L(\lambda_n) - \langle L(\lambda_n) \rangle \right)^2}} - \frac{F(\lambda_n) - \langle F(\lambda_n) \rangle}{\sqrt{\sum \left(F(\lambda_n) - \langle F(\lambda_n) \rangle \right)^2}} \right]^2}$$

Where the mean of the vector L is given by

$$< L(\lambda) > = \frac{1}{N} \cdot \sum_{1}^{N} L(\lambda_n)$$

And similarly for the vector F. Note that a large distance between spectra means a low correlation (high dissimilarity) and vice versa. We sometimes, for convenience, define (1 – distance) as the ZMDA-correlation, that we often simply call the ZMDA distance.

4.3 Procedure to calculate the Mahalanobis distance

Euclidian, ZMDA and Bhattacharyya distance (and many other distance measures) require only the spectrum of the filter ($\lambda_F(i)$, i = 1 … N) where N is the number of spectral components, and the spectrum of the target ($\lambda_T(i)$, i = 1 … N). In contrast, to calculate the Mahalanobis distance, we need, besides the spectrum of the target, a composite spectrum of a "training area" and the *covariance matrix* of the spectra of the training area. Consider the training area to consist of M samples (NUM_SAMP), each sample having components $\lambda_m(i)$, I = 1 …N, m = 1 … M, so that the sample space may be represented by an "observation" matrix with NUM_FREQS rows and NUM_SAMP columns. Ideally, pixels included in the set of training pixels should be most descriptive of the object we are training for.. Pixels that merely represent undesirable background reduce the discrimination power of the covariance matrix because the decrease the signal-to-noise ratio of the training area. The elimination of background noise is a significant contribution of an evolutionary clustering algorithm. We *normalize* this matrix by subtracting the row-average from each element in the row (that is we subtract the mean value of all samples at a given frequency value); call this matrix t_s. It's covariance matrix is $t_s * t_s^T$, (superscript T indicates the transpose) which is now a NUM_FREQS by NUM_FREQS symmetrical matrix. At this point, another normalization may be performed by dividing each row by its main-diagonal element.

The next step is to invert the covariance matrix, say covi = inv(cov). As long as we use sufficiently more observation points than we have frequency components, a simple Gauss-Jordan inversion usually works well, should the matrix be ill-conditioned, we recommend performing the inversion by a QR decomposition algorithm. Having obtained the inverted covariance matrix covi, the final step consists of calculating the Mahalanobis distance between each candidate pixel and the training area, which is:

$$M_d = sqrt((v_F - \langle v_F \rangle)^T \times \mathrm{cov}\, i \times (v_T - \langle v_T \rangle))$$

Large values of M_d indicate small correlation, we use some appropriately scaled value of (1 -$M_{d.}$) calling it Mahalanobis correlation.

5. FEATURE REDUCTION ALGORITHM SPECIFICATIONS

5.1 Justification for feature reduction

Reducing the number of features for pattern recognition in multispectral images may be advantageous for a number of reasons:

1. reduction of memory requirements for storing image
2. reduction of processing time
3. increase of recognition performance

While the advantages listed under 1 and 2 are fairly obvious, there is no simple rule that correlates performance in pattern discrimination with the number of components in the feature vector. Whether or nor *feature reduction* enhances pattern recognition depends on the individual application, and on the intended use of the target recognition. The experiments performed in this research frequently indicated better performance with reduced features. Lack of resources did not allow a systematic study of this important problem; however, we do report here some cases where the reduction in feature resulted in improved recognition-performance.

5.2 Objectives of the algorithm

For a given recognition task with limited resources, find a set of center wavelengths and associated bandwidths that optimize a specified recognition fitness function. In a simple case, the fitness-function can be a weighted sum of missed detections and false alarms. The selected center-wavelengths do not have to be equidistantly spaced and the bandwidth allocated to the individual frequency bands do not have to be all the same. Constraints in equipment may often dictate number of wavelength bands and associated bandwidths.

5.3 Specific requirements for the developed algorithm

Use an SOC-700 multispectral image acquisition system:

640 x 640 pixels with 12 bit resolution

Calibrate to 640 x 640 floating point reflectance values

Maximum spectral resolution: 120 wavelengths with 4 nm bandwidth

Search Objects primary object = painted arrow at x=603; y=442 in image FV1

Number of pixels in primary search object: Given by the evolutionary clustering algorithm: 23 pixels

5.4 Parameter definitions for the evolutionary algorithm:

Population size: 10

Mutation Operators:

- Add a population member
- Delete a population member
- Change number of center wavelengths
- Change values of center wavelengths
- Change individual wavelength at each center wavelength
- Vary detection threshold

5.5 Pseudo code for the evolutionary algorithm

Initialize population

While (number of generations < max allowed number)

{

Calculate fitness score for each population member

Sort population

Delete worst 50% of population and make remaining pop parents of new pop members

Create offspring by mutating parents

}

5.6 Calculation of the fitness score for one single population member.

For each pixel in the image, calculate the Mahalanobis distance to the primary reference point. If distance is less than threshold, declare pixel to be a member of the pattern. Perform a table lookup to determine if pixel belongs either to the primary pattern or to a secondary pattern. If pixel was declared as being a member of the reference pattern but is not contained in the table, then increment the false alarm counter. If pixel was declared not to be a member of the pattern but is contained in the table, increment the missed detection counter. The weighted ratio of missed detections versus false alarms is the fitness value for that population member.

6. REPRESENTATIVE RESULTS

6.1 ZMDA distance with 120 component feature vector

Figure 3 compares two spectra, both measured with the full wavelength band of 120 contiguous wavelengths. It shows, on top, the reflectance values for two adjacent pixels, the central pixel of the primary training area, and the spectrum for the pixels at the origin of the coordinate system (shown at the bottom).

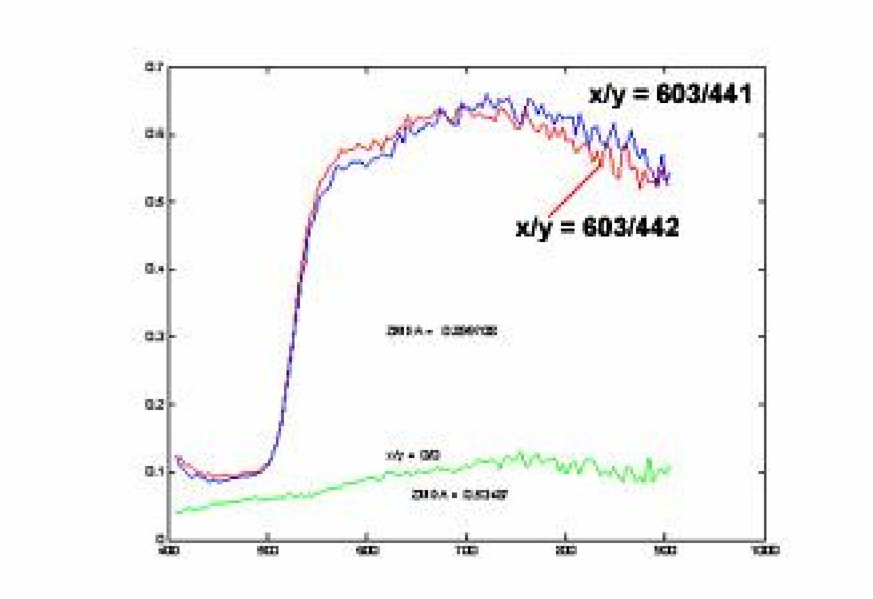

Fig 3. Comparison between spectra of pixels that belong to the training area versus a pixel far removed from the training area.

It is clear that the two spectra of the pixels belonging to the search area are much more similar to each other than to the pixel at the origin. Figure 4 shows an intensity plot for the ZMDA distance for all the pixels of the entire image FV2.

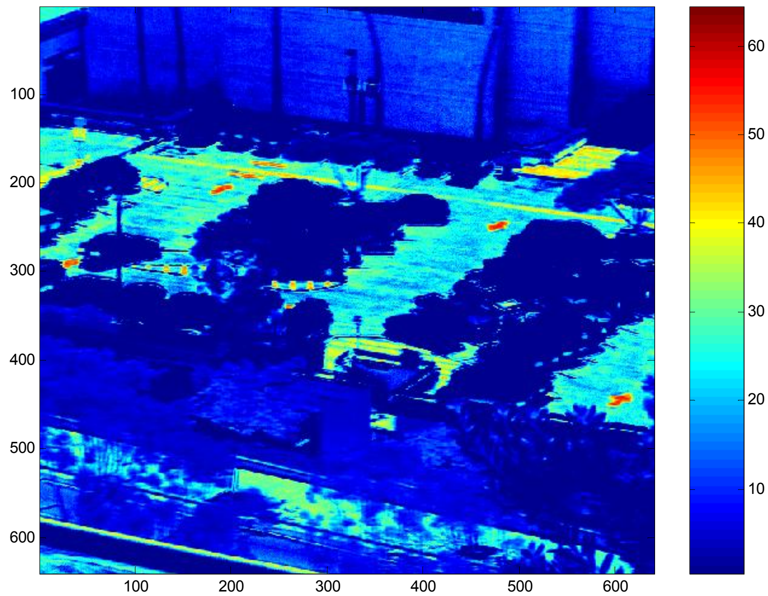

Fig 4. ZMDA distances to center-pixel of primary search object for the entire scene FV2

This figure indicates that the ZMDA distance is an acceptable distance measure for a search for areas similar to the primary search area. The ZMDA distance between the two spectra of the reference area is 0.899; the ZMDA distance between the reference spectrum and the spectrum at the origin is 0.5348. This means that the ratio of the spectrum between two "good" pixels and between a good and a "bad" pixel is 0.5348/0.899 = 0.594. Clearly, we would like to see a much stronger discrimination between the spectra belonging to the pattern and the spectra of those pixels that are not members of the search pattern. Later in this section, we will show that by a) reducing the number of features and by b) replacing the ZMDA distance with the Mahalanobis distance, the ratio of the distances becomes much larger. The Mahalanobis distance between the two spectra belonging to the search pattern is 1.89, whereas the distance between the spectrum at the origin and the spectrum at the search pattern is 2,390; in other words, the *ratio* of the two distances is now 1264. It is this enormous difference in the ratios between distances between members of the search pattern and non-members which makes the Mahalanobis distance an excellent discriminator

6.2 Combining the clustering algorithm with the feature selection algorithm

When comparing the overall performance of the image recognition process using the clustering and/or feature selection algorithm, it is important to keep in mind that a *third parameter* namely the distance measure used in these algorithms, also affects performance. The relationship between clustering, feature selection and distance measure is too complex to be described by a few simple rules or tables. The *intent* of this paper is to alert researchers to this complexity and hopefully to prevent some premature, generalized conclusions. If the paper succeeds in convincing the reader that the combination of

- evolutionary clustering algorithm
- an evolutionary feature selection algorithm
- the selection of the Mahalanobis distance as the distance measure

can provide superior pattern recognition performance, then the authors will be satisfied.

Figures 5 and 6 demonstrate how Mahalanobis correlations can find objects in an image other than the one from which the training covariance matrix was obtained. Before the calculations for figures 5, 6, and 7 were performed, the number of wavelengths was reduced by the evolutionary feature reduction algorithm from 120 to 5. The cluster shown in figure 5 was obtained by applying the evolutionary feature reduction algorithm to image FV2.

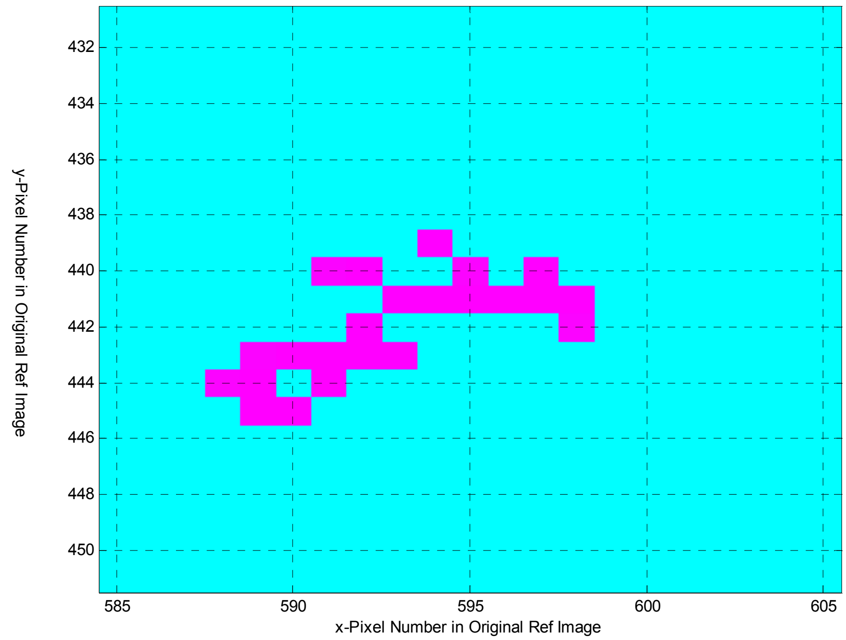

Fig 5. Cluster found by the evolutionary clustering algorithm in image FV2. The number of features is 5; the cluster was found in 20 evolutionary generations using ZMDA as distance measure.

Next, the covariance matrix for the training area comprised of the 23 pixels shown in figure 5, was calculated. Based on this covariance matrix, we computed the Mahalanobis correlations of all the pixels in a 75 x 75 pixel area centered at 600/445 in image FV1. Note that this is a different image than the one shown in figure 5. Figure 6 clearly confirms that thee process of using *one image* for the calculation of the covariance matrix and then using *another image* for finding an object provides very high Mahalanobis correlations.

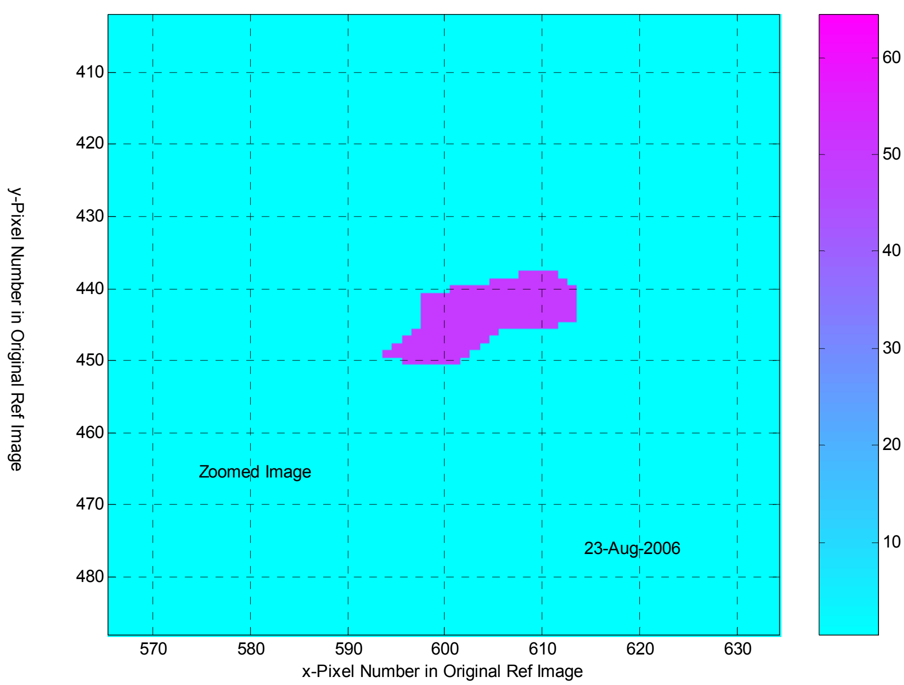

Fig 6. Intensity plot of Mahalanobis correlation values between 75 x 75 pixels (search area) and pixel 600/445.

The final picture in this sequence, figure 7, simply uses different scaling for the intensity plot of the Mahalanobis correlation strengths. The value of figure 7, besides being a nice image of the target area, is to make it very clear that selecting the most suitable visual representation of correlation results can enhance the value of a particular pattern recognition solution.

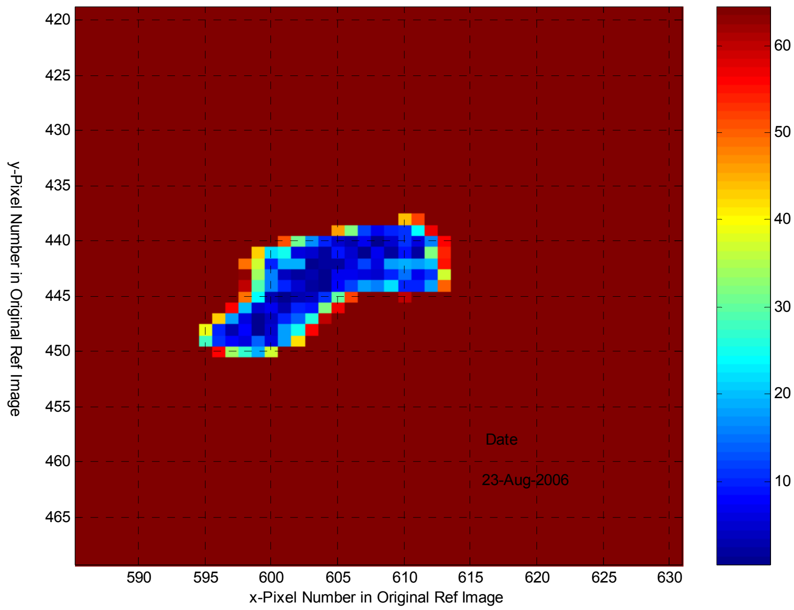

Fig 7: The same Mahalanobis correlation intensities as shown in figure 6, but different scaling for the intensity plot

By displaying these two images, we want to demonstrate more than just two nice looking figures; we want to point out the importance of proper visualization in image analysis. Selecting the most suitable representation and visualization of results in pattern recognition often enhances the value of a particular solution.

6.3 Fitness function value and Receiver Operating Characteristic (ROC).

As long as we are only interested whether or not a pixel belongs to a specified pattern, the problem is essentially a binary hypothesis testing problem. Reference 5 provides a good overview of binary hypothesis testing where the probability of detection versus the probability of false alarms are represented by ROC curves.

Figure 8 depicts a ROC curve (the fitness function of one particular population member in the evolution of a reduced feature set. The distance measure used was Mahalanobis distance between an arbitrary pixel and the composite cluster of the reference area.. The probability of detection was defined as the number of correctly classified pixels (out of 409,600 pixels), divided by the numbers of pixels in the image that were defined as belonging either to the primary or the secondary search area.

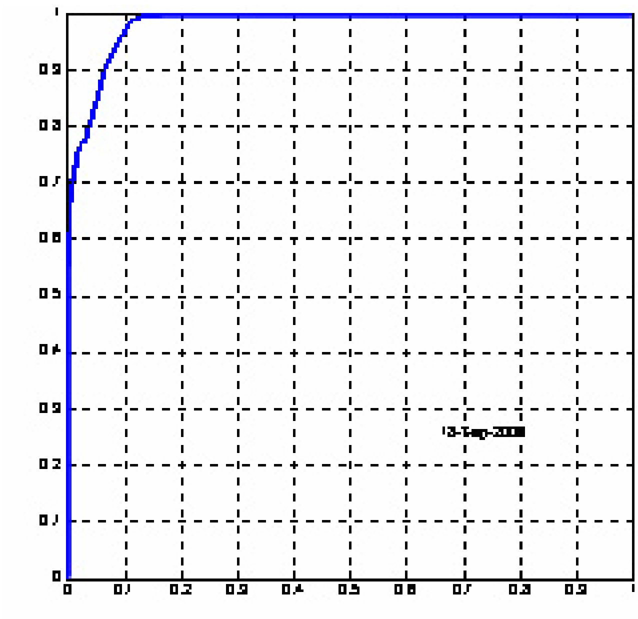

Fig 8. Example of a ROC curve for the analysis of image FV2 using Mahalanobis distance; Abscissa: Probability of false alarm; Ordinate: Probability of detection.

7. CONCLUSIONS AND RECOMMENDATIONS

The most important conclusion that can be drawn from this research is the fact that the Mahalanobis distance often constitutes a better discriminator than distance measures that rely simply on the comparison of two spectra of single pixels. The fact that the ZMDA distance measure worked as well as it did can partially be attributed to the very high signal-to-noise ratio in the the particular target images we analyzed. Presumably, if we would repeat a similar study using images with much lower signal-to-noise ratios, caused for example by motion of the objects or of the camera, the superiority of the Mahalanobis distance over the ZMDA distance measure would be more pronounced.

Additional research to better define the advantages and disadvantages of decreasing the number of features in various pattern recognition problems is recommended.

REFERENCES

1 D. Landgrebe, "Hyperspectral Image Data Analysis", *IEEE Signal Processing Magazine*, Jan 2002, pp 17 – 28.
2 http://cobweb.com.purdue.edu/~biehl/MultiSpec/description.html
3. D. Landgrebe, *Signal Theory Methods in Multispectral Remote Sensing (Wiley Series in Remote Sensing and Image Processing),* Hoboken, New Jersey*,* John Wiley and Sons *2003.*
4. http://www.microimages.com/getstart/hyprspec.htm
5. B.V.K. Vijaya Kumar, Abhijit Mahalanobis, and Richard D. Juday, *Correlation Pattern Recognition*, Cambridge University Press, 2005.