

Detecam: An Automated System for Change Detection in Bitemporal Images

Christian Fernández¹, M. Ángeles Reyes¹, Fernando Pérez² and J. Manuel Gálvez³

¹Centro Superior de Informática

²Departamento de Estadística, Investigación Operativa y Computación

³Departamento de Física Fundamental y Experimental, Electrónica y Sistemas

Universidad de La Laguna. Islas Canarias. Spain

e-mail: {wcsi,wcsi,fdoperez, jmgalvez}@ull.es

Phone: +34-922-319184, Fax: +34-922-319202

Abstract

Change detection is an important part of image interpretation and automated geographical data collection. There are several approaches to change detection, from image differencing to Principal Component Analysis. One of the techniques that offer best results is Iterative Principal Component Analysis (IPCA). In this paper we present some modifications to IPCA that improves its performance. In particular we show a new initialisation and a new model for the probabilistic density of pixel change. These modifications are integrated in the Detecam system that automates the detection of changes in aerial images. Experimental results for this approach are shown in several types of real images.

Keywords: Change Detection, Iterative Principal Component Analysis, Spatiotemporal Analysis, Multispectral Analysis.

1. Introduction

The Detecam system provides a solution for the problem of change detection on the terrestrial surface from multitemporal images. This system has been developed as a tool in the maintenance and update of cartographic maps. This is one of the working areas of the company GrafCan S.A. (www.grafcan.com) located in the Autonomous Community of the Canary Islands (Spain). The company is dedicated to Geographical Information Systems (GIS), a field of increasing importance in the last years due to the importance of its applications: house census, environmental planning, localization of public services, verification of city-planning norms, etc. These applications are of importance to private and public organisms that need a massive processing of geographical information.

One of the main costs associated to GIS is the information maintenance cost, since geographical information changes temporally. One way to detect these variations is the use of pairs of images of the same area at different times. A human operator then detects changes by means of the visual analysis of images. Human visual analysis is favoured by the implicit incorporation of intelligent processing associated to the operator. But, on the other hand, and also due to the explicit intervention of the operator, this analysis is not free of disadvantages due to operator fatigue, operator inconsistencies or operator costs. Therefore, any improvement oriented to automate manual processes

would generate a positive reduction in maintenance costs.

In this paper we present the Detecam system that has been developed for GrafCan. It consists of a set of techniques used in the detection of changes both in aerial and satellite images. Detecam contains all the necessary tools for image processing and visualization. In addition, the obtained changes can be displayed in visual form or like a map of probabilities for their later processing.

In order to detect the changes produced in an area during a determined period of time a pair of orthophotos (air photographs rectified for orthogonal projection) are obtained with a determined temporal difference that is usually one or two years. These images are georeferenced so that exists a pixel-to-pixel correspondence between these two images. The aerial images used by GrafCan cover all the extension of the Canary Islands. For that reason its content is variable with zones of coast, mount, or urban areas. The planning of flights contemplate the acquisition of the aerial images so that at every moment the sun is on the vertical of the observation point, thus avoiding, as far as possible, the presence of shadows. In spite of this, it is not always possible a planning of flights with total absence of shadows so they are usually present in images. Moreover, although the images are taken at the same time of the year, the climate conditions can be different. We may have, for example, a green field at a time, due to abundant rains, and two years later the same zone with clearer tones, due to the shortage of rains.

2. Change Detection in bitemporal images

The analysis of the observed differences when comparing an image sequence of the same scene at different moments depends strongly on the change source.

The actual changes in multitemporal aerial images of a same scene may be originated by diverse factors like:

- Creation or disappearance of urban structures created by man (new building constructions, highways, etc.)
- Changes due to a seasonal and/or natural origin (changes in the vegetation, floods, different atmospheric conditions, etc.)
- Changes due to acquisition conditions of the sequence of images (point of observation, illumination, sensors, atmospheric conditions, etc.)

In the detection of changes it is necessary to make some comparison between the images obtained with a certain temporal separation. The final goal is to evaluate the degree of change between the two images, or areas of interest, supposing that both represent the same space location. To compare the images it is often necessary to pre-process them as a first step to obtain these degrees of change. Among such pre-processing operations are of special importance image registration and image intensity normalization.

A crucial aspect in the detection of changes is the definition of features to carry out the comparison. At the present moment two different strategies are widely employed: techniques based on a pixel level comparison of images and techniques based on scene model definition and matching. Although methods based on pixel-to-pixel analysis of images are of relatively simple implementation, they usually show high sensitivity and low semantic information. On the other hand the comparison of multitemporal images based on high level models are less prone to changes not directly related to the structural content of the scene. Nevertheless model definition and matching is a very complex computational problem. To analyse the aerial images provided by GrafCan where content is variable and where changes are generated by a great variety of sources we have employed a multispectral pixel-to-pixel analysis.

2.1 Multispectral Analysis Techniques

Multispectral analysis is focused on the values of brightness of the images in their different spectral

bands. The basic premise for the detection of changes in these strategies is that changes in the terrestrial surface are reflected in changes of the brightness values between an image $I(t_1)$ captured at time t_1 and its corresponding image $I(t_2)$ of the same region but taken at time t_2 . In addition, brightness variation due to changes in the terrestrial surface must be greater than brightness changes caused by other factors. The impact of these factors can be partially reduced selecting appropriately the data. For example, the acquisition of the image at the same time of the year can reduce problems due to differences in the angle of the sun and changes of vegetation.

From the first studies in [1], the development of techniques of change detection based on the analysis of multispectral data has undergone a continuous evolution and several approaches have been developed: Image differencing [2], Image quotient [3], Vegetation Index Difference [4], Image regression [5] Principal component Analysis (PCA) [6], Change Vector [7] and Iterative Principal Component Analysis (IPCA) [8].

In our system we have employed a modification of IPCA to detect image changes.

3 Iterative Principal Component Analysis (IPCA)

The IPCA approach [8] is a variation of the classical PCA approach. It uses a bitemporal feature space for a single spectral band i where each pixel x is denoted by a point $\mathbf{x}_i = (x_i(t_1); x_i(t_2))^T$. Then, assuming a linear relation between unchanged pixels, we expect all unchanged pixels to lie in a narrow elongated cluster along a principal axis. On the other hand, the pixels, which do have experienced 'Change' in their spectral appearance, are expected to lie far out from this axis. Thus, the amount of change is quantified by the magnitude of the second principal component (PC2): $c_i'(\mathbf{x}_i) = g_{1,i}(x_i(t_1) - m_{i,1}) + g_{2,i}(x_i(t_2) - m_{i,2})$, where $g_i = (g_{1,i}, g_{2,i})^T$ is the second eigenvector of the overall covariance matrix C_i and $m_i = (m_{i,1}, m_{i,2})^T$ are the mean values of $\mathbf{x}_i(t_1)$ and $\mathbf{x}_i(t_2)$ (See Figure 1).

A problem with classical PCA change detection is that the principal components are conventionally estimated as the eigenvectors of the covariance matrix C_i computed from all pixels \mathbf{x}_i , including those that have experienced change. Thus, the 'No Change' axis is prone to error. In the iterative approach the problem is addressed determining the cluster mean m_i and the covariance matrix C_i from all pixels \mathbf{x} but weighted with their respective probabilities $P(NC|\mathbf{x})$ to be 'No Change' pixels.

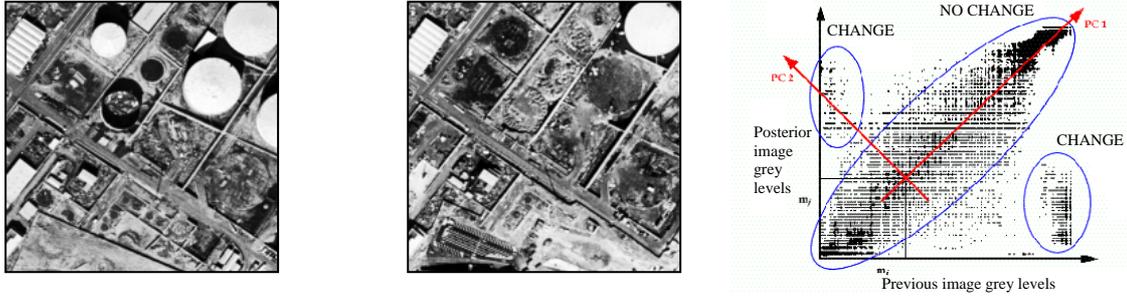


Figure 1. Left: Industrial area of Santa Cruz de Tenerife (Canary Islands) in 1996. Center: The same area two years later. Right: Bitemporal histogram and principal components

A typical problem of remotely sensed imagery is that the registration of imagery only yields registration accuracies of some pixels at best. Then in image areas of high texture, even small misregistration errors will cause a large amount of spurious change detection. To avoid this effect all change components $c'_i(\mathbf{x}_i)$ are normalized by its local variance $\sigma_{loc,i}^2(\mathbf{x})$:

$$c_i(\mathbf{x}_i) = c'_i(\mathbf{x}_i) / \sqrt{\sigma_{loc,i}^2(\mathbf{x})} \quad (1)$$

The local variance $\sigma_{loc,i}^2(\mathbf{x})$ is estimated from the spectral variances $\sigma_{loc,I_1,i}^2(\mathbf{x}), \sigma_{loc,I_2,i}^2(\mathbf{x})$ in a local neighbourhood $N(\mathbf{x})$ of pixel \mathbf{x} in image $I(t_1)$ and $I(t_2)$ in spectral band i from:

$$\sigma_{loc,i}^2(\mathbf{x}) = g_{1,i}^2 \sigma_{loc,I_1,i}^2(\mathbf{x}) + g_{2,i}^2 \sigma_{loc,I_2,i}^2(\mathbf{x}) \quad (2)$$

To classify each pixel into one of two classes: $w_1 =$ 'Change' or $w_2 =$ 'No Change' the usual Bayesian decision approach is employed. Therefore a pixel is assigned to the class that has the maximum *a posteriori* probability $p(w|\mathbf{x})$.

The normalized conditional probability density derived in each spectral band is:

$$p_i(\mathbf{x}_i | w) \propto \exp\left(-\frac{1}{2} \frac{c_i(\mathbf{x}_i)^2}{\sigma_{w,i}^2}\right) \quad (3)$$

and all bands are assumed to be independent. The within-class variance $\sigma_{w,i}^2$ is estimated from data itself during the iteration.

Then the a posteriori probabilities are evaluated as:

$$P(w|\mathbf{x}) = \frac{P(w)P_{con}(\mathbf{x}|w)\prod_i p_i(\mathbf{x}_i|w)}{\sum_w P(w)P_{con}(\mathbf{x}|w)\prod_i p_i(\mathbf{x}_i|w)} \quad (4)$$

$$\text{where } P(w) = \frac{\sum_{\mathbf{x}} P(w|\mathbf{x})}{\sum_{w,\mathbf{x}} P(w|\mathbf{x})}$$

and p_{con} is a contextual probability that allows the probability of a pixel \mathbf{x} to be influenced by the probabilities of its neighbourhood $N(\mathbf{x})$ and it is defined as:

$$p_{con}(\mathbf{x}|w) \propto \exp(-\beta U(\mathbf{x}|w)), \quad (5)$$

$$U(\mathbf{x}|w) = \sum_{\mathbf{x}' \in N(\mathbf{x})} (1 - P(w|\mathbf{x}'))$$

Parameter β defines the magnitude of the contextual influence. For $\beta=0$ the influence is vanishing and $\beta=1$ is a common choice.

The probabilities and the necessary parameters are estimated during an iterative process using the current conditional probabilities. At each iteration step and for each spectral band i the 'No Change' cluster centre m_i is updated along with the second principal axis g_i , the change components c_i and probabilities $P(w|\mathbf{x})$ for each pixel. Scatter widths $\sigma_{w,i}^2$ for both the 'No Change' and the 'Change' cluster are reestimated, along with the a priori probabilities. The algorithm in [8] can be stated as follows:

Step 0

Register the two images $I(t_1)$ and $I(t_2)$

Step 1

Initialise the probabilities for all pixels $P(w|\mathbf{x})$ where $w = \{CH, NC\}$

Pre-compute the local spectral variance estimates $\sigma_{loc,I_1,i}^2(\mathbf{x}), \sigma_{loc,I_2,i}^2(\mathbf{x})$ for all spectral bands and all pixels \mathbf{x}

Step 2

for all n spectral bands i do

2.1 Determine principal axes from all pixels weighted with the current probabilities $P(NC|\mathbf{x})$ and the inverse of the combined local variance $\sigma_{loc,i}^2(\mathbf{x})$ in spectral band i

2.2 Compute the 'Change' components $c'_i(\mathbf{x}_i)$ and normalize them into $c_i(\mathbf{x}_i)$ evaluating its quotient with the combined local variance in spectral band i

2.3 Compute the *CH* and *NC* class variances $\sigma_{CH,i}^2(\mathbf{x})$ and $\sigma_{NH,i}^2(\mathbf{x})$ from all pixels weighted with the current probabilities $P(CH|\mathbf{x})$ and $P(NC|\mathbf{x})$ respectively.

2.4 Compute the spectral probability densities $p_i(\mathbf{x}_i|CH)$ and $p_i(\mathbf{x}_i|NC)$

Step 3

Compute current context probabilities $p_{con}(\mathbf{x}|CH)$ and $p_{con}(\mathbf{x}|NC)$ from the current probabilities $P(w|\mathbf{x})$

Step 4.

Compute current a posteriori probabilities $P(w|\mathbf{x})$, the estimation for class priors and the relative number of probabilities $P(w|\mathbf{x})$ that have already converged

Step 5.

Stop if all probabilities $P(w|\mathbf{x})$ have converged, else starts over from Step 2

Thus in each iteration principal components are weighted with the estimated ‘No Change’ probabilities.

4 IPCA modifications

We have implemented several modifications of the original IPCA algorithm that improves its performance. These modifications are described below:

4.1 Initialisation

The unsupervised process of classification employed by IPCA requires a posteriori initial probabilities in Step 1. The appropriate selection of these probabilities influences directly the quality of the final results. In [8] it is considered to assign a value of 0.5 to all the a posteriori probabilities, although it is emphasized that a more appropriate initialisation would be recommendable. In fact this is the case, since the proposed starting values causes the algorithm not to evolve since it starts in a local minima. We propose a new initialisation step for the probabilities using a set of pixels that belong to the ‘Change’ and ‘No Change’ classes with high confidence.

To obtain high confidence ‘No Change’ and ‘Change’ pixels image edge information is employed. This proposed method is based on the observation that structures in image like edges are invariant to a great extent to illumination changes. To obtain edges the Sobel operator is employed and a map of edges for each image are generated and thresholded. From edges that exist in both image, randomly chosen pixels create an initial ‘No Change’ class (with estimated probability one) and for edges not in both images the ‘Change’ class is also created. To avoid the inherent noise in the

edges, each selected pixel is assigned with the average brightness level on its neighbourhood.

Once the ‘No Change’ and ‘Change’ pixels are selected the a posteriori probabilities are estimated. First covariance matrix is evaluated, using only ‘No Change’ pixels. From this matrix principal components are obtained so change components $c'_i(\mathbf{x}_i)$ can be calculated for all pixels \mathbf{x} . Next the densities for each band i of spectral conditional probability for each class $p_i(\mathbf{x}_i|w)$ are estimated using the edge based selected points. With these estimations, and supposing $p_{con}(\mathbf{x}|w) = 1$ (initially contextual conditional probability is not considered), the initial probabilities $P(w|\mathbf{x})$ are evaluated for all pixels and the iterative process can be initiated.

4.2 The spectral conditional probability density

In [8] spectral conditional probability densities for the ‘Change’ and ‘No Change’ classes have zero mean. This approach is correct for the ‘No Change’ class since principal components are obtained from covariance matrix with variances and covariances weighed by the probabilities of ‘No Change’ $P(NC|\mathbf{x})$. Then, due to the properties of the principal component transform, the mean of change component $c(\mathbf{x}_i)$ multiplied by $P(NC|\mathbf{x}_i)$ is equal to zero. Nevertheless, this property is not valid for the case of the ‘Change’ class and, therefore, its spectral conditional probability density is not necessarily centred in zero.

Then, we propose to model the conditional probability density of the ‘Change’ class introducing the mean parameter $\mu_{CH,i}$ as follows:

$$p_i(\mathbf{x}_i | CH) \propto \exp\left(-\frac{1}{2} \frac{(c_i(\mathbf{x}_i) - \mu_{CH,i})^2}{\sigma_{CH,i}^2}\right) \quad (6)$$

and the evaluation of $\mu_{CH,i}$ is done iteratively in the algorithm.

In practice, the first proposed modification improves the convergence speed and the second improves class separation.

5 The Detecam system

The Detecam system integrates all the necessary tools for change detection. Its design guidelines have been to build a system that comprises not only the modified IPCA algorithm but also all the necessary pre-processing and post processing tools for change detection. System use should be easy and intuitive so that operators do not need new skills.

5.1 System features

The main features of the system are:

Image processing:

- Image import and export
- Image adjustment and equalization
- Image thresholding
- Edge detection image filtering
- Dilation and erosion

Image pair processing:

- Bitemporal histograms
- Image pair registering
- Image pair normalization
- Change detection methods:
 - Image differencing
 - PCA
 - Modified IPCA

Change visualization

- Change overlay over image pairs
- Colour HSV fusion of changes

5.2 Experimental results

The system has been tested on several images. In this section we present several results for black and white and colour orthophotos from several locations in the Canary Islands and a satellite image from an urban area in Madrid (Spain)

- **Black and white orthophotos**
In this example we show the results of the change

detection process for two black and white orthophotos with 1:5000 scale (0.5 meters per pixel). In Figure 3 we can see the two images that were taken in 1996 and 1998 over a region in S/C Tenerife, (Canary Islands). As we can see major changes comes from the disappearing of petrol tanks. The parameters employed in the modified IPCA algorithm have been:

-Local variance neighbourhood: 3x3

-Context neighbourhood: 7x7, $\beta=1$

and the algorithm converged after 6 iterations.

Results image show that main changes are detected. We can see also how shadows produce some errors in the algorithm as we can see near some petrol tanks.

- **Colour orthophotos**

In this example we show the results of the change detection process for two colour orthophotos with 1:10000 scale (1 meter per pixel). In Figure 4 we can see the two colour images (printed in black and white) that were taken in 1996 and 1998 over a rural area in Gran Canaria (Canary Islands). In this case we have a truly multispectral image with 3 components corresponding to the Red, Green and Blue (RGB) components. The parameters employed in the modified IPCA algorithm have been:

-Local variance neighbourhood: 3x3

-Context neighbourhood: 5x5, $\beta=1$

and the algorithm converged after 6 iterations.

Results image show that main changes are detected. In this case changes in terrain colour introduce some errors in the matching process

- **Black and White satellite images**

In this example (Figure 5) we show the results of

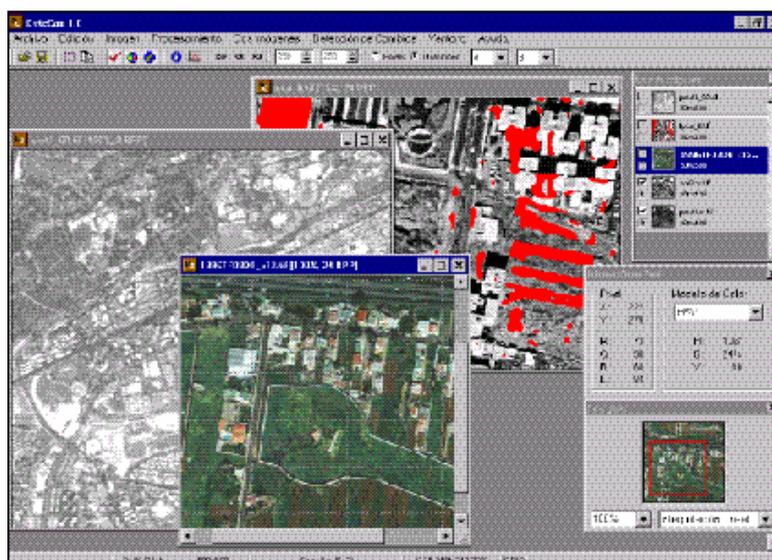


Figure 2 The Detecam system

the change detection process for two black and white satellite orthophotos from the IRS-1C satellite with a spatial resolution of 5 meters per pixel. Images show a region corresponding to the city of Madrid (Spain). The parameters employed in the modified IPCA algorithm have been:

-Local variance neighbourhood: 3x3

-Context neighbourhood: 7x7, $\beta=1$

and the algorithm converged after 3 iterations.

The results image show that main changes are detected. In this case registration errors introduces some errors in the matching process.

6 Conclusions and future improvements

Change detection is an important part of image interpretation and automated GIS data collection. In this paper we have presented the Detecam system that automatics the detection of changes with aerial images. This system uses a variation of the IPCA method that improves its performance.

However, at the present, there is no general-purpose method comparable to a human operator and the system can only be used in quality control. Future improvements of the system include the emulation of the actual image changes detected by the operator using an adaptive system like neural networks. Since there is a database of changes detected by the operator training of the system in various image types

Acknowledgements

The authors would like to than all the facilities and support provided by GrafCan

References

- [1] H. Lillestrand (1972). Techniques for Change Detection. IEEE Transactions on Computers, Vol. 7, pp. 654-659.
- [2] D.L. Williams y M.L. Stauffer (1978). Monitoring Gypsy Moth Defoliation by Applying Change Detection Techniques to Landsat Imagery. Processings of the Symposium for Vegetation Damage Assessment, American Society for Photogrammetry , pp. 221-229.
- [3] P.J. Howarth and G.M. Wickware (1981). Procedures for Change Detection Using Landsat Digital

Data. International Journal of Remote Sensing, Vol. 2, pp. 277-291.

[4] R.F. Nelson (1982). Detecting Forest Canopy Change Due to Insect Activity Using Landsat MSS. Photogrammetric Engineering and Remote Sensing, Vol. 49, pp.1303-1314.

[5] K. Ingram, E. Knapp and J.W. Robinson (1981). Change detection technique development for improved urbanized area delineation, Technical memorandum CSC/TM-81/6087, Computer Sciences Corporation, Silver Springs, Maryland, USA.

[6] G.F. Byrne, P.F. Crapper, and K.K. Mayo (1980). Monitoring Land Cover Change by Principal Component Analysis of Multitemporal Landsat Data. Remote Sensing of Environment, Vol. 10, pp. 175-184.

[7] W.A. Malila (1980). Change Vector Analysis: An Approach for Detecting Forest Change with Landsat. Processings Annual Symposium on Machine Processing of Remotely Sensed Data, IEEE, pp. 326-336.

[8] R. Wiemker, A. Speck, D. Kulbach, H. Spitzer and J. Bienlein (1997).Unsupervised Robust Change Detection on Multispectral Imagery Using Spectral and Spatial Features. Proceedings of the Third International Airborne Remote Sensing Conference and Exhibition, Copenhagen,Denmark.

<http://kogs-www.informatik.uni-hamburg.de/projects/Censis.html>

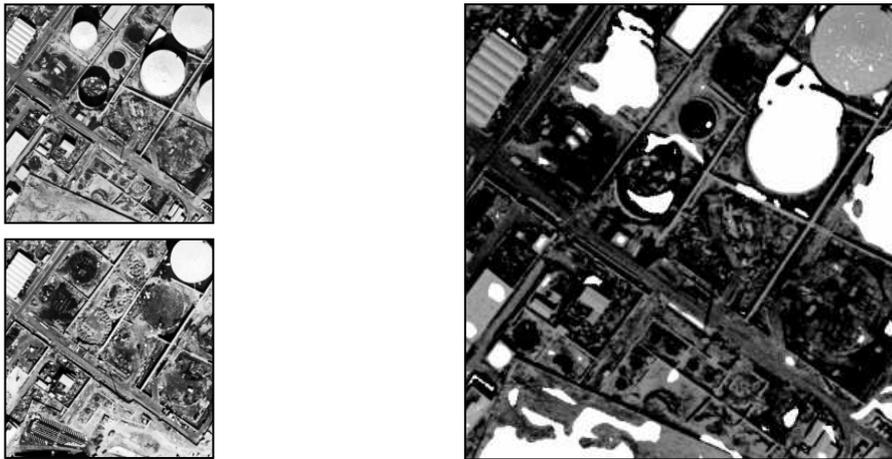


Figure 3 Pair of images black and white images taken in 1996 and 1998 over a region in Santa Cruz de Tenerife (Canary Islands). Changes are shown in white over a low brightness version of upper left image.

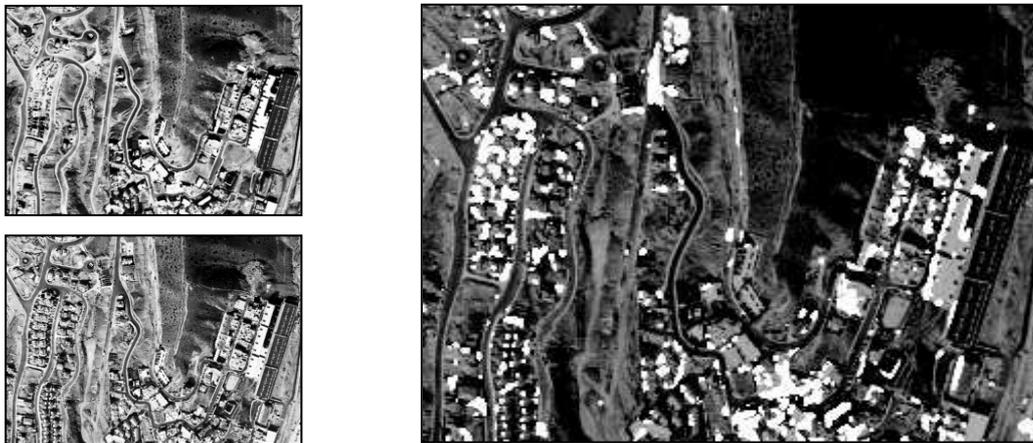


Figure 4 Pair of color images (printed in black and white) taken in 1996 and 1998 over a region in Gran Canaria (Canary Islands). Changes are shown in white over a low brightness version of upper left image.

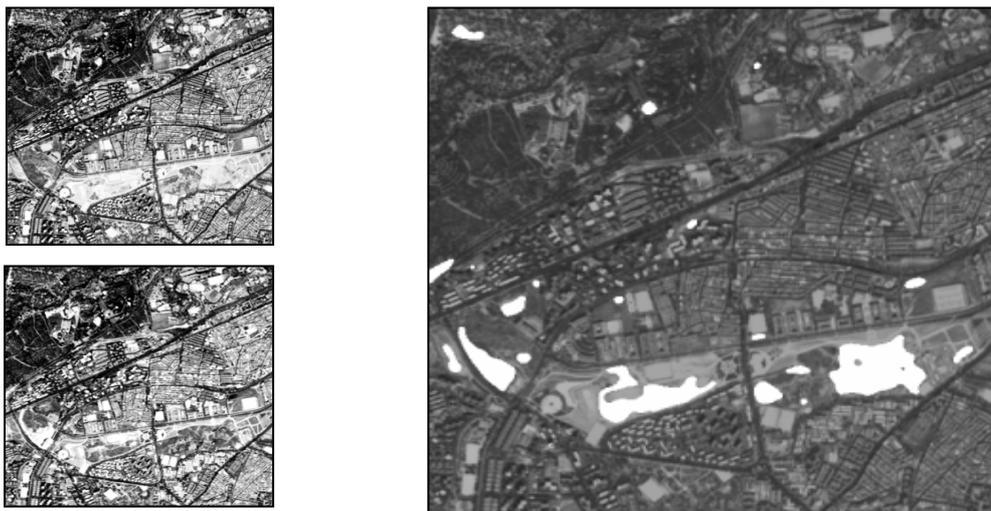


Figure 5 Pair of satellite images taken in 1999 and 2000 over a region in Madrid (Spain). Changes are shown in white over a low brightness version of upper left image.