

Analysis and validation of grid DEM generation based on Gaussian Markov Random Field

Fernando J. Aguilar ^(a), Manuel A. Aguilar ^(a), José L. Blanco ^(a), Abderrahim Nemmaoui ^(a) and Andrés M. García-Lorca^(b)

(a) Department of Engineering. University of Almería, Spain.(b) Department of Geography, History and Humanities. University of Almería, Spain.





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Introduction

Goal:

2

Efficient generation of accurate Grid Digital Elevation Models from scattered elevation data including grid elevations uncertainty estimate



Introduction: Mathematical Framework

Gaussian Markov Random Field (GMRF) to estimate the maximum a posteriori (MAP) grid elevations and their vertical uncertainty





Introduction: Mathematical Framework

The joint probability distribution to be maximised would the following one:

$$p(m,z) \propto e^{\left(-\sum_{C_o} E_o(n_{c_o}) - \sum_{C_p} E_p(n_{c_p})\right) - \left[\sum_{c_o} E_p(n_{c_p}) - \sum_{c_o} E_p(n_{c_p})\right] - \left[\sum_{c_o} E_o(n_{c_o}) - \sum_{k=1}^{L} \frac{(m_{ik} - m_{jk})^2}{(1 - P(d_{i,j}))^2} - \sum_{c_o} E_o(n_{c_o}) - \sum_{k=1}^{M} \frac{(m_{ik} - z_k)^2}{(\sigma_s^2)^2} - \sum_{c_o} E_o(n_{c_o}) - \sum_{k=1}^{M} \frac{(m_{ik} - z_k)^2}{(\sigma_s^2)^2} - \sum_{c_o} E_o(n_{c_o}) - \sum_{k=1}^{M} \frac{(m_{ik} - z_k)^2}{(\sigma_s^2)^2} - \sum_{c_o} E_o(n_{c_o}) - \sum_{c_o} E_o($$



Study Site and Dataset

Very dense greenhouse covered area located at Almería, southern Spain





Study Site and Dataset

Coloured LiDAR point cloud from PNOA (National Plan of Aerial Orthophotography of Spain).

Sensor: Leica ALS60; Flight Height: 2700 m; Date: September 2015 Point density: 0.87 points/m2; Single point returns Reference System: ETRS89 UTM 30N; Orthometric elevations (EGM08-REDNAP) Vertical error (at open terrain GPS-RTK derived Check Points): 0.14 m





Methods

DSM accuracy assessment



Results: Sensitivity analysis for σ_p

The lower the tolerance parameter, the higher the smoothing GMRF derived DSM

	Observed points: 10% of			Observed points: 1% of the		
	the original dataset ⁽¹⁾			original dataset ⁽²⁾		
-	$\underline{\sigma}_{R}(m)$	<u>rmse_z</u>	mean	$\sigma_{p}(m)$	<u>rmse_z</u>	mean
		(m)	error (m)		(m)	error (m)
	0.2	0.803	<mark>0.008</mark>	0.2	1.274	0.011
	0.6	0.765	0.013	0.6	1.186	0.002
	1	0.765	0.002	1	1.148	0.011
	1.4	0.761	0.007	1.4	1.146	0.029
	1.8	0.758	0.008	1.8	1.141	-0.0018
	2.2	0.760	0.003	2.2	1.143	0.010
	2.6	0.761	0.002	2.6	1.158	- <mark>0.001</mark>
	3	0.762	0.008	3	1.140	0.000
	4	0.761	0.004	4	1.153	0.008
	10	0.761	0.007	10	1.162	0.031

EGS (1) = 10.74 m; EGS (2) = 33.97 m



Results: GMRF vs TLI

Qualitative comparison (case 10% observed points; EGS = 10.74 m)



Results: GMRF vs TLI

Qualitative comparison (case 90% observed points; EGS = 1.13 m)

1 m GMRF DSM







Qualitative results





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Qualitative results (10% observed points; EGS = 10.74 m)



- 1 m GMRF DSM
- LiDAR points



Results: GMRF vs TLI

Quantitative results (10% observed points; EGS = 10.74 m)



Leptokurtic and unbiased residual distributions



Results: DSM vertical uncertainty







2 m GMRF DSM

Results: Real-world application



The results provided by the proposed GMRF interpolation method may be deemed as very promising, producing visually pleasing and accurate digital elevation models.

GMRF yielded similar qualitative and quantitative results as compared to TLI method. Both methods do not require to specify the local support or kernel.

As a bonus, the mathematical framework implemented through GMRF algorithm makes possible to easily retrieve the maximum a posteriori estimation of every interpolated elevation point (mapping vertical uncertainty) and also include break lines, at least theoretically, to obtain high quality DTMs.





Thank you very much for your kind attention



Open code available at: https://github.com/3DLAB-UAL/dem-gmrf