PULSE COUPLED NEURAL NETWORK FOR AUTOMATIC FEATURES EXTRACTION FROM COSMO-SKYMED AND TERRASAR-X IMAGERY

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ABSTRACT

In this paper we test an unsupervised neural network approach for extracting features from very high resolution X-band SAR images. The purpose of this study is buildings recognition in images of low density urban areas, acquired by COSMO-Skymed and TerraSAR-X satellites, by means of Pulse Coupled Neural Network (PCNN), a relatively novel unsupervised algorithm based on models of the visual cortex of small mammals. The features retrieved from geo-referenced SAR images are compared against the ground truth provided by corresponding optical images. The accuracy yielded by PCNN is quantitatively evaluated and critically discussed, also in comparison with commonly used feature extraction techniques.

Index Terms— Pulse Coupled Neural Network (PCNN), COSMO-Skymed, TerraSAR-X, features extraction

1. INTRODUCTION

With the recent launches of COSMO-Skymed and TerraSAR-X satellites, a growing amount of very-high resolution images will be available. COSMO-SkyMed (COnstellation of small Satellites for the Mediterranean basin Observation) is an Earth observation satellite funded by the Italian Government and conducted by the Italian Space Agency (ASI). It is made up of four satellites, equipped with X-band synthetic aperture radar (SAR) sensors with global coverage of the planet, called COSMO 1 – 4 and related ground infrastructures. Observations of an area of interest can be repeated several times a day in all-weather conditions. The first satellite of the constellation was launched on 7th June 2007, the second on 8th December 2007 and the third on 24th October 2008 [1]. The new German radar satellite TerraSAR-X was successfully launched on June 15th ,2007. With its active antenna , the spacecraft acquires X-band radar images of the entire planet whilst circling Earth in a polar orbit at 514 km altitude. TerraSAR-X is designed to carry out its task for five years and provides radar images with a resolution of up to 1 m [2].

The data provided by these missions might be exploitable for several applications such as urban planning, civil protection, risk management, agriculture, coastal zone monitoring. However, these application need filtering, detection, segmentation, classification, or pattern recognition, hence suitable models and techniques should be worked out for SAR high-resolution data to effectively design the needed algorithms. In fact, while many studies have appeared on feature extraction from medium-high resolution SAR images, less investigation, mainly due to the lack of public data, has been devoted to feature extraction in high-resolution, especially satellite, SAR imagery.

In this paper we investigate an unsupervised neural network approach for extracting features from very high resolution X-band SAR images. The Pulse-Coupled Neural Network (PCNN) is a relatively novel technique based on models of the visual cortex of small mammals [3],[4]. When applied to image processing, it yields a series of binary pulsed signals, each associated to one pixel or to a cluster. In literature, interesting results have been already reported by several authors in applications of this model to image segmentation, including, in few cases, the use of satellite data [5],[6]. This study discusses the PCNN technique in automatic SAR image feature extraction and applies it to a set of experimental data consisting of pre-processed COSMO-Skymed and TerraSAR-X images taken over test sites containing both natural and man-made features. Sub-areas of the images are considered and the PCNN signal features (waveform and epoch dependence) are employed to identify buildings within selected regions of interest.

2. DATA SET DESCRIPTION

In this work Pulse Coupled Neural Network has been applied to a set of two radar images. The first is a Spotlight Cosmo-Skymed image acquired on Fucino region (Italy) on November 22nd, 2008. This is a flat country, characterized by cultivated lands and small villages.

Fig. 1 COSMO-Skymed image taken over Fucino region, Italy (spatial resolution of 1 m), Copyright ASI.

Fig. 3 TerraSAR-X image taken over Tor Vergata university, Rome, Italy (spatial resolution of about 3 m), © Infoterra GmbH

Fig. 2 Ground truth from Google Earth (left) and corresponding ROI overlapped to COSMO-Skymed image (right)

Fig. 4 Ground truth image from Google Earth (left) and corresponding ROI overlapped to TerraSAR-X image (right)

To test PCNN capability in buildings recognition, a sub-area has been selected (Fig. 1). Ground truth provided by corresponding optical image is depicted in Fig.2. Second test image was taken over Rome (Italy) on November 24th, 2007, by TerraSAR-X satellite, operating in Stripmap mode. Because of the huge number of man-made features in this city, the smaller area of the Tor Vergata university was considered (Fig. 3). Although ground truth from Google Earth (Fig. 4) shows big buildings and small houses in this place, SAR imagery is hardly interpretable due to strong speckle and very high resolution. Therefore ground truth, represented by red ROIs in figure, was more roughly selected on smaller houses.

3. PULSE COUPLED NEURAL NETWORKS (PCNN)

The architecture of a PCNN is rather simpler than most other neural network implementations. PCNN do not have multiple layers and receive input directly from the original image, forming a resulting "pulse" image. The network consists of multiple nodes coupled together with their neighbors within a definite distance, forming a grid (2D-vector). The PCNN neuron has two input compartments: linking and feeding. The feeding compartment receives both an external and a local stimulus, whereas the linking compartment only receives a local stimulus. When the internal activity becomes larger than an internal threshold, the neuron fires and the threshold sharply increases. Afterward, it begins to decay until once again the internal activity becomes larger. This process gives rise to the pulsing nature of PCNN, forming a wave signature which is invariant to rotation, scale, shift or skew of an object within the image. This last feature makes PCNN a suitable approach for feature extraction in very-high resolution imagery, where the view angle of the sensor may play an important role. PCNN system can be defined by the following expression:

$$F_{ij}[n] = e^{\alpha_F \delta_n} F_{ij}[n-1] + S_{ij} + V_F \sum_{kl} M_{ijkl} Y_{kl}[n-1] \quad (1)$$

$$L_{ij}[n] = e^{\alpha_L \delta_n} L_{ij}[n-1] + V_L \sum_{kl} W_{ijkl} Y_{kl}[n-1] \quad (2)$$

where S_{ij} is the input stimulus to the neuron (i,j), F_{ij} and L_{ij} are respectively the values of the Feeding and Linking compartment. Each of these neurons communicates with neighboring neurons (k,l) by means of the weights given by M and W kernels. Y is the output of a neuron from the previous iteration, while V_F and V_L indicate normalizing constants. The output of feeding and linking compartment are combined to create the internal state of the neuron, U:

$$U_{ij}[n] = F_{ij}[n]\{1 + \beta L_{ij}[n]\} \quad (3)$$

A dynamic threshold, θ, is also calculated as follow:

$$\theta_{ij}[n] = e^{\alpha_\theta} \theta_{ij}[n-1] + V_\theta Y_{ij}[n] \quad (4)$$

In the end, the internal activity is compared with θ to produce the output Y, by:

$$Y_{ij}[n] = \begin{cases} 1, \text{if } U_{ij}[n] > Y_{ij}[n] \\ 0, \textit{otherwise} \end{cases} \quad (5)$$

The result of a PCNN processing depends on many parameters. For instance, the linking strength, β, affects segmentation and, together with M and W, scales feeding and linking inputs, while the normalizing constants scale the internal signals. Moreover, the dimension of the convolution kernel affects the propagation speed of the autowave. With the aim of developing an edge detecting PCNN, many tests have been made changing each parameter.

4. FEATURES EXTRACTION

Developed PCNNs (see Fig. 5) were applied to SAR imagery as an edge detection algorithm. Firstly, best output from PCNN was selected and filtered to remove those elements with perimeter values less than a certain threshold. The average dimension of ground truth objects has been taken as reference to this end.

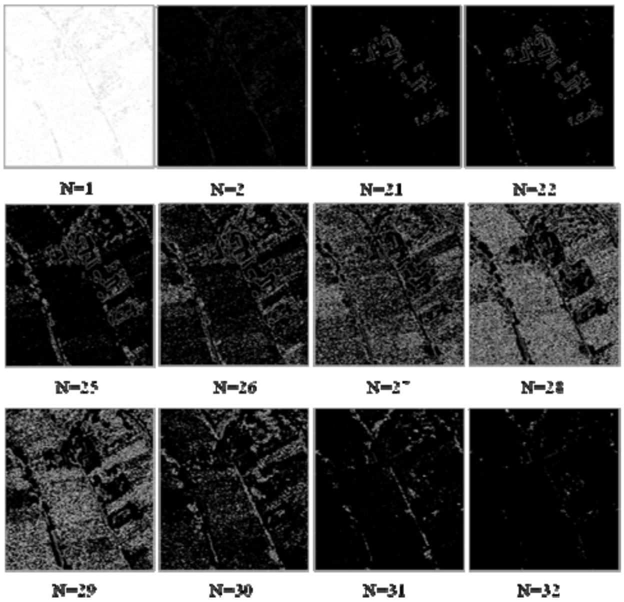

Fig. 5 Iterations of the PCNN algorithm applied to the COSMO-Skymed image. As the iterations progress, the autowaves emanate from the original pulse regions and the shapes of the objects evolve through the epochs due to the pulsing nature of PCNN

Then a region growing technique was used to fill the remained polygons. Features extraction employing PCNN was also compared with other known edge detection methods, based on convolution filters made available within the ENVI software processing libraries. Also in this case a mask was created to highlight the objects whose edged have been detected by the filter. The results we achieved are displayed in Fig. 6 and Fig. 7. The evaluation of the accuracy of the PCNN was performed comparing the output with the ground survey using confusion matrices. An high value of the overall accuracy does not necessarily mean a good precision in buildings recognition. In fact first neurons that fire, identifying an edge, are those characterized by a strong backscattering. In the SAR data set we employed, brightest pixels are mainly due to double bound effects and volume scattering of trees (because of the short X-band wavelength). So neurons might fire only over the corners of man-made features and not over the entire buildings, or they might wrongly fire over the vegetation.

5. CONCLUSIONS

In this paper we have investigated PCNN performance extracting features of very high resolution SAR imagery. The unsupervised neural network approach seems to be a good starting point in buildings identification, especially if compared with other commonly used edge detections techniques.

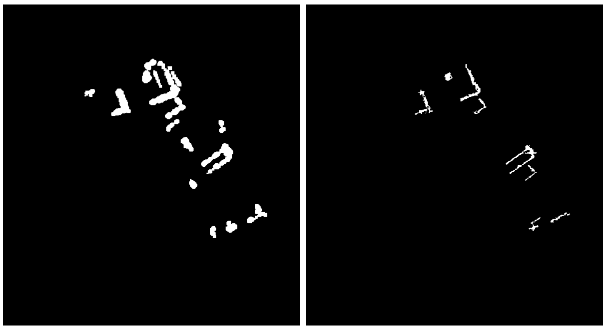

Fig. 6 Buildings recognition in the COSMO-Skymed image: PCNN output (left); mask obtained after a common edge detection process (right)

Overall accuracy = 97.39%

	Ground Truth (Percent)		
Class	Unclassified	Buildings	Total
Unclassified	98.50	59.52	97.76
Buildings	1.50	**40.48**	2.24
Total	100	100	100

Tab. 1 Confusion matrix obtained for the COSMO-Skymed image used as input for the PCNN

Overall accuracy = 98.18%

	Ground Truth (Percent)		
Class	Unclassified	Buildings	Total
Unclassified	99.75	83.13	99.44
Buildings	0.25	**16.87**	0.56
Total	100	100	100

Tab. 2 Confusion matrix obtained for the COSMO-Skymed image processed with a common edge detection algorithm

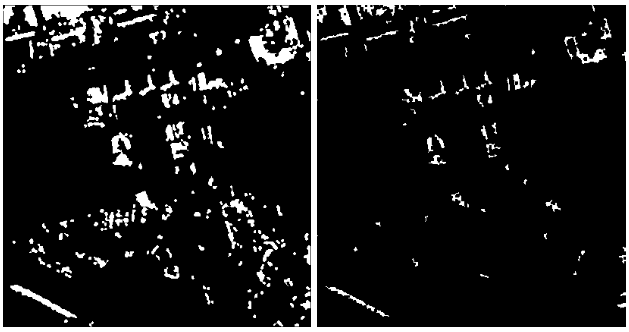

Fig. 7 Building recognition in the TerraSAR-X image: PCNN output (left); mask obtained after a common edge detection process (right)

Overall accuracy = 91.94%

	Ground Truth (Percent)		
Class	Unclassified	Buildings	Total
Unclassified	95.14	43.48	90.86
Buildings	4.86	**56.52**	9.14
Total	100	100	100

Tab. 3 Confusion matrix obtained for the TerraSAR-X image used as input for the PCNN

Overall accuracy = 92.62%

	Ground Truth (Percent)		
Class	Unclassified	Buildings	Total
Unclassified	99.19	80.13	97.61
Buildings	0.81	**19.87**	2.39
Total	100	100	100

Tab. 4 Confusion matrix obtained for the TerraSAR-X image processed with a common edge detection algorithm

6. AKNOWLEDGEMENTS

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