A REMOTE SENSING IMAGE PROCESSING FRAMEWORK FOR DAMAGE ASSESSMENT IN A FOREST FIRE SCENARIO

Anca Popescu, Corina Vaduva, Daniela Faur, Inge Gavat, Mihai Datcu

University Politehnica Bucharest

ABSTRACT

In natural hazards management applications Earth Observation (EO) image processing methods are based on segmentation and classification. The result primary consists of thematic maps which are readily interpretable. We propose a complete EO image processing chain, which generates an end product with increased information content organized in thematic layers. The processing chain integrates four main components: image classification, identification of high anomaly areas relative to the entire scene context, spectral and texture change detection, and the integration of different information layers. The processing chain was tested in a fire management scenario, using a pair of Landsat5-TM images for the Pagami Creek forest fire which was active from August to October 2011.

***Index Terms*—**Image anomaly/change detection, Natural hazards management, Information theoretical measures

1. INTRODUCTION

Remote sensing and digital processing of satellite images are geo-spatial tools that support various applications for natural disaster management. They stand at the basis of the development of a number of automated systems for the prevention of such phenomena. Satellite technological resources are constantly directed to monitor the weather status and geological events in order to anticipate potential hazards and to minimize their effects on people's lives. When the event occurs, a rapid, effective and reliable response of authorized institutions is essential. To this purpose, because generally the affected areas are hardly accessible, it is necessary to gather information remotely and satellite image processing provides an efficient solution in terms of cost and coverage. In this context, efforts are directed towards the development of automated methods to extract and process the information contained in satellite images. Typical Earth Observation (EO) image processing methods are based on segmentation and classification, resulting in thematic maps readily interpretable. In this paper we advance towards an integrated solution, which brings together several stages of data processing and aims at constructing a product organized on information layers.

To this end, we propose a complete EO image processing chain, where the end product has increased information content, due to the fact that it is not just a thematic map, but the result of a vertical representation of informational layers. Each organization level gives a different category of descriptors, which makes the product easily adaptable to the application and the user. The basis of the processing chain is represented by a raw level, where the areas with the most interesting information content relative to the entire scene are identified. Climbing up the vertical representation of the product, more layers of information are added, comprising knowledge about the degree of change between image pairs, either spatial or spectral, up to the top level where the information is refined and the areas which are representative for a given application and hazardous event are precisely delineated. These areas are being associated a meaningful sense which is adaptable to the application in the sense that the user can pick which of the information layers are the most relevant. The processing chain thus integrates the following components (figure 1):

a) A classification component that extracts the landcover types present in the scene

b) An information theory based component, which exploits the relation between entropy and chaos for coarse delineation of areas of high anomaly relative to the entire scene information

c) A change detection component that integrates spectral and textural changes occurring between two passes of the imaging sensor before and after the occurrence of the event

d) A vector contour component that delineates the areas of interest and integrates the different information layers

2. IMAGE PROCESSING CHAIN FOR INFORMATION RETRIEVAL

This section describes the proposed processing chain, its component modules, and the interaction between the different levels of information. Typically, in disaster management applications, the employed data consists of a pair of satellite images of the affected area before and after the occurrence of the event risk hazard. There are certain requirements on the data that should be considered (remote sensing data, including airborne and spaceborne data, vary in spatial, radiometric, spectral and temporal resolution.

Thus, in addition to the user needs, one must also take into account the scale of the area, the data availability, characteristics, cost and time constraints). The proposed processing chain is applicable to average resolution images, due to the fact that as the resolution increases, the degree of heterogeneity of data is so high that the processing methods are much more specific. Moreover, it consists of a series of processing modules. Each of them helps users define symbolic models with several levels of abstract representation.

2.1. Image classification component

The first processing level involves image classification. The classification is performed on the image pair, and gives a first identification of the regions that will be processed. Depending on the application, the classification can be computed in a multi-class approach (for the case where there are different categories of landcover that are affected by the risk event) or in a single-class approach, if the a priori data about the particular landcover is sufficient. The authors have employed the ISODATA algorithm due to the fact that it is less sensitive (for example as compared to K-Means) to clusters which have varying variances. Since the analyzed data includes mostly forest pixels, clusters will tend to have elongated shapes which imply a high variability.

2.2. Anomaly detection component

The second level of abstract representation refers to the retrieval and extraction of the regions that have significant information content relative to the scene context. To this end, one must define the term "significant". When the risk event occurs, it has a visible effect on the scene content. If we consider the initial scene to be the input of a system characterized by the event model, the information transmitted through the system is affected. Thus, the areas of interest will break the scene pattern. This process of retrieving the areas that are "interesting" for the understanding of the event is called "anomaly detection". A domain that ensures suitable measures to describe image information content considering probabilistic measures is information theory. Considering the gray levels of pixels in the image as particular realizations of a random variable the probability density function of the variable determines the amount of image information. Further mutual information is used to describe the relationship between two random variables (features space and class space) and Kullback Leibler divergence to reveal differences between the two probability density functions [1]. In the probabilistic framework the amount of information represents uncertainty. Given the image as a discrete random variable, Shannon's entropy is the average amount of information:

$$H(X) = -\sum_i^n p(x_i)\, log\, p(x_i) \qquad (1)$$

Mutual information is defined as the difference:

$$I(X,Y) = H(X) - H(X|Y) = \sum_X \sum_Y p(x_i, y_j) \log \frac{p(x_i,y_j)}{p(x_i)p(y_j)} \qquad (2)$$

It takes into account the dependence between variables. Our goal is to make further use of the primitive feature extraction results of the first level to code the image information content. The image features reflects the physical parameters of the imaged scene. From the generated content index obtained in the classification process the mutual information between image space and class space is:

$$\Im(I,\omega) = \sum_k \sum_i p(\omega_i|I_k)p(I_k) log \frac{p(\omega_i|I_k)}{p(\omega_i)} \qquad (3)$$

Where $p(\omega_i|I_k)$ indicates the posterior probabilities of signal classes given a certain image tile I_k (~ 90 x 90 pixels per tile) from the image. Prior probabilities for signal classes and images are given by $p(\omega_i)$ and $p(I_k)$ respectively. This measure indicates the information transmitted from image data through feature extraction and unsupervised clustering to the class space. Further based on Kullback Leibler divergence once can compute the information between image space and class space. The KL divergence is applied to determine "the complexity" of a single image tile relative to the entire image.

$$D(p,q) = \sum_k \sum_i p(\omega_i|I_k) log \frac{p(\omega_i|I_k)}{q(\omega_i)} \qquad (4)$$

It shows how much a single image tile I_k is a typical mixture of the complete image content. Fig 4 depicts the anomaly map as resulted from KL divergence, considering I_k an image tile (200 x 200). Smaller tile dimensions increase the accuracy of the delimited area characterized as "significant" post risk event.

2.3. Change detection component

At this point we obtained a model of the scene with a higher degree of sensitivity. Next, we want to assign a meaning which is specific to the application. For this purpose, we advance to the third level of abstraction, in which the pair of images is used to detect changes. Our choice for this step was to construct the "change" pattern as a combination of spectral and texture representations. Change Detection is a measurement of the changes in informational topics contained within the data which allows for a specific description of the process that generated the change. Changes that occur after a risk event translate into differences in the geometry of the scene, as well as in spectral and texture differences.

2.3.1. Spectral change detection

To identify changes at the spectral level, we make use of an information theory method, based on the rationale that the negative of the logarithm of the probability of an amplitude level in one image conditional to the level of the same pixel in the other image conveys information about the degree of spectral change. This a posteriori probability will likely be maximized where risk event had pronounced effects. The algorithm steps are presented in the next paragraph.

First the local means at each pixel position are computed, using a $(2p+1)\,x\,(2p+1)$ window sliding over the images, where p is typically larger or equal to 5. The contribution of each pixel inside the sliding window is multiplied by normalized coefficients summing to $(2p+1)^2$ and decaying toward the edges with Gaussian slope. Next, the scatter-plot plane (of the filtered images) is partitioned into an $(L\,x\,L)$ array of rectangular blocks, in order to get a 2-D histogram $h(i,j)$, where i matches the level of image g_2 and j the level of image g_1. Further on, the number of scatter-plots in each block is normalized to the overall number of points. Next, a Gaussian-shaped filter is applied to the discrete normalized 2-D histogram and yields the discrete joint probability density function (PDF), which is used to compute the discrete conditional 2D-PDF [2]:

$$p(i|j) = \frac{p(i,j)}{p(j)} = p(i,j)/\sum_i p(i,j) \qquad (5)$$

The joint probability $p(i,j)$ is scaled to its maximum along the column in order to make sure that there is no change (the logarithm is zero) when $p(i,j)$ attains this maximum. The rescaled conditional probability is:

$$q(i|j) = \frac{p(i,j)}{\max_i p(i,j)} = \frac{p(i|j)\sum_i p(i,j)}{\max_i p(i,j)} \qquad (6)$$

Finally, the conditional information of g_2 to g_1 at (m,n) is:

$$C(m,n) = -\log\left(q(\lfloor\bar{g}_2(m,n)\rfloor|\lfloor\bar{g}_1(m,n)\rfloor)\right) \qquad (7)$$

2.3.2. Texture change detection

Further on, we give a different interpretation to the risk phenomenon. If we consider the initial scene as an information source, the event "codes" the source, and the result is a secondary source with different entropy. Due to the fact that the Earth Observation images are usually governed by an intrinsic order, the existence of a natural disaster increases the degree of chaos in post-event satellite images. Thus, by exploiting the well known relationship between entropy and chaos, it becomes natural that the post-event image entropy is higher, at least for the affected areas, as compared to the entropy of the initial source. Moreover, entropy is a measure of texture. We employ the Rényi entropy to describe the redundancy of the coded source as a measure of change. The Rényi entropy as a descriptive measure was used in multimedia as well as in remote sensing applications. [3] use local directional Rényi entropy to build a local image descriptor for image feature extraction. The authors use the measure of entropy to measure the local saliency of images and define a descriptor with invariant properties to transformations such as translation, rotation, scale, illumination, occlusion, deformation and viewpoint variation and apply the method on multimedia images for object recognition purposes. [4] use the Rényi entropy as a similarity metric for clustering applications. In information theory, the Rényi entropy is an extension of Shannon's entropy through the relaxation of the additivity constraint. The Rényi entropy quantifies the diversity, uncertainty or randomness of a system:

$$H_\alpha(p) = \frac{1}{1-\alpha} ln \sum_{i=1}^{N} p_i^\alpha \qquad (8)$$

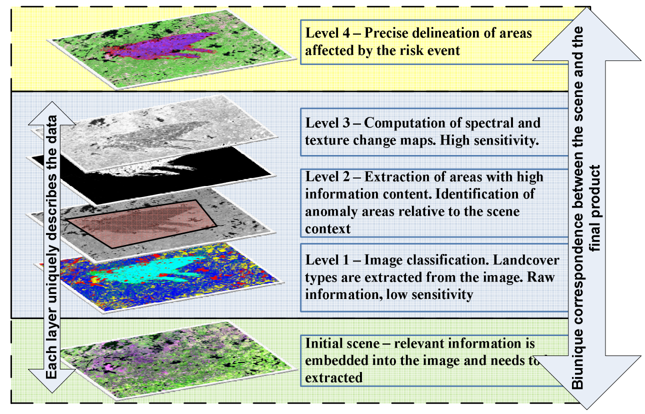

Figure 1. Representation of information levels in processing chain

In the above equation the parameter α is greater or equal to 0 and it becomes obvious that when α=1 the Rényi entropy tends to the Shannon entropy. For a random variable X taking values with probabilities given by the *p* series, the Rényi entropy is a continuous positive decreasing function of α. Finally, we reach the top representation of information, in which the product is refined. For a precise delineation of the affected areas, a vectorization process is applied, which extracts the information related to the contour geometry of the area detected as abnormal or changed and overlays the vector file over the data. The overlay is performed on pre and a post event image, based on the GIS coordinates, for a better visualization and localization of the affected area.

3. TEST SCENARIO - RESULTS ON FOREST FIRE EXTENT EVALUATION

Our application is based on a forest fire scenario. Remote sensing images have been widely used for fire mapping, due to the fact that they provide a broad sight over wide areas. Burnt areas maps are usually extracted from the normalized vegetation index (NDVI), based on a combination of red and near-infrared bands, which reflect the green vegetation. The processing chain proposed in this paper however, is not limited to burnt area detection applications and the results presented are only explanatory, without loss of generality. On August 18, 2011, a large fire was ignited by lightning in the Pagami Creek forest, in Minnesota, USA (figure 2). Nearly 93,000 acres were damaged in this natural disaster that began in the Boundary Waters Canoe Area Wilderness, approximately 14 miles east of Ely, and lasted almost 3 months. Landsat5-TM images were made available by Earth

Observatory [5], courtesy of the U.S. Geological Survey. The images have 30 m spatial resolution, and have been acquired on August 3 and October 6, 2011.

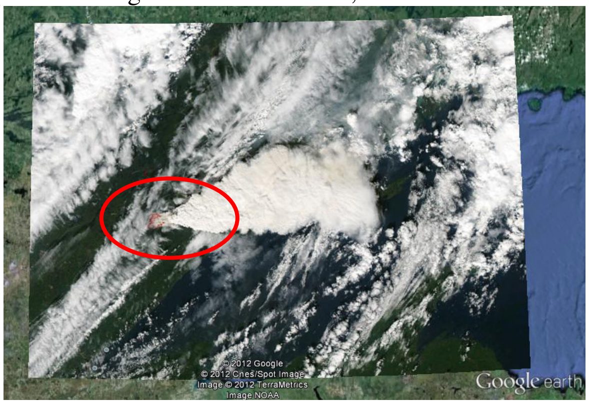

Figure 2. Moderate Resolution Imaging Spectroradiometer (MODIS) on NASA's Terra satellite image on 12.09.2011. The smoke trace from the fire is visible. The red ellipse marks the burnt area.

In the following we discuss the intermediary results of the processing chain, as well as the final product in which they are integrated. Figure 3 (left) depicts the original Landsat5-TM image in which the bands 7, 4, and 2 were chosen for representation. All bands have 30 m spatial resolution. We have chosen this representation of the data because it provides a natural-color rendition and penetrates atmospheric particles and smoke. Bright green represents healthy vegetation. Since the event occurred in late summer there is no heavy growth of vegetation and thus it does not appear saturated. Bare soil is represented by pink areas, while orange and brown indicate sparsely vegetated areas. The middle image in figure 3 depicts the post-event data, in the same combination of spectral bands. The fire appears red. This is a typical representation of Landsat5-TM [6] data for fire management applications and post-fire analysis of burnt/non-burnt areas.

The rightmost image in figure 3 depicts the result of the first processing level, the classification of post-event data with 5 relevant classes. The healthy forest appears dark blue and green, lakes and water bodies/courses appear red, yellow depicts rocky areas and turquoise indicates the area affected by fire. Figure 4 presents the results of the second processing level. The left most image represents the coarse anomaly map. The post-event image was divided into 20 x 20 regions. Each of the 400 image tiles were assigned an anomaly score, which was defined as the complexity of the tile relative to the entire image. Higher scores (lighter tones) indicate a higher complexity and thus mark the corresponding areas as "potentially interesting". This process leads however to a reduction of the resolution of detection, proportional to the size of the tile window. The most relevant tiles were retained by applying a threshold on the anomaly map. The rest of the tiles were discarded. This is indicated in the middle and rightmost images in figure 4, where the contour line of the "abnormal" region was marked onto the pre- and post-event images (previously converted into a single band).

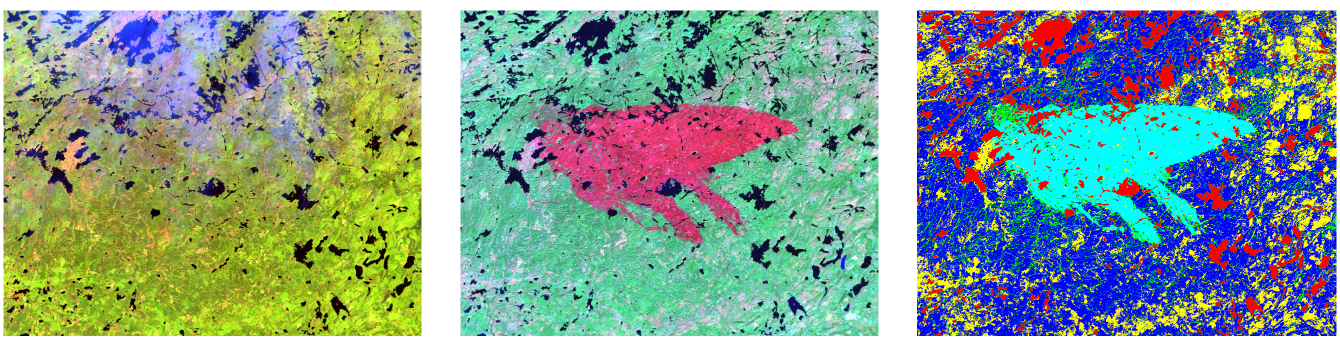

Figure 3. Landsat5-TM image pre-event; Landsat5-TM image post-event. Classification of post-event data ISOdata, 5 classes

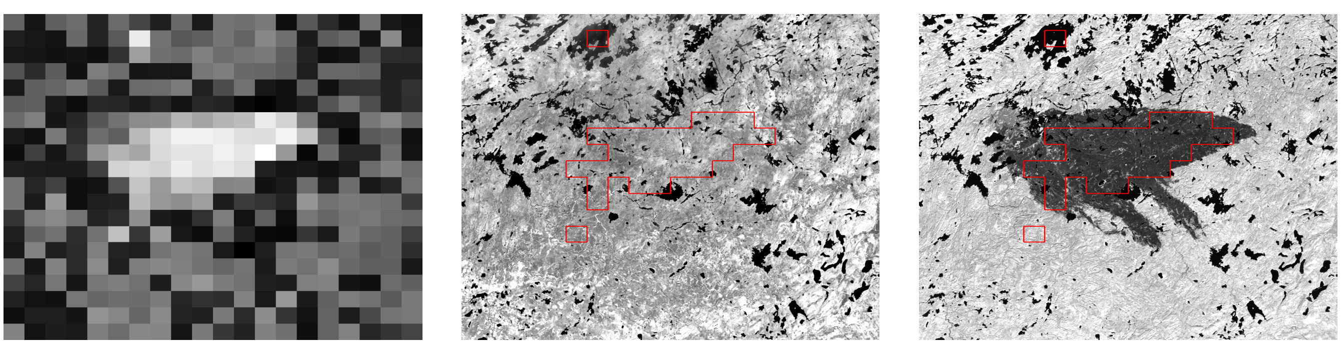

Figure 4 Anomaly map; Abnormal area overlay on pre-event; Abnormal area overlay on post-event

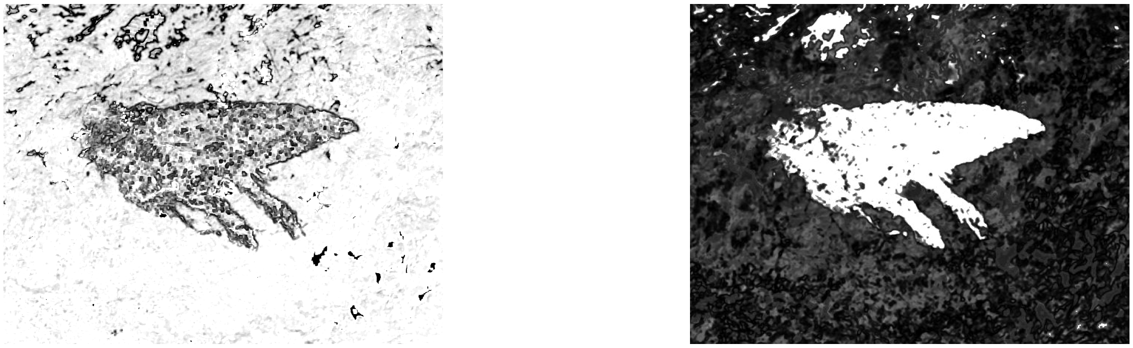

Figure 5. Textural change detection map; Spectral change detection map

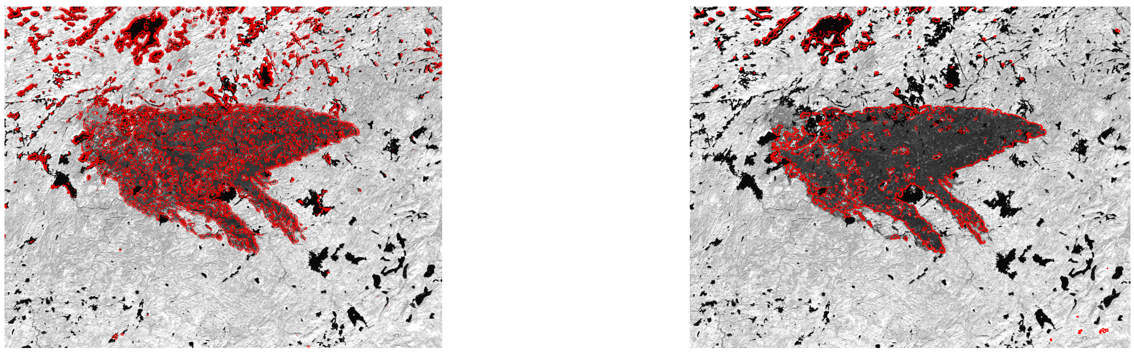

Figure 6. Delineation of areas affected by textural change; delineation of areas affected by spectral change on post-event data

Figure 5 depicts the change detection maps. The left image presents the textural changes (indicated by darker tones) that occurred between the two passes, while the image on the right refers to the spectral changes indicated by the lighter tones. The time lag between acquisitions is 2 months. Thus, although the most visible change is due to the fire, other changes can be visible that can be caused by differences of the water level around the lakes, as well as changes in the canopy. Figure 6 presents the contour lines of the changed areas.

4. CONCLUSIONS

This paper introduces an Earth Observation image processing chain applicable to medium resolution data. The processing chain integrates four main components: data classification, delineation of areas of high anomaly relative to the entire scene information, spectral and textural change detection, and vector contour line stacking for the integration of different information layers. The processing chain was tested using a pair of Landsat5-TM images for the Pagami Creek forest, in Minnesota, for the assessment of the damage extent caused by a fire lasting form August to October 2011. The results show that the processing chain is suitable for effective risk management applications, providing the user with a reliable end product with a complex layered informational structure. This work has been conducted in the frame of the Exploratory Research Project PNCDI-II TOMOSAR, EL 10-12-01.

5. REFERENCES

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