DETECTION OF MAJOR CHANGES IN SATELLITE IMAGES

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ABSTRACT

We address in this paper the problem of detecting changes between two photographs of the same scene taken at different dates. Considering that both images are already accurately registered our problem reduces to a) detect changes between corresponding pixels, and b) determine whether these changes are a clue of a major change in the scene. The solution of a) involves the use of spectral invariant features, since we consider the general situation of comparing photographs coming from different spectral channels. The answer to b) implies the computation of an absolute threshold above which a region of the image will be detected as having "meaningful changes". In order to do that, we apply a recently introduced method yielding accurate false alarm rates for each detection. We show that this method permits to help significantly photo-interprets in their search for major changes in a scene. This will be illustrated by a striking application, the detection of the explosion of the AZF chemical plant in Toulouse (France) in September 2001.

1. INTRODUCTION

The detection of changes between two snapshots of the same landscape, taken at different dates, is a recurrent issue in the image processing literature (see e.g. [1, 2]), and still remains as a not fully resolved problem. The difficulty of the problem arises from three major causes:

a) the brightness and color of objects change from one date to the other, therefore all the gray level values may change between the snapshots

b) objects can change from one season to the next: it is specially the case for the farming areas, where the fields are redrawn or the crops change completely their look

c) occlusions: mainly clouds, but also dust, the width of the river beds, vehicle traffic, etc.

Points a), b), and c) are very strong arguments against the possibility of having a change detector with a reasonable false alarms rate. Objection a) however can be overcome by using a representation of the images based on their topographic map [3], which is invariant to contrast changes. In [4] it has been proved experimentally that this representation is also invariant to spectral changes (i.e. two images of the same scene coming from different spectral channels have almost the same topographic map).

Argument b) implies that farming activities and season changes will produce big changes in the landscape which will modify not only the texture, but also the geometry of the image. The same is true for argument c). As a consequence, the false alarm rate of any automatic change detector will always be relatively high.

We must not, however, give up solving a more restricted but important version of the problem, namely the detection of major changes in urban zones. Our goal here is to help the human operators by providing them with an ordered list of regions where a meaningful change has occurred. It is therefore a tool that simplifies the nearly impossible task of visually compare two satellite images.

In the next sections we will show the possibility of detecting and classifying those regions in the image with a 'meaningful' geometric change. In Section 2 the concept of 'meaningful change' will be explained. The proposed detector is described in Section 3. Finally Section 4 displays the results of the method when applied to the comparison of two very large satellite images of the city of Toulouse (France), before and after the explosion of the AZF chemical plant in September 2001. It is in practice impossible to detect by visual exploration such changes.

2. A GENERAL DETECTION PRINCIPLE

In [5], [6], and [7], a computational method was proposed to decide whether a given geometric structure (or *gestalt*) in a digital image (computed by any segmentation or grouping method) is reliable or not. This method gives *absolute thresholds*, depending only on the image size, permitting to decide when a given geometric structure is perceptually relevant or not.

The method applies Helmholtz principle. This principle yields computational grouping thresholds associated with each gestalt quality. It can be stated in the following generic way. Assume that atomic objects O_1, O_2,...,O_n are present in an image. Assume that k of them, say O_1,...,O_k, have a common feature, say, same color, same orientation, position etc.. We are then facing the dilemma: is this common feature happening by chance or is it significant and enough to group O_1,... O_k ? In order to answer this question, we make the following mental experiment: we assume *a priori* that the considered quality has been randomly and uniformly distributed on all objects O_1, ...O_n. Then we (mentally) assume that the observed position of objects in the image is a random realization of this uniform process. We finally ask the question: is the observed repartition probable or not ? If not, this proves *a contrario* that a grouping process (a gestalt) is at stake. Helmholtz principle states roughly that in such mental experiments, the numerical qualities of

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the objects are assumed to be equally distributed and independent. Mathematically, this can be formalized by

Definition.(**ε-meaningful event [5]**) We say that an event of type "such configuration of geometric objects has such property" is ε-meaningful if the expectation of the number of occurrences of this event is less than ε under the uniform random assumption.

As an example of generic computation we can do with this definition, let us assume that the probability that a given object O_i has the considered quality is equal to p. Then, under the independence assumption, the probability that at least k objects out of the observed n have this quality is

$$B(p,n,k)=\sum_{i=k}^{n}\binom{n}{i}p^i(1-p)^{n-i},$$

i.e. the tail of the binomial distribution. In order to get an upper bound for the number of false alarms, *i.e.* the expectation of the number of geometric events happening by pure chance, we can simply multiply the above probability by the number of tests we perform on the image. This number of tests N_{conf} corresponds to the number of different possible positions we could have for the searched gestalt. Then, in most cases, a considered event will be defined as ε-meaningful if

$$NFA = N_{conf}B(p,n,k) \leq \varepsilon.$$

We call the left hand member of this inequality the "number of false alarms" (NFA). The number of false alarms of an event measures the "meaningfulness" of this event: the smaller it is, the more meaningful the event is. We refer to [5] and [7] for a complete discussion of this definition. To the best of our knowledge, the use of the binomial tail, for alignment detection, was first introduced by Stewart [8]. In the case of our application, we shall use the method in the following way : a catastrophe in an urban scene yields major local changes in the topographic map of the image. In particular, the orientation of the gradient of the image will vary strongly in the region. The above presented general method applies in that a large deviation of the density of changes will be detectable by having a very low NFA.

3. DETECTION OF MEANINGFUL CHANGES

In the following, we assume that we have two images I_1, I_2 of the same scene which have been **accurately registered**. This last condition is important in order to assure the reliability of the detection method. Images I_1 and I_2 may correspond to different spectral channels and to very different dates, with therefore drastic changes in the grey level local and global dynamics. Recently, in [4, 9], an automatic registration method, which can cope with this situation, has been proposed. The main point is to compare image features which are invariant with respect to contrast changes or to a change of spectral channel. For each pixel in images I_1 and I_2 we compute the **orientation of the gradient**:

$$O(x,y)=\left(\frac{u_x}{\|u\|},\frac{u_y}{\|u\|}\right)$$

where $u_x=\frac{\partial u}{\partial x}$, $u_y=\frac{\partial u}{\partial y}$ are computed by standard finite differences over four pixels, and $\|u\|=(u_x^2+u_y^2)^{\frac{1}{2}}$ is the gradient magnitude.

We call $O_1(x,y)$ the orientation of the gradient in image I_1 and $O_2(x,y)$ the orientation of the gradient in image I_2, for the same registered pixel (x,y).

The direction of the gradient is only a reliable information when the observed gray level fluctuations are above the quantization noise, therefore we only compute this direction for pixels whose gradient magnitude $\|u\|$ is above some threshold well above this quantization noise. (We have chosen this threshold as equal to 5 in all images). When the gradient magnitude is larger than the threshold, we say that the orientation is **observable**. We can then compare the orientations of images I_1 and I_2 at each point (x,y), and three situations can occur:

- both images have an observable orientation at (x,y),
- only one of the images has an observable orientation at (x,y),
- none of the images have an observable orientation at (x,y).

In the following, only the first, more reliable, situation will be taken into account: only the points where both images have observable orientations will be compared. The situation where only one or the other image has observable orientations can be equally treated with a slight generalization of the method presented here ; it may be useful (e.g.) for the detection of floods or other major climatic changes.

Let us define the following measurable quantities: for all the pixels (x,y) with observable orientation, we compute the magnitude of the angle between orientations $O_1(x,y)$ and $O_2(x,y)$, which is a number between 0 and π. We call this value "difference of orientations at (x,y)" and we denote it as $DO(x,y)$. We consider then a resemblance threshold (accuracy) $\phi \in]0, \frac{\pi}{2}[$. We decide that both images look alike at (x,y) if $DO(x,y)$ is smaller or equal than ϕ. This resemblance threshold is not a parameter of the method in that we can try as we shall see as many realistic thresholds as desired and then choose the best detections among the different alarms proposed at different thresholds.

A "difference image" can be computed based on this threshold: In order to make things visually intuitive, pixels above the threshold are marked as 'white' (gray level 255), pixels below the threshold are marked as 'black' (gray level 0) and the rest of the pixels (the ones with no observable orientations in both images) are marked as 'gray' (gray level 128).

Defined this way, darker regions in the "difference image" are good candidates for major changes zones. It is not enough however to take the local extrema of the black pixels density function, in order to infer from them which regions correspond to highly changed zones. In fact, these changes can be very localized and intense, but also scattered and faint, and a precise quantization of their meaningfulness must be performed. The main point in the detection of such changes, in size or intensity, is to define a common measure, their "meaningfulness" or NFA, permitting to order them.

Definition. We say that a region in the difference image has been affected by a **meaningful change** if a) its density of black pixels is above the average and **b**) its density of white pixels is below the average. This definition remains informal, until the right information-theoretical formulae yielding the meaningfulness thresholds are given.

The average density of black or white pixels is computed as the ratio of the number of black or white pixels in the image and the total number of observable pixels. We call p the average density of black pixels, which gives an estimate of the probability of having a pixel in the scene that has changed its gradient direction, due to multiple and uncontrolled factors, between the dates when the images were taken. If we observe a big enough window in the image, containing N observable pixels, we must expect to have Np black pixels. Any excess of black pixels with respect to this value may become meaningful. We apply the theory explained in the previous Section to quantize this 'meaningfulness'. We note

- N_F is the number of windows which are tested all over the image. The size of these windows is variable since the size of the regions where a change has occurred is *a priori* unknown.
- For each window containing l pixels with observable orientations we call k the number of black pixels.
- We call **number of false alarms** of the window the number $NFA(l, k, p) = N_F B(l, k, p)$, where $B(l, k, p)$ is the tail of the binomial distribution.

$NFA(l, k, p)$ is interpreted as the expectation of the number of windows having an excess of black pixels (with respect to the average) greater or equal to the one observed, considering a random image of black and white pixels having the same densities than the original image. In the case we consider different thresholds for the orientation comparison, we call q the number of different tested thresholds and the NFA becomes $NFA(l, k, p) = qN_F B(l, k, p)$

Algorithm for the detection of major changes

- We first consider a set of threshold values $\phi_1, \phi_2, ..., \phi_q$ (ranging, in practice, from 30° to 45°), and we compute, for each ϕ_i, the associated difference image.
- For each difference image compute the average density of black pixels (p_i), which is interpreted as the probability, for a pixel, of being black.
- Consider a set of windows with variable size which are moved all over the difference image. For each window:
  - Compute the average number of white pixels inside the window. If this number is above the average of the whole image, not enough changes have occurred inside the window, then pass to the next window.
  - Compute k, the number of black pixels, and l the number of observable points.
  - If $NFA(l, k, p_i) < 1$ consider the window as meaningfully changed and add it to a list of meaningful windows. Associate to each window its 'meaningfulness value' ($NFA(l, k, p_i)$).

This algorithm provides a list of zones with meaningful change, which can be sorted by the meaningfulness values (the smaller the value, the more meaningful the zone).

4. EXPERIMENTS

We shall only present one, but really significant experiment. The input data for this experiment is a couple of satellite images (Figures 1 and 2) provided by CNES (Centre Nationale d'Études Spatiales, France) consisting of two views of the city of Toulouse (France), before and after the explosion of the AZF chemical plant in September 2001.

The original size of the images is 2000×2000 pixels, with a resolution of 10 meters per pixel. In our experiments we have applied the algorithm described in the previous section to compute the meaningfulness of all the possible squared windows of sizes ranging from 10×10 to 50×50 pixels. The 200 top windows in our list are displayed in Figure 3. Most of these 200 results (in particular the top 50) correspond to the location of the explosion. The other ones correspond to another region were major changes have occurred due to urban remodelling. The redundancy in the detection (many squares in the same location) is an issue that will be addressed in our future research. A detail of the explosion spot in displayed in Figure 4. Actually, our algorithm also detected in this pair image a boundary region where registration was inaccurate. The presented results come after correction of this registration failure. Now, this also means that a technical application of the presented algorithm might be the quality assessment for image registration.

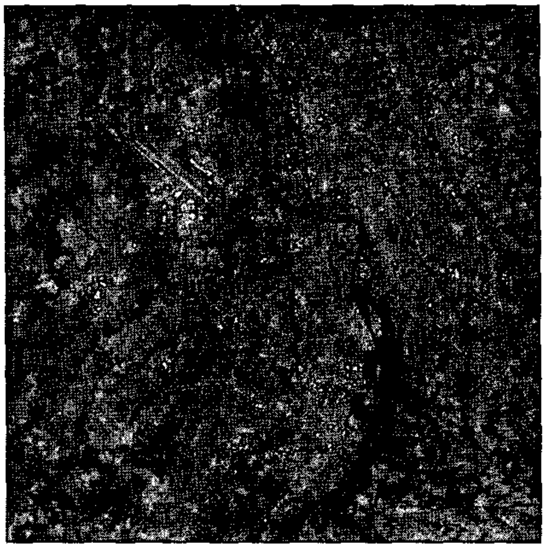

Fig. 1. Image of Toulouse (France) before the explosion of the chemical plant

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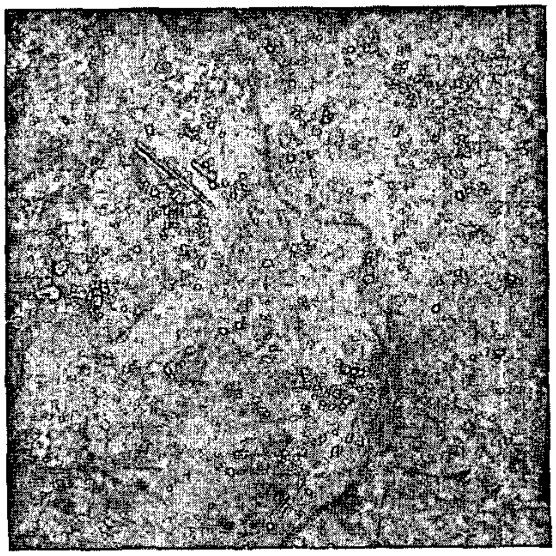

Fig. 2. Image of Toulouse (France) after the explosion of the chemical plant

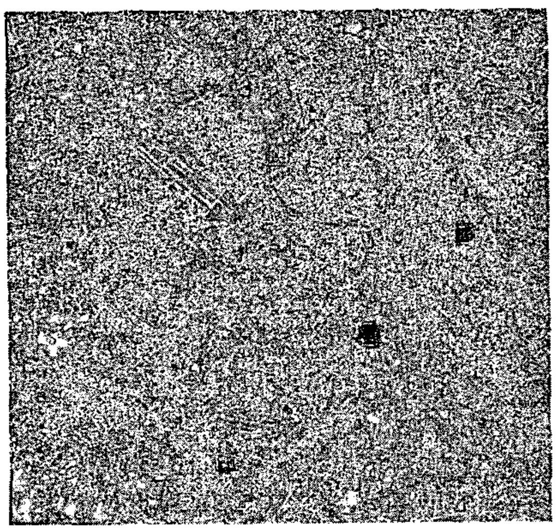

Fig. 3. This figure displays the top 200 meaningful regions in the difference image computed from images in Figures 1 and 2. The scale of the test windows ranges from 10 to 50 pixels. Most of the meaningful windows are located at the explosion spot and the other ones in a region where urban remodelling occurred.

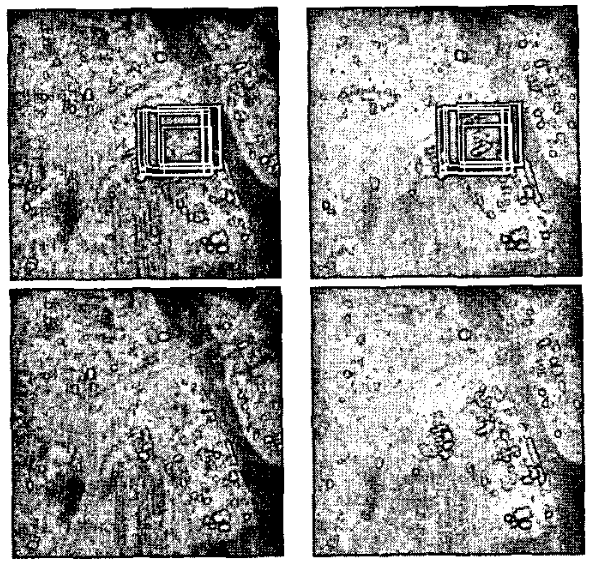

Fig. 4. Detail of the detection for images 1 (left) and 2 (right).

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