PULSE COUPLED NEURAL NETWORKS FOR AUTOMATIC CHANGE DETECTION AT VERY HIGH SPATIAL RESOLUTION

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1. INTRODUCTION

World population growth affects the environment through the swelling of the population in urban areas and by increasing the total consumption of natural resources. Monitoring these changes timely and accurately might be crucial for the implementation of effective decision-making processes. In this context, the contribution of satellite and airborne sensors might be significant for updating land-cover and land-use maps. Indeed, the recent commercial availability of very high spatial resolution visible and near-infrared satellite data has opened a wide range of new opportunities for the use of Earth-observing satellite data. In particular, new systems such as the latest WorldView-2 and WorldView-1, characterized by the highest spatial resolution, now provide additional data along with very high spatial resolution platforms, such as QuickBird or IKONOS, which have already been operating for a few years.

If on one side this makes available a large amount of information, on the other side, the need of completely automatic techniques able to manage big data archives is becoming extremely urgent. In fact, supervised methods risk to become unsuitable when dealing with such large amounts of data. This is even more compelling if applications dedicated to the monitoring of urban sprawl are considered. In these cases, the big potential provided by very high spatial resolution images has to be exploited for analyzing large areas, which would be unfeasible if completely automatic procedures are not taken into account.

In this abstract, a novel neural network approach for the detection of changes in multi-temporal very high spatial resolution images is proposed. Pulse-coupled neural networks are a relatively new technique based on the implementation of the mechanisms underlying the visual cortex of small mammals. The visual cortex is the part of the brain that receives information from the eye. The waves generated by each iteration of the algorithm create specific signatures of the scene which are successively compared for the generation of the change map. The proposed method is completely automated since analyzes the correlation between the time signals associated to the original images. This means that no pre-processing, except for image registration, is required. Furthermore, PCNNs may be implemented to exploit at the same time both contextual and spectral information which make them suitable for processing any kind of sub-meter resolution images.

2. PULSE COUPLED NEURAL NETWORKS

Pulse Coupled Neural Networks entered the field of image processing in the nineties, following the publication of a new neuron model introduced by Eckhorn *et al.* [1]. Interesting results have been already shown by several authors in the application of this model in image segmentation, classification and thinning [2][3], including, in few cases, the use of satellite data [4][5]. Hereafter, the main concepts underlying the behavior of PCNNs are briefly recalled. For a more comprehensive introduction to image processing using PCNNs refer to [6].

2.1. The Pulse Coupled model

A PCNN is a neural network algorithm that, when applied to image processing, yields a series of binary pulsed signals, each associated to one pixel or to a cluster of pixels. It belongs to the class of unsupervised artificial neural networks in the sense that it does not need to be trained. The network consists of nodes with spiking behavior interacting each other within a pre-defined grid. The architecture of the network is rather simpler than most other neural implementations: there are no multiple layers that pass information to each other. PCNNs only have one layer of neurons, which receives input directly from the original image, and form the resulting *pulse* image.

The PCNN neuron has three compartments. The *feeding* compartment receives both an external and a local stimulus, whereas the *linking* compartment only receives the local stimulus. The third compartment is represented by an active threshold value. When the internal activity becomes larger than the threshold the neuron fires and the threshold sharply increases. Afterwards, it begins to decay until once again the internal activity becomes larger. Such a process gives rise to the pulsing nature of the PCNN. The schematic representation of a PCNN is shown in Figure 1.

Each neuron that has any stimulus will fire at the initial iteration, creating a large threshold value. Then, only after several iterations the threshold will be small enough to allow the neuron to fire again. This process is the beginning of the *autowaves* nature of PCNNs. Basically, when a neuron (or group of neurons) fires, an autowave emanates from that perimeter of the group. Autowaves are defined as normal propagating waves that do not reflect or refract. In other words, when two waves collide they do not pass through each other.

For each unit, i.e. for each pixel of an image, the PCNNs provide an output value. The *time signal* $G[n]$, computed by:

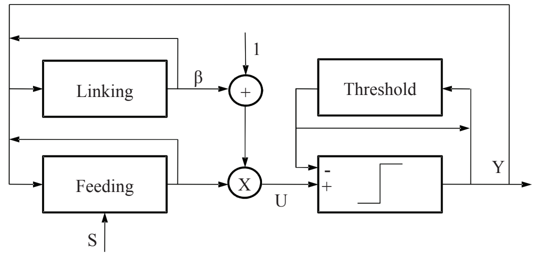

Fig. 1. Schematic representation of a PCNN neuron.

$$G[n] = \frac{1}{N} \sum_{ij} Y_{ij}[n] \tag{1}$$

is generally exploited to convert the pulse images to a single vector of information. In this way, it is possible to have a *global* measure of the number of pixels that fire at epoch $[n]$ in a sub-image containing N pixels. The signal associated to $G[n]$ was shown to have properties of invariance to changes in rotation, scale, shift, or skew of an object within the scene [6].

3. CHANGE DETECTION WITH PULSE-COUPLED NEURAL NETWORKS

The development of fully automatic change detection procedures for very high spatial resolution images is not a trivial task as several issues have to be considered. The crucial difficulties include possible different viewing angles, mis-registrations, shadow and other seasonal and meteorological effects which add up and combine to reduce the attainable accuracy in the change detection results. However, this challenge has to be faced to fully exploit the big potential offered by the ever-increasing amount of information made available by ongoing and future satellite missions.

PCNNs can be used to individuate, in a fully automatic manner, the areas of an image where a significant change occurred. In particular, the time signal $G[n]$, computed by Equation 1 was shown to have properties of invariance to changes in rotation, scale, shift, or skew of an object within the scene. This last feature makes PCNNs a suitable approach for change detection in very high resolution imagery, where the view angle of the sensor may play an important role.

In particular, the waves generated by the time signal in each iteration of the algorithm create specific signatures of the scene which are successively compared for the generation of the change map. This can be obtained by measuring the similarity between the time signals associated to the former image and the one associated to the latter. A rather simple and effective way to do this is to use a correlation function operating between the outputs of the PCNNs.

The performance of the algorithm was evaluated on different panchromatic satellite sensors, such as QuickBird and WorldView-1. Qualitative results are reported in the rest of this abstract.

3.1. Automatic Change Detection in Data Archives

The study area includes the suburbs of Atlanta, Georgia (U. S. A.). The images were acquired by QuickBird in February 26, 2007 and by WorldView-1 in October 21, 2007 for an approximately extension in area of $25km^2$ ($10,000 \times 10,000$ pixels). The size of this test case represents an operative scenario where PCNNs give evidence of their potentialities in detecting automatically hot spot areas in data archives. Many changes occurred although the small time window, mainly corresponding to the construction of new commercial and residential buildings.

PCNN confirmed to have good capabilities in the automatic detection of the hot spots corresponding to urban areas which underwent changes. For this test case, where the images have comparable viewing angles, PCNNs did not provide any intermediate outputs, with the correlation values alternatively very close to 0 or 1. This avoided to search for optimum thresholds to be applied for the final binary response.

The accuracy is satisfactory, as 30 out of the 34 objects appearing on the ground reference were detected with 6 false alarms, mainly due to presence of leaves on the trees in the WorlView-1 image. The missed objects are basically structures that were already present in the first acquisition (e.g. foundations or the first few floors of a building) but not completed yet, or small isolated houses.

3.2. Automatic Change Detection in Severe Viewing Conditions

The study area includes the area of Washington D. C. (U. S. A.). The images were acquired by QuickBird in September 23, 2007 and by WorldView-1 in December 18, 2007 for an approximately extension in area of $9km^2$ ($7,000 \times 5,000$ pixels). In this case, the images have been acquired with very different view angles (QB: off-nadir=18°, target azimuth=355° and sun elevation=48° – WV1: off-nadir=28°, target azimuth=284° and sun elevation=24°) to investigate the performance of PCNNs in this particularly condition. Only one change occurred in the area due the small time window, corresponding to the demolition of a building.

Also in this case, PCNN detected correctly the only hot spot of change. Differently from the previous case, where values were close to 0 or 1, non-changed areas show correlation values slightly bigger than 0. This may be expected due to the very different view angles of the imagery used. For example, the same building is viewed from different directions, occluding different portions of the scene, such as roads or other buildings. However, false alarms are characterized by correlation values more than two times smaller than real changes. Therefore, in this extreme case, the search for an optimum threshold appear to be straightforward.

4. CONCLUSIONS

The potential of a novel automatic change detection technique based on PCNNs was investigated. This new neural network model is unsupervised, context sensitive, invariant to an object scale, shift or rotation. Therefore, PCNNs own rather interesting properties for the automatic processing of satellite images.

The approach aiming at discovering changed subareas in the image (the *hot spots*) rather than analyzing the single pixel was here preferred. This might be more convenient when large data sets have to be examined, as it should be the case in the very next years when new satellite missions will be providing additional data along with the ones already available.

The application of PCNNs to sub-meter resolution images of urban areas produced promising results. For the Atalanta area, 30 out of the 34 objects appearing on the ground reference were detected with 6 false alarms, mainly due to presence of leaves on the trees in the WorlView-1 image. The goal of the Washington D. C. scene was to demonstrate the robustness of PCNNs when applied to images acquired with very different view angles. Also in this case, the results were satisfactory since false alarms showed less significant correlation values with respect to real changes.

5. REFERENCES

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