Spatial Accuracy Assessment of Digital Surface Models: A Probabilistic Approach

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Outline

- Goals and objectives
- Uncertainty prediction
- Spatial variability
- Why we need uncertainties
- Bayesian inference
- Forward model
- 2-step hierarchical inversion
- Results from real data
- Future work
Goals and objectives

- **Digital Surface Models with error maps**
  - Provide the **uncertainties** to allow for error propagation
  - Automatic parameter estimation (e.g. orientation...)
  - Dense disparity maps with sub-pixel accuracy

- **Why use stereo optical images**
  - Availability, coverage, redundancy, price

- **Requirements**
  - **Raw and well-sampled images, (coarse) reference DSM**

- **Necessary tools**
  - Probability theory, signal processing, computer vision, applied math, and some Physics!
Uncertainty prediction

- Classical approaches in photogrammetry
  - Error assessment using reference data sets
  - Global accuracy measures in general (RMS...)
  - Some predictors exist (slope, land cover), but rely on validation

- Proposed method
  - Predict, rather than assess the spatial accuracy
  - Use all the available information (images, coarse DSMs)
  - No need for a more accurate, reference DSM!
  (except when we need to validate the method)
Why uncertainty is spatially variable

because stereo cues are spatially variable!

- **Image quality**
  - Spatially variable noise, bad data

- **Missing data**
  - Localized clouds and occlusions

- **Scene information content**
  - Textureless areas
  - Strong variations due to reflectance

adaptive uncertainty maps carry important information!
Why we need to evaluate uncertainties correctly

- **Data fusion**
  - Probabilistic framework to combine multiple uncertain objects
  - Use **variances**, and also **correlations** between variables

- **Error propagation**
  - From the observation noise to the end result!
  - Strong dependence on the **spatial variability of error**:
    - *Flood hazard maps* - avoid under- or overconfident estimates
    - *Fuzzy contour maps* - display the spatial accuracy
Example: flood maps

disparity map $[-10,10]$

error map (std dev) $[0,1]$

$\Delta > T$

$P(\Delta > T)$

uniform error

$P(\Delta > T)$

spatially variable error map

different results!
Yes we can compute uncertainty rigorously ...thanks to Bayesian inference

\[ p(\theta \mid \text{observations}) = \frac{p(\text{observations} \mid \theta) \times p(\theta)}{p(\text{observations})} \]

**OBJECTIVE:**
posterior probability density function (pdf)

- Eliminate the unwanted parameters (integration)
- Compute the **optimal parameters** of interest (optimization)
- Compute the related **uncertainties** (derivatives)
- **Model selection** and assessment (comparison)

likelihood
image formation model

prior model
(a priori knowledge about the observed object)

evidence
(useful for model comparison)
Basic ingredients & mathematical tools

Forward modeling:
- All parameters are random variables
- Data - image formation model (rendering + degradations)
- Prior - object modeling
- Graphical models convenient for design and understanding

Proposed Bayesian inference scheme:
- Marginalization or integration w.r.t. nuisance parameters
- Approximations (otherwise intractable)
- Deterministic optimization (for speed)
- Uncertainty evaluation
Forward model
1. Underlying 2D “reflectance map”

- Common reflected radiance map

- Model this map as a 2D image:
  - Use the Nyquist-Shannon sampling theorem
    - Frequency cut-off (limited optical resolution)
    - Band-limited image representation using B-Splines
    - Resampling through B-Spline interpolation

Representation - sum of splines
Spline kernel
Forward model
2. Radiometric change model

Spatially adaptive parametric model

- **Multiplicative** changes - include reflectance effects (non-Lambert, lighting variations), shadows, atmospheric attenuation, instrumental artifacts...
- **Additive** changes - include atmospheric haze, clouds, instrumental biases...
- **Additive noise** - approx. Gaussian, independent pixels

changes are spatially variable, so should be the model parameters
Forward model

3. Smoothness priors for disparities or surfaces

- **Arbitrary** disparity: surface deformation
  - Applications: earthquakes, change detection...

- **Constrained** disparity for DSM reconstruction
  - Epipolar lines *if the exterior orientation is known!*
  - Rigorous sensor model for along-track stereo:
    - $\Delta_x$ very smooth
    - $\Delta_y$ directly related to the surface topography

  *example: planetary surface modeling*

Self-similar process based on image gradients

Markov Random Field:
spatial interactions btw. neighbors
Graphical model (forward model)

- Oriented graphical model or Bayesian network
  - Easily build the joint probability density function (pdf)
  - Use the graph structure for an efficient, hierarchical inversion
Inference: invert the forward model

- Marginalize all the nuisance variables (not of interest)
- Use explicit values for known parameters
- Estimate unknown parameters automatically and plug in the results
Step 1 - disparity inference

- Marginalization of A,B,C,X approx. by area-based matching
- Multigrid approach for both disparity and image data (coarse to fine)

$$P(\Delta_y \mid Y^1, Y^2)$$
How the disparity inference works

- **Compute the posterior marginal pdfs**

  Iterative optimization of an energy functional
  (nonlinear search: conjugate gradient, LBP, graph cuts...)

  \[
  \log P(\Delta_x, \Delta_y | Y^1, Y^2) = D(\Delta_x, \Delta_y, Y^1, Y^2) + \text{Prior}(\Delta_x) + \text{Prior}(\Delta_y)
  \]

  - *data term*
  - *smoothness penalty*

- **Gaussian approximation: optimum & variance**

  (marginal pdf of 2 neighbors $\rightarrow$ covariance)

  - optimal disparity $+\,$ uncertainties
  - $dx, dy$
  - *vertical*
  - *self*
  - *horiz.*
Step 2 - orientation via surface matching

\[ P(\Theta \mid \Delta_y, DSM_{\text{ref}}) \]

Bayesian surface matching (cartesian coordinates!)

optimal orientation parameters + uncertainties (covariance matrix)
Step 3 - probabilistic DSM and error structure

- Vertical errors: mostly due to errors on $\Delta y$ (transformed using $\Theta$) Markov Random Field structure

- Planimetric errors: due to errors on $\Theta$ (transformed using $x,y$) highly correlated

$P(DSM \mid \Delta y, \Theta)$

inverse sensor model

$(x,y,\Delta y) \rightarrow \Theta \rightarrow (X,Y,Z)$

From image space to cartesian ground frame
Results - disparity inference

Area of interest: Nanedi Valles on Mars (location 6.0°N, 312°E)
Data used: Mars Express HRSC orbit 0905, stereo channels s1 and s2 (30 m ground resolution), 2048x4096 region of interest, raw unprojected data.
Results - surface matching, DEM generation

Local Linear Reconstruction

Reconstructed DEM (local ENU frame)

Reference DEM (MOLA) (local ENU frame)

Reference for local ENU frame: 6.0°N, 312°E, 3396200 m

unit: meter
Results: DEM and error map

Reconstructed DEM (unit: meter)
local ENU frame

Error map (std dev) (unit: meter)
local ENU frame

Horizontal cross-section (Y=0) + error envelopes (1 std dev)
Results - disparity inference

Data used: ALOS PRISM free sample data, stereo channels nadir and backward, downsampled to 20 m ground resolution, 512x512 pixels region of interest, raw unprojected data

input stereo images (enhanced)  disparity map [-20,20]  error map (std dev) [0=black, 1=white]
Results - vector disparity map
RAW SPOT 5, multidate, 128x128 pixels @ 3.5m

images Y1, Y2 [0,255]
correlation map
change map
x and y std dev maps
Results - vector disparity map

RAW SPOT 5, multidate, 1024x1024 pixels @ 3.5m

Color-coded vector disparity map, linear correction applied
(area near Bam, Iran; across-track stereo pair)
Work in progress, future work...

- **Methodology:**
  - **Automatic orientation:** piecewise linear pushbroom model
  - **GCP-based orientation:** use Bayesian inference
  - **Visualization:** probabilistic contour maps
  - **Fuzzy orthorectification**
  - **3D surface recovery from n images (n>2)**
  - **Uncertainty validation**
    (sparse GCP, LIDAR points, accurate ref. DEM)

- **Applications:**
  - **Aerial coastal imaging:**
    3D change monitoring
    (Intergraph DMC)
  - **Data fusion from large satellite data sets**
    (Terra/ASTER)