Edge Detection in Urban Areas using Multichannel SAR Interferometry

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Abstract—Building edge detection is a task of increasing importance in last decays. In this paper we propose a novel approach to handle this problem using jointly both SAR amplitude and phase data. The technique is based on a stochastic estimation and on Markov Random Field (MRF). The algorithm computes the building edge map looking for the discontinuities of both phase and reflectivity using jointly the amplitude and the phase of SAR images. Compared to classical amplitude based edge detectors and to phase based ones, the proposed method shows an improvement in terms of detection accuracy and false alarm rate.

Index Terms—Edge Detection, SAR Interferometry, Markov Random Fields.

I. INTRODUCTION

Building edge detection is becoming a task of increasing importance in last decays thanks to the development of new high resolution Synthetic Aperture Radar (SAR) sensors. Historically, building edge detection has been performed using the amplitude of the SAR images. The main approaches of this class are the ratio-based techniques for edge detection, that guaranty CFAR [1], [2], and stochastic methods based on Markov Random Field (MRF) [3].

In last years, approaches exploiting the phase of Interferometric SAR (InSAR) data have been proposed [4], [5], [6], showing interesting results. These methods start from the idea of finding building edges from the height information embodied in the interferometric phase. The proposed by [5] is based on the hypothesis of rectangular footprints of the buildings, while the one proposed by [4] requires a previous detection of shadowing areas in SAR images.

The presented method starts from results obtained by [6]. Ferraioli proposed a stochastic approach based on the idea of finding building edges in an urban scenario image by modeling the image as a Gaussian Markov Random Field (GMRF) [7] with local hyperparameters. The local hyperparameters were seen as an indicator of the spatial correlation of the pixels. The detection of the building edges was carried out by estimating the hyperparameters.

In this work, we extended the approach of [6] by using jointly amplitude and interferometric phase of SAR images in order to retrieve building edges. This evolution allows us to include both reflectivity discontinuities (connected to the amplitude images) and phase discontinuities (connected to interferometric images). The joint estimation allows us to
improve the building edge detection both in terms of false alarm rate and detection probability.

In Section II the proposed detector of building edges is presented. Results on simulated data are presented in Section III.

II. JOINT BUILDING EDGE DETECTION

Let us model both the pixel phases and the pixel reflectivity (i.e. the labels) using Markov Random Fields (MRF) [8]. Using MRF, the behavior of a pixel is related to the pixels belonging to its neighborhood \(\mathcal{N}\). An MRF can be conveniently analytically expressed in terms of joint distribution:

\[
 f(1, \theta) = Z(\theta)^{-1} \cdot \exp \left( -U(1, \theta) \right) \tag{1}
\]

where \(U(1, \theta)\) is the energy function, \(1\) is the vector containing the labels to be modeled (phase values or reflectivity values in our case), \(Z(\theta)\) is the partition function and \(\theta\) is the hyperparameter, a parameter used to tune the model to achieve the best possible pdf fitting.

In particular, we use Local Gaussian MRF (LGMR), which is a Gaussian MRF with local hyperparameters. According to this model, the energy function is set to be:

\[
 U(1, \theta) = \sum_{p=1}^{N} \sum_{q \in \mathcal{N}_p} \frac{(l_p - l_q)^2}{2\theta_{p,q}} \tag{2}
\]

Differently from GMRF, the LGMR uses one hyperparameter for each couple of pixels, instead of a single hyperparameter for the whole image.

The proposed edge detection is based on the estimation of these hyperparameters. Given two neighboring pixels \(p\) and \(q\), the local hyperparameter \(\theta_{p,q}\), in fact, can be seen as an indicator of the spatial correlation of neighboring pixels. A high value of \(\theta_{p,q}\) means that the probability that two pixels \(p\) and \(q\) have very different label (phase or reflectivity) values is high. A low value of \(\theta_{p,q}\) means that the probability that \(l_p\) and \(l_q\) are very different is small. For our problem, this practically means that a high value of \(\theta_{p,q}\) corresponds to a transition between different label values (an edge in phase or in reflectivity between \(p\) and \(q\)); a low value of \(\theta_{p,q}\) means no label transition (no edge). Clearly, \(\theta_{p,q}\) is unknown and it has to be estimated starting from the available data. Thus, the estimation of \(\theta_{p,q}\) corresponds to edge detection.

If the label values \(l_p, l_q\) are known (complete data problem), the hyperparameter can simply be calculated, considering a neighboring system of 8 pixels (8 nearest pixels), in closed form as:

\[
 \hat{\theta}_{p,q}^2 = \sum_{q \in \mathcal{N}_p} \frac{(l_p - l_q)^2}{9} \tag{3}
\]

The hyperparameter \(\hat{\theta}_{p,q}\) is set to be the mean between the hyperparameter \(\hat{\theta}_p\) and the hyperparameter \(\hat{\theta}_q\). The details on how these closed forms have been obtained can be found in [6].

However, the labels are not known (incomplete data problem), so the Expectation Maximization (EM) algorithm [8] turns to be efficient in order to provide an estimation of the hyperparameters.

The hyperparameter estimation for the pixel \(p\), using the EM algorithm at the \((k + 1)\)-th iteration is:

\[
 \hat{\theta}_{p}^2(k + 1) = E \left( \sum_{q \in \mathcal{N}_p} \frac{(l_p - l_q)^2}{9} | \mathbf{d}, \hat{\theta}_p^2(k) \right) \tag{4}
\]

The conditional expectation of the labels \(l\) given the measured data \(\mathbf{d}\) (the noisy phase or amplitude) and the current estimation \(\hat{\theta}_{p}^2(k)\) is performed. Clearly, to perform the expectation over \(l\), samples of this random vector at the \(k\)-th iteration are mandatory. The sampling is performed starting from the \(a\ posteriori\) distribution of \(l\) by using the Metropolis Algorithm [8].

Let us see how to generate the labels samples needed for the hyperparameters estimation.

A. Generation of Labels Samples

In order to generate the label samples required by the EM algorithm, we use the logarithm of \(a\ posteriori\) distribution of the labels. The log-likelihood function is the sum of two terms [9]:

\[
 l = \sum_{p} \sum_{q \in \mathcal{N}_p} \frac{(l_p - l_q)^2}{2\theta_{p,q}} + \sum_{p} \log Z(\theta) + \sum_{p} \log U(1, \theta)
\]
• **Log-likelihood of the amplitude.** For a two looks amplitude image, the negative log-likelihood is given by

\[ A(e_p|a_p) = 2\frac{e_p^2}{a_p^2} + 4\log a_p \]  

(5)

where \( e_p \) is the square root of the mean of the two measured amplitude for the pixel \( p \), while \( a_p \) is the reflectivity.

• **Log-likelihood of the phase.** The log-likelihood function of the interferometric phase is given by

\[ f(\phi_p|\varphi_p; \gamma_p) = \frac{1}{2\pi} \frac{1-|\gamma_p|}{1-|d|^2} \left(1 + \frac{d\cos^{-1}(-d)}{(1-|d|^2)^{1/2}}\right) \]  

(6)

\[ d = |\gamma_p| \cos(\phi_p - \varphi_p) \]

where \( \phi_p \) is the noisy interferometric phase, \( \varphi_p \) is the “true” phase and \( \gamma_p \) is the coherence coefficient of the pixel \( p \).

The a posteriori distribution of \( \mathbf{l}_p = [a_p \ \varphi_p]^T \) is obtained, starting from the sum of the log-likelihood function of amplitude and phase and adding the a priori information. The a priori distribution of \( \mathbf{l}_p \) is given in our case by (1), with the energy function given by (2). So the a posteriori energy of \( \mathbf{a} \) and \( \varphi \) is:

\[ E(a, \varphi|e, \phi) = \sum_p^N [A(e_p|a_p) + f(\phi_p|\varphi_p; \gamma_p)] + U(a, \theta) + U(\varphi, \theta) \]  

(7)

where \( N \) is the size of the considered image. The a posteriori energy 7 is then used by the Metropolis Algorithm [8] in order to provide the samples of amplitude and phase necessary to perform the hyperparameter estimation (4).

**B. Summary of the Edge Detection Algorithm**

Given the previously explained theory, let us summarize how the proposed algorithm for building edge detection works. Starting from noisy interferometric and amplitude data at the \( k \)-th iteration, samples of pixel phase \( \varphi \) and of pixel reflectivity \( a \) are generated from the a posteriori distribution (7), using the Metropolis algorithm. These high probability samples are used in order to obtain the new estimation of the parameters \( \hat{\theta}(k+1) \) (4). Once the hyperparameters have been estimated, a comparison with a threshold is made. If \( \hat{\theta}_{p,q}^2 \) is bigger than the threshold, than an edge is set between pixel \( p \) and pixel \( q \). Otherwise no edge is set.

Fig. 1. (a) Simulated scenario, (b) one amplitude image - logarithmic scale, (c) interferogram
III. Numerical Experiments

The proposed method has been tested on simulated data. A 64 × 64 profile has been constructed with 5 structures characterized by different heights and similar reflectivity (see figure 1(a)). From this scenario, two SAR images have been simulated using the SRTM interferometric configuration. Simulation did not take into account the presence of geometrical distortions, such as layover. The intensity images (figure 1(b) shows one of the two images) were corrupted by speckle, while the interferometric phase noise has been added to the interferogram (figure 1(c)). Simulation results have been compared to the InSAR edge detector [6] in order to show the improvement allowed by the joint estimation. In the paper [6] comparisons with other methods have been presented, showing the better accuracy of the method. Since in this paper we present an improvement of that method, other comparisons have been omitted.

Figures 2(a) and 2(b) show the hyperparameters map obtained using each method; the more noisy background is due to amplitude image but as will be shown in few lines, this noise does not represent a problem for the detection. In Figures 3(a) and 3(b) a threshold has been applied, in order to have an on-off decision; thresholding completely remove the noisy background of the hyperparameter map computed with the joint approach. It can be noted the improvement of the joint method in terms of better corner edges reconstruction and a better global accuracy. Figure 4(a) represents the false alarm rate behavior varying the threshold applied of the proposed method, the phase based one and a third amplitude based approach which consists of a chain with a Lee filter and a
Fig. 4. (a) False alarm probability for joint phase and magnitude method (blue), phase based method (black) and Lee filter + Sobel detector (red). (b) Receiver operating characteristic (roc) curves for joint phase and magnitude method (blue), phase based method (black) and Lee filter + Sobel detector (red) Sobel detector. Figure 4(b) represents the ROC curves for all the three methods; the improvement of the joint estimation over the phase only one and the advantage in terms of detection probability versus false alarm rate can easily be noted.

IV. CONCLUSION

In this paper a novel approach for building edge detection has been proposed. The method uses a stochastic approach in conjunction with Markov Random Field. The method is based on the idea of jointly exploit both amplitude and phase of SAR images. Results obtained on simulated data are encouraging and show the potentialities of the approach, achieving a better accuracy compared to other techniques. The next step of the work will be the application of the algorithm to real data sets in order to confirm the accuracy obtained in the simulated scenario.

REFERENCES