PROBABILISTIC SURFACE CHANGE DETECTION AND MEASUREMENT FROM DIGITAL AERIAL STEREO IMAGES

André Jalobeanu[1], *Cristina Gama*[1] *and José Alberto Gonçalves*[2]

[1] Geophysics Center of Évora - University of Évora, Portugal
[2] Geospatial Sciences Research Center - University of Porto, Portugal

1. ABSTRACT

We propose a new method to measure changes in terrain topography from two optical stereo image pairs acquired at different dates. The main novelty is in the ability of computing the spatial distribution of uncertainty, thanks to stochastic modeling and probabilistic inference. Thus, scientists will have access to quantitative error estimates of local surface variation, so they can check the statistical significance of elevation changes, and make, where changes have occurred, consistent measurements of volume or shape evolution. The main application area is geomorphology, as the method can help study phenomena such as coastal cliff erosion, sand dune displacement and various transport mechanisms through the computation of volume changes. It can also help measure vegetation growth, and virtually any kind of evolution of the surface.

We first start by inferring a dense disparity map from two images, assuming a known viewing geometry. The images are accurately rectified in order to constrain the deformation on one of the axes, so we only have to infer a one-dimensional parameter field. The probabilistic approach provides a rigorous framework for parameter estimation and error computation, so all the disparities are described as random variables. We define a generative model for both images given all model variables. It mainly consists of warping the scene using B-Splines, and defining a spatially adaptive stochastic model of the radiometric differences between the two views. The inversion, which is an ill-posed inverse problem, requires regularization, achieved through a smoothness prior model. Bayesian inference allows us to recover disparities as probability distributions. This is done on each stereo pair, then disparity maps are transformed into surface models in a common ground frame in order to perform the comparison. We apply this technique to high resolution digital aerial images of the Portuguese coast to detect cliff erosion and quantify the effects of weathering.

2. INTRODUCTION AND PROBLEM STATEMENT

Optical images are quite inexpensive compated to other data sources such as LIDAR or SAR, and the recent digital sensors have reached a signal-to-noise ratio allowing for accurate photogrammetric measurements to be made. The use of image pairs acquired almost simultaneously strongly reduces the intensity changes due to temporal variations of ground reflectance and illumination, which provides an increased accuracy with respect to multi-date observations when it comes to surface model generation. Therefore we use digital aerial stereo image pairs as our main data source. Comparing accurate surface models derived from data acquired at different dates can help measure the topography variations. But in order to make physical measurements, one needs to know the error as well. Unfortunately no method exists that is able to provide a quantitative error estimate, and state of the art methods only propose various ad-hoc indicators of local correlation or matching quality, which are, in practice, difficult to interpret in terms of elevation uncertainty.

We wish to predict the accuracy, rather than assess it using ground truth, as done usually. Some authors have proposed to derive predictors based on terrain characteristics such as slope or curvature, however these techniques do not take into account the data themselves. Instead, we propose to use the image content to determine the local accuracy, since the presence of edges, textures and noise have an obvious impact on it. We believe that error estimates are consistent only if they carry the uncertainty arising from the observation noise and the lack of information in the input data. Thus, stochastic modeling allows us to use the image content to build a probability distribution of the stereo parallax, or disparity, directly related to the topography via a geometric transform. We describe the relation between small, matching image patches through a Gaussian process. This is the major assumption made in this work; it is valid only if the camera quality is high (no geometric patterns, few dead pixels, no compression noise).

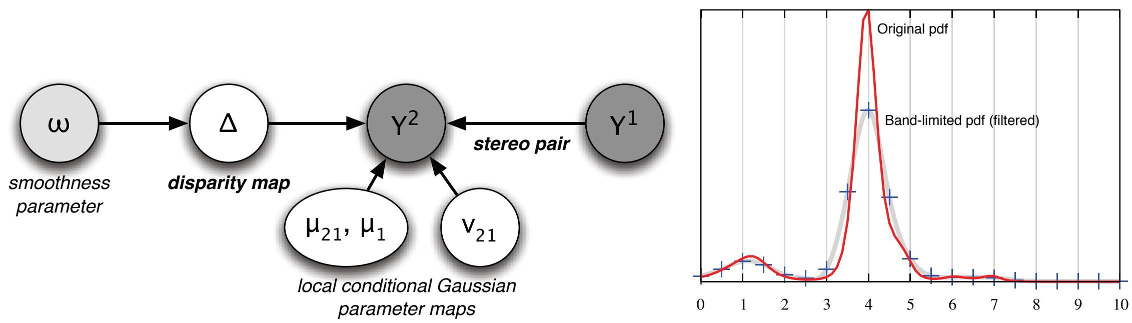

Fig. 1. Left: Bayesian network stating how images Y^1 and Y^2 are stochastically related to each other through the disparity map Δ and the radiometric variation parameters. Right: band-limiting and sampling of the probability density of the disparity.

In order to measure ground elevation variations and give a consistent measure of their uncertainty, we require a sub-pixel estimation accuracy for the disparity, and the robustness with respect to local radiometric variations between the images. Usually in photogrammetry, disparity is measured by maximizing the normalized cross-correlation between two small image patches. This approach is among the most robust to local radiometric variations, however it produces enough false matches so that a filtering step is required in order to denoise the result. Numerous approches have been developed [1], some able to perform sub-pixel estimations, other based on statistics; however no rigorous probabilistic method has ever been devised that meets the requirements stated above, to our knowledge. The filtering never takes into account the accuracy of each measured disparity value, it only uses these values. Conversely, in our approach accuracies act like weights, allowing to automatically filter out the most uncertain measurements.

3. PRINCIPLES OF THE PROPOSED METHOD

For simplicity and without compromising the performance, one of the images is set as a reference. We assume that one of the images can be derived from the other via a geometric transform, involving accurate resampling using high-order B-Spline interpolation [2], and a spatially variable uncorrelated additive noise process. This noise accounts for local radiometric changes due to variations of the viewing geometry and non-Lambertian reflectance properties. A conditional Gaussian distribution is used to model it. This allows for a simple parametrization using a mean μ_1, conditional mean μ_{21} and conditional variance v_{21}. All the parameters are spatially adaptive, with one set of parameters every 2×2 pixels, and an appropriate small window size and a fuzzy weighting scheme to avoid blocking artifacts. This Gaussian process can accomodate various image formation alternatives, such as the local additive and multiplicative change maps from [3]. The deformation field Δ is modeled by a set of parameters, one every 2×2 pixels, such that for each disparity variable at a specific location, there is a set of Gaussian parameters describing the relation between the two fuzzy windows centered respectively on this location in image 2, and on this location shifted by the disparity in image 1. Subpixel shifting is achieved through B-Spline resampling, and a rigid motion is assumed within each window. This assumption is valid only if we use a multigrid approach, in which the disparity is progressively estimated from coarse to fine. Thus scaling and rotation effects become negligible, as the disparity map from the coarser scale is used as an initial estimate and we only have to infer a residual motion.

This helps provide a fast solution to the disparity estimation problem; however, in the end, a continous deformation field [8] has to be used to refine the result and compute the uncertainties at the optimum rigorously, as the window-based approach produces biased accuracy estimates due to unrealistic assumptions.

Within the generative model approach, the disparity map is also governed by a probability distribution. We use a first order Markov Random Field [4] to define a simple smoothness prior, based on the squared differences of neighboring disparity values. A global parameter ω (to be estimated) controls the amount of smoothness. The full model is illustrated by Fig. 1 (left), where nodes denote random variables, groups of converging arrows conditional distributions, and terminal nodes prior distributions.

The inversion is carried out through Bayesian inference [5], which merely consists of integrating out the unwanted variables related to the Gaussian process (this is also known as marginalization), and computing the probability density of Δ given only Y_1 and Y_2. In practice it involves several steps, and a few approximations in order to make it tractable.

The main steps of the algorithm can be described as follows:

- Marginalization [6], to compute the local likelihood function $P(Y_1, Y_2 \,|\, \Delta_i)$ for each disparity variable Δ_i, which involves the computation of v_{21} from local statistics;

- Outlier rejection, based on the extreme values of the conditional variance v_{21}, to eliminate spurious matches in areas dominated by noise;

- Convolution with a band-limiting kernel so that the resulting function can be sampled without aliasing; typically we use $1/2$ pixel sampling, as illustrated in Fig. 1 (right);

- Fast Loopy Belief Propagation (LBP) [7] optimization using the sampled likelihood and the smoothness prior, which provides an optimal disparity map very efficiently;

- Conjugate Gradient optimization (differential method) initialized with the disparity map estimated using the fast LBP method, using a continuous deformation field (instead of a uniform shift within each window) as defined in [8].

- Computation of the second derivatives of the negative log likelihood function at the optimum, using also a continuous deformation field, to form the diagonal of the precision matrix (non-diagonal terms come from the smoothness prior);

- Approximate block inversion of the precision matrix to obtain the covariance matrix, as the full matrix is too large to be inverted directly [9].

The error estimates arise naturally from the probabilistic formulation of the problem. A multivariate Gaussian approximation [6] enables us to provide a practical, minimal parametrization of the probability distribution of disparities. Then, in the ground frame, the surface model elevations derived from disparities are also Gaussian variables, and the difference between two probabilistic elevations is also Gaussian, which simplifies all the subsequent analysis steps. For instance, one can test an hypothesis such as elevation change by simply comparing the absolute difference with a threshold depending on the confidence level, fixed beforehand by the user.

4. CONTRIBUTIONS, LIMITATIONS AND FUTURE WORK

The main contributions are: The design of an appropriate image formation model accounting for radiometric variations due to the difference in viewing angle; The use of high-order B-Spline interpolation to reduce resampling artifacts; An original disparity likelihood evaluation based on marginalization and local statistics; The use of low-pass filtering to limit the bandwith of this function before sampling, so a fast LBP algorithm can be used directly to compute the optimal disparity map with subpixel accuracy; Gaussian approximations, approximate matrix inversion and probabilistic subtraction in order to obtain a local topography variation and the related uncertainty. Some points are still under investigation, such as a fully automated regularization, and the effects of the departure from the local Gaussian assumptions which can cause spurious matches difficult to filter out. In the current version of the method, only two images are used, however the reliability of the measurement technique could greatly benefit from a larger number of images, as long as they are acquired within a short time interval to reduce illumination variations. Indeed, redundancy could help detect and better eliminate false matches and the related likelihood functions.

5. REFERENCES

[1] M. Brown, D. Burschka, and G. Hager, "Advances in computational stereo," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 28, no. 8, pp. 993–1008, 2003.

[2] P. Thévenaz et al., "Interpolation revisited," *IEEE Trans. on Med. Imaging*, vol. 19, no. 7, 2000.

[3] A. Jalobeanu and D.D. Fitzenz, "Inferring deformation fields from multidate satellite images," in *IEEE International Geoscience & Remote Sensing Symposium*, Boston MA, USA, Jun 2008.

[4] H. Rue and L. Held, *Gaussian Markov Random Fields: Theory and Applications*, Chapman & Hall / CRC, 2005.

[5] J. Bernardo and A. Smith, *Bayesian Theory*, John Wiley and Sons, Chichester, UK, 1994.

[6] A. Gelman, J.B Carlin, H.S Stern, and D.B Rubin, *Bayesian Data Analysis*, Chapman & Hall, 1995.

[7] Jian Sun, Nan-Ning Zheng, and Heung-Yeung Shum, "Stereo matching using belief propagation," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 25, no. 7, 2003.

[8] A. Jalobeanu and D.D. Fitzenz, "Robust disparity maps with uncertainties for 3d surface reconstruction or ground motion inference," in *ISPRS Proc. of Photogrammetric Image Analysis*, Munich, Germany, Sep 2007.

[9] A. Jalobeanu and J.A. Gutiérrez, "Inverse covariance simplification for efficient uncertainty management," in *27th MaxEnt workshop*, Saratoga Springs, NY, July 2007.