ON-BOARD CHANGE DETECTION WITH NEURAL NETWORKS

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ABSTRACT:

The aim of this paper is to describe a potential on-board change detection chain by earth observation satellites (optical and SAR). The benefits of such an on-board chain are multiple : reduction of the amount of data to transmit from board to ground and autonomy of the system for example. We describe particularly one component of the chain : a detection/classification module based on the neural network, this type of algorithm being a part of a more global future fusion-based classification module. First experiments have allowed to validate the algorithm based on neural networks and first results are satisfying. The continuation consists first to enlarge the classification module with the implementation of other classification algorithms and to compare them with a more exhaustive set of data.

1. INTRODUCTION

With the increase of on-board satellite computation capabilities, certain tasks, processed nowadays on ground, will be treated directly on-board in the next future.
The paper is in the field of on-board change detection between two images taken at different times by optical or radar SAR earth observation satellite sensors.
The benefits of an on-board change detection is multiple. By determining in an image what change of interest (in regard to a particular mission) happened, it will be possible, among others :
To reduce the amount of data to transmit from board to ground by sending only the changes,
To have a hierarchy in data transmission by sending relevant information first, and less relevant information after,
To enhance autonomy of systems,
To exploit at best on-board capacities ...

In the paper, we propose a potential on-board change detection chain by earth observation satellites (optical and SAR) and we describe and validate the principle of one component of the detection/classification module based on the neural network. First experiments of validation are also given.

2. PROBLEMATIC OF ON-BOARD CHANGE DETECTION

2.1 Problematic

We suppose that an observation satellite has on-board two images of a given area taken at time t1 and t2 with t2>t1. The image 1 is the reference image. The problem is to detect *on-board* changes of *interest* between the two images for a given mission (ex.: research of planes).
As we have introduced it in the previous section, this process has many interests. We illustrate hereafter the reduction of amount of data transmitted to the ground by the use of selective compression : low compression ratio (few distortions) is applied to the changes of interest detected and high compression ratio is used for the information where less relevant information is present in regard to the mission.

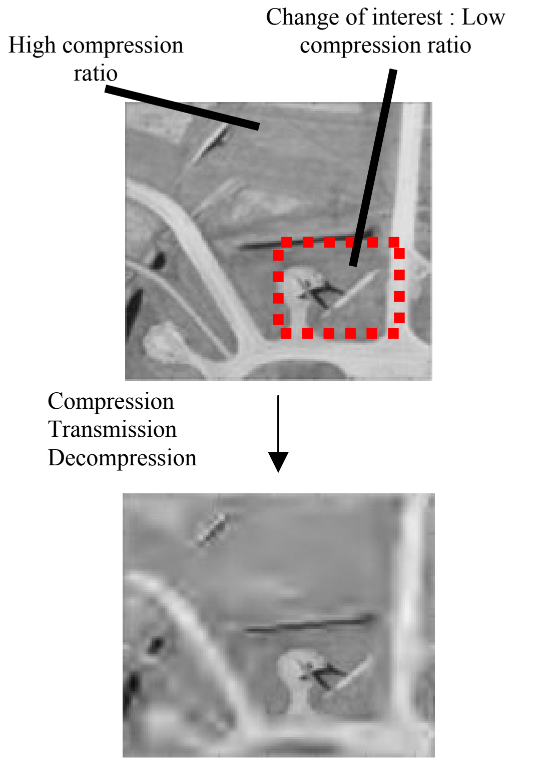


Figure 1. Selective compression after change detection

2.2 Hypothesis

The two images are supposed to come from spatial optical or radar sensor. In this paper, we focus on two images of the same nature : optical/optical (visible) or SAR/SAR (radar). We place us in the field of high and very high resolution sensors : metric and submetric, the resolution of images 1 and 2 being very closed.

A typical on-board processing chain using change detection is illustrated below :

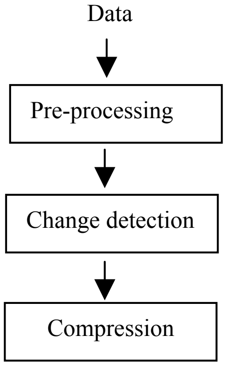


Figure 2. Typical on-board processing chain using change detection

When data have been acquired, a set of pre-processing is necessary to put the two images in the same space representation :

- Image geometric co-registration allows to represent data in the same geometric space. We suppose that the two different orbits at time t1 and t2 are close enough to avoid strong distortions due to very different satellite points of view.
- Resolution of the two images is supposed to be very closed. If there is a slight difference, resolution will be put in a same common value.
- Radiometric calibration can be applied in order to compensate radiometric non relevant differences.
- SAR processing allows to transform radar SAR raw data into an interpretable SAR image. This task is very exepnsive in computation time. Concerning the case of SAR images, only the magnitude of the complex information is taken in account in our work, no phase information has been introduced in algorithms and no multi-polarization images are used.
- An image filtering can be applied before the change detection, a compromise should be found between smoothing and loss of relevant information.

The set of pre-processing is supposed to be done before the change detection.

Concerning the change detection, one can distinguish :

- Detection: a changed is detected in an image,
- Classification: the change detected is classified (ex: plane/not plane),
- Identification: the recognized object is identified (ex: a plane of type A),
- Analysis: parameters of the classification (ex: speed and direction of the plane).

Under the terms change detection, we put in the paper the detection/classification. The reason is that the classification is used here to enhance the global performances of the detection.

2.3 Limitations

Change detection with Automatic Target Recognition (ATR) has a number of well-known problems, in particular:

- The environment is by nature unstable: humidity, temperature, luminosity,
- There are residual errors after pre-processing which can be interpreted as changes,
- The number of target classes and aspects is very high,
- There are inconsistencies in the SAR signature of target.

Everything can change between the two images and the problem of change detection is a real challenge, even on ground with big computation resources. On-board ATR is subject to the CPU and memory limitations due to resources which are limited compared to the ground. To be realistic, we deliberately restrict the problem and we suppose in the stage of the work that the user as defined a kind of target of interest, the number of targets of interest being equal or less than two (even equal to one in the first experiments we have done).

3. OVERVIEW OF A POTENTIAL CHANGE DETECTION PROCESSING CHAIN

In the on-board change detection that we describe here, there are three main steps illustrated hereafter: detection, classification and selection of change of interest.

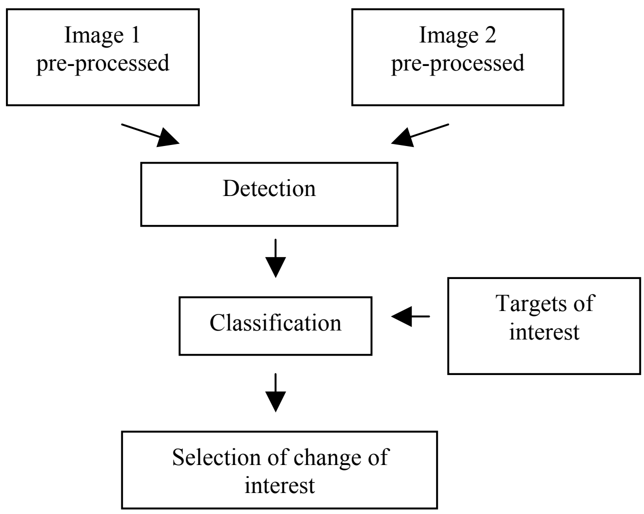


Figure 3 : on-board change detection processing chain

Detection: The aim of this step is to detect as many as possible "real" changes of interest between the two images. Performances are generally expressed in terms of probability of detection (Pd) and probability of false alarm (Pfa). Typical algorithms are used and described in the next paragraph.

Classification: Many classifiers exist. On a general point of view, our aim is to test N algorithms, each of them having its own properties in terms of performances, robustness and reliability. A final fusion algorithm will combine the results of each classifier.

This classification structure allows to take in account different classifiers and to active them in function of the context and the situation (including CPU time available for example). In the article we test one of the N classifier : a neural network classifier with a pre-processing based on edge extraction combined with mathematical morphology.

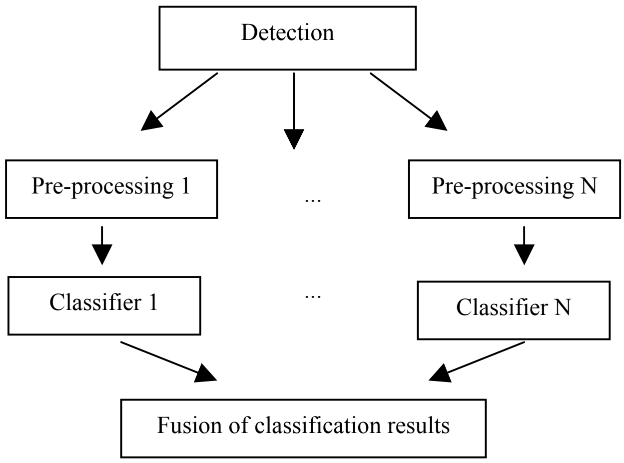


Figure 4: Fusion of classifiers

Selection: after changes being classified, the selection keeps the changes of interest in regards of the mission. This step is considered in its simplest version and is not described in our paper.

4. TECHNICAL DESCRIPTION OF THE CHAIN

In this paragraph, we describe the detection and pre-processing/classification steps of the change detection chain described in the previous paragraph.

4.1 Detection

As input of the detection, we have the images 1 and 2 pre-processed.

The output of the detection will be the image 2 split in blocks, a decision being taken for each block : change detected/change not detected.

A typical processing applied to detect changes between two images is done by the computation of a correlation coefficient ρ and its comparison to a threshold:

$$\rho = \frac{E[I_1 I_2] - E[I_1]E[I_2]}{\sqrt{\mathrm{var}(I_1)\,\mathrm{var}(I_2)}} \tag{1}$$

E =expectation, var = variance, I_i = window in the image i.

Two geographic corresponding areas in image 1 and 2 have a high correlation coefficient if there is no relevant change between the two areas.

In practice, to avoid bad computation due to imperfection in the data pre-processing (residual errors in co-registration for example) an area is determined in image 2, the correlation kernel, and the maximum ρ is computed on a neighborhood of the corresponding area in image 2, as illustrated in the next figure.

In the case of SAR, correlation computation is often applied even if the noise is multiplicative for SAR image. An alternative is to use a feature based correlation measure rather than a classical correlation coefficient.

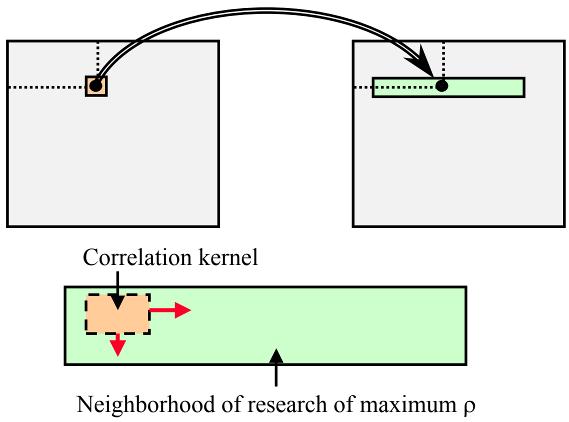


Figure 5: Correlation computation

In practice, the image 2 is split in blocks, and at the output of the detection a decision is taken for each block: change detected/change not detected.

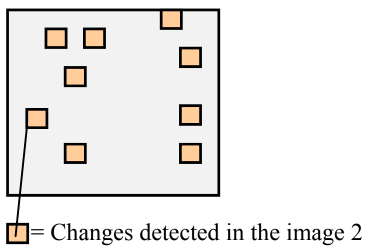


Figure 6: Output of the detection

4.2 Classification pre-processing: edge extraction, morphological operations

As input of the classification pre-processing, there are blocks of image 2 where changes have been detected. The output will be a classification pre-processing of these “change” blocks.

Whatever the classifier, classification pre-processing is a crucial step where data are represented in a space which, hopefully, enhances classification performances. We have chose to apply an edge extraction as a pre-processing.

Concerning optical images, for extracting edges a Sobel filter is applied [3]. The principle consists to find places in the image where intensity values change rapidly. The Sobel filter computes gradient on horizontal and vertical axis at the position [i,j] of the image by convolution:

$$\frac{\partial A}{\partial y} \approx \frac{\Delta A}{\Delta i} = h_i * A[i,j], \quad \frac{\partial A}{\partial x} \approx \frac{\Delta A}{\Delta j} = h_j * A[i,j] \qquad (2)$$

with $h_i = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$, $\quad h_j = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix}$

hi et hj, also called masks, are the convolution kernel of an impulse finite response filter.

Gradient norm is then given by:

$$\left|\nabla A[i,j]\right| = \sqrt{\frac{\partial A}{\partial x}^2 + \frac{\partial A}{\partial y}^2} \qquad (3)$$

Concerning the SAR, operators used in optics are not adapted to SAR imagery because their False Alarm Ratio (FAR) depends on the radiometry [4], which makes impossible a good threshold setting for edge extraction. Adaptations have been proposed (log transformation, normalization) to have a Constant False Alarm Ratio (CFAR), but considering an edge as a maximum of the first derivative is not adapted to the multiplicative nature of the speckle noise.

We used the Ratio Of Exponentially Weighted Averages (ROEWA) operator proposed by Fjørtoft [4].

Let us consider two windows on both sides of a pixel, with $\hat{I}_1$ and $\hat{I}_2$ as average intensity. The Ratio Of Averages (ROA) operator can be defined as :

$$r_m = \max\left(\frac{\hat{I}_1}{\hat{I}_2}, \frac{\hat{I}_2}{\hat{I}_1}\right) \text{ or } \qquad r_n = \min\left(\frac{\hat{I}_1}{\hat{I}_2}, \frac{\hat{I}_2}{\hat{I}_1}\right) \qquad (4)$$

This operator exhibits a CFAR and better results than differential methods. But large sizes of windows are necessary to filter the speckle, and it raises the problem of multi-edge detection. In fact edges too close to others risk not to be detected. So Fjørtoft proposed to used the ROEWA operator. The intensity values in each windows are weighted exponentially to compute the averages (μ_1 and μ_2). The maximum ratio is chosen :

$$r_{\max} = \max\left(\frac{\mu_1}{\mu_2}, \frac{\mu_2}{\mu_1}\right) \qquad (5)$$

Fjørtoft showed that it is an optimal tradeoff between localization precision and speckle reduction when the reflectivity jumps follow a Poisson distribution. ROEWA is computed vertically and horizontally, then with analogy to gradient-based operators for optical images, the magnitude is computed.

As for the correlation coefficient computation, in practice, to avoid bad computation due to imperfection in the data pre-processing or in the edge extraction, a morphological operation based on dilation-erosion is applied to the edge image. So finally the classification pre-processing is edge extraction and dilate/erosion morphological operations.

We illustrate hereafter the classification processing of a plane in an optical image:

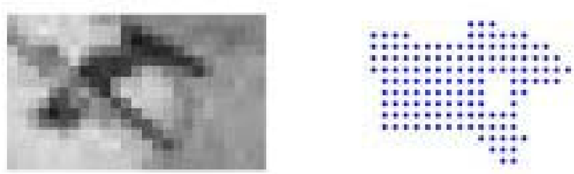


Figure 7: optical Image and classification pre-processing

4.3 Classification with neural networks

As input of the classification, there are pre-processed blocks of image 2 where changes have been detected.

As output of the classification, each block will be classified as target of interest/target not of interest.

4.3.1 Neural networks

The first motivation of the development of neural networks was to reproduce the human capabilities for some tasks that computers reproduce imperfectly and with heavy computations. The recognition of objects independently of their size, orientation and environment is particularly eloquent. This idea failed in 1960 because of the lack of mathematics tools adapted to the conception and analysis of complex networks. Research had restarted around 1980, with success. But even today, a real reproduction of the human neural network is still not reached for the simple reason that nobody really knows the real working of human neural networks.

A formal neuron makes a non linear function with parameters w (weights) of the input x : Y = f(x1, x2,..xN ; w1,w2, ...wp). As an example, the sigmoid function hyperbolic tangent is often used

$$y = th\left[w_0 + \sum_{i=1}^{n-1} w_i x_i \right] \quad (6)$$

The process of estimation of the weights w is called learning. In the paper, the learning is supervised : that means that some points (x,y) are known and allow to estimate the weights. The estimation is often done by methods based on the gradient algorithm. When the weights are estimated, the neural network is able to give an estimate of the output y for a given x (a priori not known).

The neuron simply realizes a parametric non-linear function of its input. One interest comes from their association in networks and the properties which follow from this composition of non-linear functions: it can be shown that *the number of adjustable parameters is as small as possible*. This can be important when the CPU resources are limited for example (on-board).
As illustrated on the next figure, a typical neural network structure is composed of input, output, weights and hidden layers. The structure of neural networks, including the number of hidden layers, is generally determined by numerical methods of model conception.

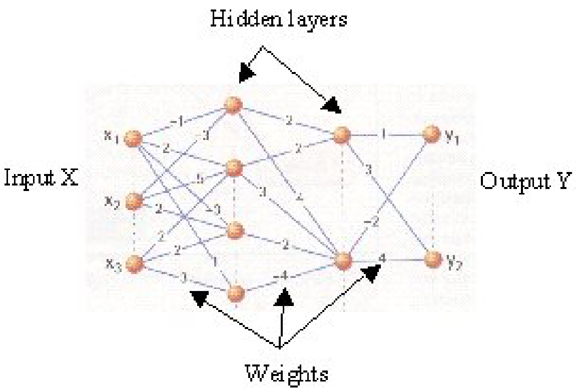


Figure 8: Typical neural networks structure

4.3.2 Neural networks and classification

Neural networks are used in many domains including the classification. For this particular case, because of progress carried out in the comprehension of fundamental properties of neural networks, it has been shown that neural networks not only give a binary decision : they can give for an object its probability to belong to every class, this allow neural networks to integrate classification systems based the fusion of many classifiers, as we intend to test it for on-board change detection.

4.3.3 Neural networks for on-board change detection

In the change detection chain described in our paper, to classify objects of interest with neural networks we used the principle of Learning Vector Quantization (LVQ) developed by Kohonen in its work on self-organizing maps [5].

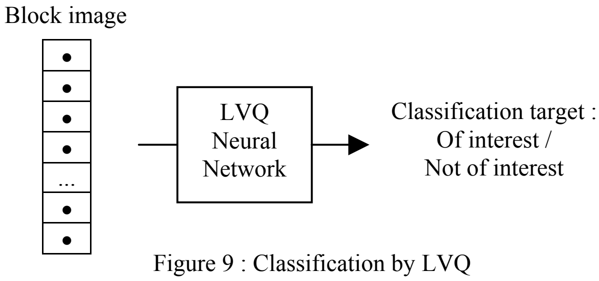


Figure 9 : Classification by LVQ

For a particular object (ex: a plane): the structure of the neural networks is determined by a set of example of target of interests and non-target of interest. The size of input, number of hidden neurons depends on the problem.

5. EXPERIMENTS

A few first experiments have been done to validate the principle of this chain and the use of neural networks. We show here two typical application of the chain on a optical image and on a SAR image.

Both cases are changes simulated : the image 1 is a real image and the image 2 with changes has been created by adding noise and removing or adding targets of interest.

Images 1 comes both for optical and SAR from airborne data and are representative of high or very high resolution earth observation satellite.

For the optical case, the image (390x650) comes from airborne and is shown here comes from airborne with high resolution around 2m. In the case of SAR, the image (215x195) shown comes from airborne with resolution very high resolution of 0.1m and has been downloaded at [6].

Block sizes for correlation processing are (15x25) for optical and (40x40) for SAR.

Target of interest are planes for the optical image and tank for the SAR image.

For both chain the detection has been done by correlation. Sobel filter is use for optical edges extraction and ROEWA for SAR edges extraction. The LVQ neural network has 10 neurons on the input layer. A set of 20 objects have been used for learning in the both cases.

For both cases, we present hereafter typical images given by the detection/classification.

The classification with neural networks gives good results (in terms of performance of classification) in this first stage of simulation. The structure used with LVQ seems a good compromise bias-variance and it yields a network base that can now be grown.

A first comparison with an algorithm based on the direct correlation with elements of the database gives promising results: performances in terms of classification are similar for both algorithms but the neural network needs less operations (around 30% or more) and less memory because its does not need to have the database in memory. This was already mentioned in the paragraph on neural network : the number of adjustable parameters is as small as possible, this explains the gain in complexity of the neural networks.

The idea was to validate the principle of this chain on a set of first simulations. The limitations of the neural network are usual ones: results are highly dependant on the exhaustivity and quality of the learning data set relative to the problem to solve. This should be study in a more complete performance analysis: we intend to implement other classifiers in the change detection chain and compare them in terms of performances, robustness and reliability with a more exhaustive set of simulated data.

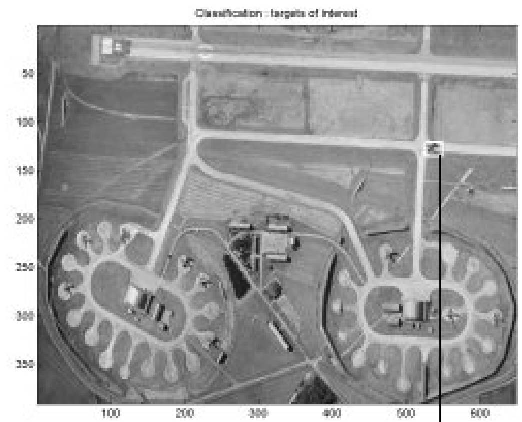
5.1 Change detection on the optical image

The following figures represent:

- The blocks where a change has been detected in image 2 after thresholding the correlation measures.

- The blocks where a plane has been recognized in image 2 after classification : the result of the classification is accurate because only the plane is kept on the image.

Figure 10 : Image 2 after detection of changes by correlation



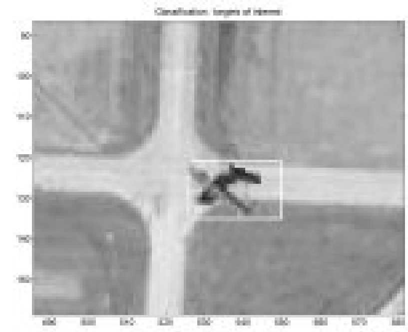


Figure 11 : Image 2 after classification of plane

5.2 Change detection on the SAR image

The following figures represent:

- The blocks where a change has been detected in image 2 after thresholding the correlation measures.

- The blocks where a tank has been recognized in image 2 after classification: the result of the classification is accurate because only the tanks are kept on the image.

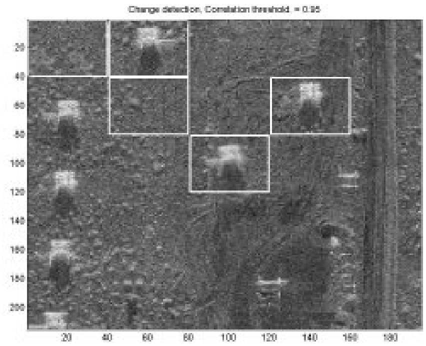


Figure 12 : Image 2 after detection of changes by correlation

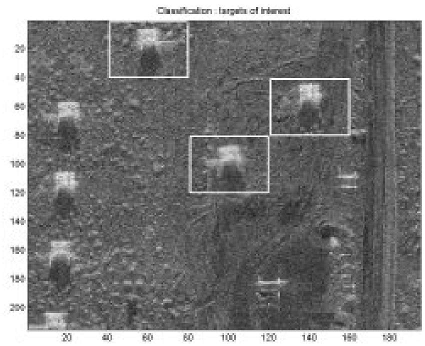


Figure 13 : Image 2 after classification of tanks

6. CONCLUSION

The aim of this paper was to describe a potential change detection chain by earth observation satellites (optical and radar) and to validate the principle of one component of the detection/classification module based on the neural network. First experiments allowed to validate the algorithm based on neural networks and first results are satisfying.

The continuation of this paper consists first to enlarge the classification module with the implementation of other classification algorithms and to compare them in terms of performances, robustness, reliability and implementability with a more exhaustive set of data.

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