A REGULARIZATION APPROACH FOR INSAR AND OPTICAL DATA FUSION

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ABSTRACT

This paper investigates the joint use of interferometric SAR and optical data for 3D reconstruction. A framework for phase filtering constrained by the discontinuities of the optical image is presented. First, both the amplitude and the interferometric phase are projected in a 3D coordinate system. The problem is then expressed as the regularization of the amplitude and phase images with the introduction as prior knowledge of the edges detected on the optical image. We define the regularized elevation in the framework of Markov random fields (MRF) and derive a smoothness prior that both preserves sharp boundaries (based on total variation minimization) and is driven by the structures present in the optical image. We apply a recent graph-cut based algorithm to perform fast regularization of the elevation field. First results on a real pair of optical and InSAR images are presented.

***Index Terms*—** Synthetic aperture radar, minimization methods, speckle

1. INTRODUCTION

Optical and synthetic aperture radar (SAR) images convey different yet complementary information on urban scenes. Methods for optical and SAR amplitude fusion have been very recently compared in the context of the 2007 Data Fusion Contest organized by the IEEE Geoscience and Remote Sensing Data Fusion Technical Committee [1]. We consider in this article the problem of fusion for 3D reconstruction in urban areas from high resolution optical and interferometric (InSAR) images. The phase difference of the InSAR data provides a dense map of heights. This map is however too noisy (due to speckle) to be directly used as a 3D model. It also suffers from holes in the shadow areas since the height can not be measured there. The height map must therefore be denoised and even extrapolated in the shadow areas. Special attention has to be given to edge preservation since man-built structures in urban areas (e.g. walls) exhibit height discontinuities. The optical image gives information on the shape (i.e. boundary) of structures. The fusion of this information with the InSAR image is however very challenging. We describe here an attempt to use both images to built a regularized 3D model with a low-level (pixel based) approach.

To perform edge-preserving denoising while dealing with missing data in the shadow areas, a markov random field (MRF) regularization approach is used. Total variation [2] is chosen as smoothing prior. This prior has been widely used since it has provable edge-preserving properties (see for example [3] for a review of total variation properties and applications). The MRF framework provides a natural way to introduce the optical and SAR amplitude edge data. We describe two options to introduce these data in the height regularization method: i) extend the height regularization to joint regularization of height, SAR amplitude and optical radiometry; ii) introduce edge information extracted from the optical/SAR images as priors. The regularization is performed through a minimization procedure. We describe an algorithm based on minimum cuts computed on a weighted graph. The motivation for using a graph-cut algorithm is two-fold: it is fast and its combinatorial nature fits well minimization problems involving non-convex energies.

The article is structured as follows. We first give an overview of the suggested method for InSAR/optical fusion. Then we describe how the InSAR image is transformed into a (noisy) height mesh. The height regularization model is then set and the fast energy minimization algorithm used is presented. First results on an excerpt of an InSAR and an optical image of an industrial zone are discussed in the last section.

2. DESCRIPTION OF THE METHOD

2.1. Overview of the method

The suggested method is summarized in figure 1. The main steps, denoted with circled numbers on the figure, are the following:
The height map in the world coordinates is obtained by projection of the points from the radar image (steps 1-2). The cloud of points is then triangulated (step 3). A valued graph is then built with nodes corresponding to each of the points in the cloud and values set using the SAR amplitude, height

The authors wish to thank the French Spatial Agency CNES for their financial support.

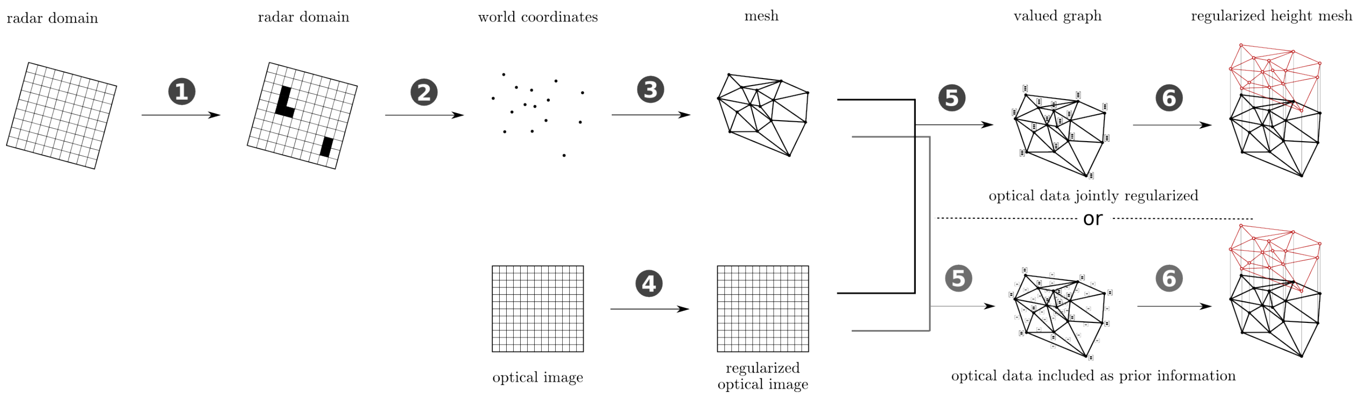


Fig. 1. Scheme of the suggested method. The numbers correspond to the algorithm steps referred to in the text.

and the optical information (step 5). To ease the introduction of optical information, the optical image is regularized prior to graph construction (step 4). Once the graph is built, a regularized height mesh is computed by defining a Markov field over the graph (step 6).

2.2. Preprocessing steps

Steps 1 to 4 are preprocessing steps required before the actual height regularization (steps 5-6). Before merging the InSAR and optical data to perform a 3D reconstruction, images must be transformed into a common coordinate system. Assuming the optical image is acquired at normal incidence, we then have to project back the InSAR data from distance sampling coordinates to 3D coordinates. Before projecting the points from radar geometry to world coordinates, shadows are detected (step 1) to prevent from projecting points with unknown (i.e. random) height. This detection is made using the Markovian classification described in [4]. Points outside the shadows are then projected based on their interferometric phase and the radar acquisition parameters (step 2). This gives a 3D cloud of points (x, y, z) in the world coordinates. The projection of this cloud on a horizontal plane is then triangulated with Delaunay algorithm to obtain a height mesh (step 3). The height of each node of the obtained graph can then be regularized (see next section). The optical image is simplified using a geometry+texture decomposition [5] before fusion (step 4). This decomposition is obtained with a TV+L1 regularization computed using the graph cut algorithm described in section 3. Figure 2 displays the gradient norm of the optical image before and after its regularization. Most irrelevant edges are removed.

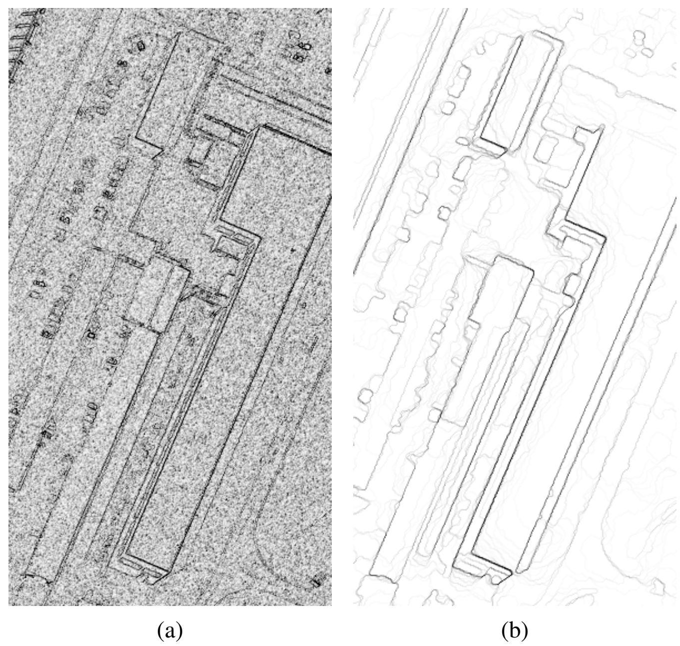


Fig. 2. Optical image regularization with TV+L1 decomposition model: (a) gradient norm of the optical image before regularization; (b) after regularization, remaining gradients correspond to the building edges.

2.3. Height regularization model

The interferometric phase is known to be very noisy due to speckle noise. A denoising step is essential to obtain a satisfying 3D reconstruction. The denoising is often performed by averaging, providing a so-called multi-look image with reduced noise variance, and, as a side effect, with a loss of resolution. We use in this paper a regularization approach that aims at reducing the oscillations due to noise while preserving the edges. The joint information of amplitude and interferometric data is used together with the optical data in a Markov random field framework. We define the regularized height field as that which maximizes the posterior probability according to the log-likelihood and prior models described below.

2.3.1. Log-likelihood model

The synthesized radar image z is complex-valued. Its amplitude $|z|$ is very noisy due to the interferences that occur inside a resolution cell. Under the classical fully developed speckle model of Goodman, the amplitude a_s of a pixel s follows a Nakagami distribution depending on the square root of the reflectivity $\hat{a}_s$. This likelihood leads to the following energetic term:

$$U(a_s|\hat{a}_s) = M\left[\frac{a_s^2}{\hat{a}_s^2} + 2\log\hat{a}_s\right] \quad .$$

In the case of SAR interferometric data, the interferometric product is obtained by complex averaging of the hermitian product γ of the two SAR images. A good approximation of the phase ϕ_s distribution is a Gaussian which leads to a quadratic energy:

$$U(\phi_s|\hat{\phi}_s) = \frac{(\phi_s - \hat{\phi}_s)^2}{\hat{\sigma}^2_{\phi_s}}.$$

The standard deviation $\hat{\sigma}^2_{\phi_s}$ at site s is approximated by the Cramer-Rao bound $\hat{\sigma}^2_{\phi_s} = \frac{1-\rho_s^2}{2L\rho_s^2}$ (with L the number of average samples and ρ_s the coherence of site s). For low coherence areas (shadows or smooth surfaces), this Gaussian approximation is less relevant and a uniform distribution model is better $p(\phi_s|\hat{\phi}_s) = \frac{1}{2\pi}$.

2.3.2. Prior model

We devise a prior model that accounts for the phase and amplitude dependency and that introduces the edges of the optical image. We have proposed recently[6] to regularize jointly phase and amplitude images using a regularization term of the following form:

$$E(\hat{a},\hat{\phi}) = \sum_{(s,t)} \max(|\hat{a}_s - \hat{a}_t|, \gamma|\hat{\phi}_s - \hat{\phi}_t|). \qquad (1)$$

These last years finding a sparse solution in regularization has attracted a lot of attention[7]. The L1 (absolute value) norm is known to lead to sparse solutions. In our case, we use the L1 norm of the (discretized) gradient. The regularized solution therefore has a sparse gradient (i.e. the regularized field has few edges). The use of the $\max()$ function introduces an edge co-location constraint since if two transitions $|\Delta_{\hat{a}}|$ and $|\Delta_{\hat{\phi}}|$ appear close from one another, the regularization penalty can be decreased by $\min(|\Delta_{\hat{a}}|, |\Delta_{\hat{\phi}}|)$ by setting them at a common location.

Two options are possible to regularize the height mesh. The first option is to jointly regularize the phase, amplitude and optical images (steps 5-6 shown at the top row of figure 1) by extending equation 1 to include the regularized optical image (i.e. use a ternary $\max()$ operator). This solution requires to set adequately the weights of each of the terms. The second option consists of introducing the optical image gradient as a prior. Equation 1 is then replaced by:

$$E(\hat{a},\hat{\phi}) = \sum_{(s,t)} G_{opt}(s,t)\max(|\hat{a}_s - \hat{a}_t|, \gamma|\hat{\phi}_s - \hat{\phi}_t|) \qquad (2)$$

with $G_{opt}(s,t) = \max(0, 1 - k_{opt}|opt_s - opt_t|)$.
When the optical image is constant between sites s and t, the $G_{opt}(s,t)$ term equals 1 and does not modify the joint TV regularization. When $|opt_s - opt_t|$ is high (corresponding to a discontinuity), $G_{opt}(s,t)$ is low, thus reducing the regularization of amplitude and phase. This modification permits to preserve the building shapes according to the optical data.

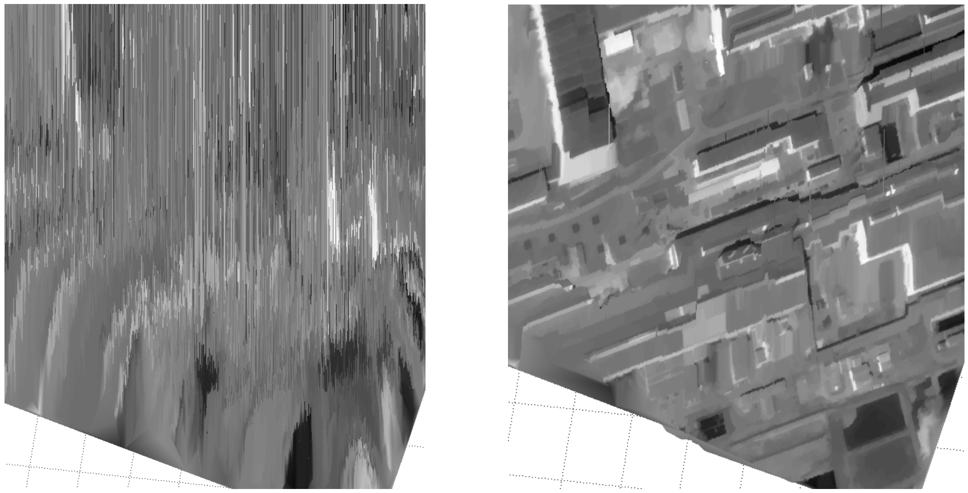
3. ENERGY MINIMIZATION ALGORITHM

In a recent work[6], we have proposed a new fast and approximate algorithm to regularize such non convex energy. We just recall the principle of the method in this paper. Minimizing a non-convex energy is a difficult task as the algorithm may fall in a local minimum. Following [8], we denote such changes *large moves*. Instead of allowing a pixel to either keep its previous value or change it to a given one (α-expansion), we suggest that a pixel could either remain unchanged or its value be increased (or decreased) by a fixed step. Such an approach has first been described independently in [9, 10, 11] and applied recently with unitary steps in [9]. We however use these large moves in a case of non-convex data term. The trial steps are chosen to perform a scaling sampling of the set of possible pixel values.

4. RESULTS AND DISCUSSION

Figure 3(a) shows an height mesh with the regularized optical image used as texture. The mesh is way too noisy to be usable. We performed a joint amplitude/phase regularization using the gradient of the optical image as a weight that eases the apparition of edges at the location of the optical image contours. The obtained mesh is displayed on figure 3(b). The surface is a lot smoother with sharp transitions located at the optical image edges. Buildings are clearly above the ground level (be aware that the shadows of the optical image create a fake 3D impression).

This approach requires a very good registration of the SAR and optical data, which implies knowledge of all acquisition parameters which, depending on the source of images, is not always possible. The optical image should be taken with normal incidence to match the radar data. The image displayed on figure 3 was taken with a slight angle that displaces the edges and/or doubles them. For the method to work well, the edges of structures must be visible in both optical and InSAR images. A more robust approach would require a higher level analysis (significant edge detection, building detection).



(a) (b)

Fig. 3. Height mesh obtained (a) by direct projection of the InSAR data points (end of step 3, fig.1); (b) after joint phase/amplitude regularization with a prior that includes the optical image gradient (end of step 6, second row of fig.1).

The framework described is quite general and can be used to fuse heterogeneous data according to their statistical distribution and to prior knowledge that can be introduced by various ways (edge co-location by joint regularization, variable weights, . . .). By defining the regularized field over a graph, it is possible to merge images with different sampling/geometry.

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