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A robust interpolation method for constructing digital elevation models from remote sensing data

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ABSTRACT

A digital elevation model (DEM) derived from remote sensing data often suffers from outliers due to various reasons such as the physical limitation of sensors and low contrast of terrain textures. In order to reduce the effect of outliers on DEM construction, a robust algorithm of multiquadric (MQ) methodology based on M-estimators (MQ-M) was proposed. MQ-M adopts an adaptive weight function with three-parts. The weight function is null for large errors, one for small errors and quadric for others. A mathematical surface was employed to comparatively analyze the robustness of MQ-M, and its performance was compared with those of the classical MQ and a recently developed robust MQ method based on least absolute deviation (MQ-L). Numerical tests show that MQ-M is comparative to the classical MQ and superior to MQ-L when sample points follow normal and Laplace distributions, and under the presence of outliers the former is more accurate than the latter. A real-world example of DEM construction using stereo images indicates that compared with the classical interpolation methods, such as natural neighbor (NN), ordinary kriging (OK), ANUDEM, MQ-L and MQ, MQ-M has a better ability of preserving subtle terrain features. MQ-M replaces thin plate spline for reference DEM construction to assess the contribution to our recently developed multiresolution hierarchical classification method (MHC). Classifying the 15 groups of benchmark datasets provided by the ISPRS Commission demonstrates that MQ-M-based MHC is more accurate than MQ-L-based and TPS-based MHCs. MQ-M has high potential for DEM construction.

1. Introduction

Digital elevation models (DEMs) are often constructed using remote-sensing techniques such as light detection and ranging (LiDAR), interferometric synthetic aperture radar (InSAR) and photogrammetry (Ouédraogo et al., 2014; Montealegre et al., 2015; Zhang et al., 2016). However, due to reasons such as the physical limitation of data collection sensors, low contrast of terrain textures, multiple reflectance, and occlusions, DEMs derived from remote sensing data often suffer from outliers (Aguilar et al., 2007; Höhle and Höhle, 2009). Spatial outliers are defined as points whose values are unusually different from their neighbors (Barnett and Lewis, 1994; Chen et al., 2008; Lu et al., 2011). In the case of DEMs, non-ground objects like vegetation, buildings and cars, not completely filtered from the ground points by classification methods (Sithole and Vosselman, 2004; Mongus and Žalik, 2012), are considered as outliers. The existence of data outliers distorts analytical results (Liu et al., 2001). For example, outliers in DEMs limit accurate recognition of landslide scarps for risk assessment (Chu et al., 2014).

If the statistical distribution of data is known, outliers can be easily detected. However, such information is usually unavailable. Noises in remotely sensed data are caused by various factors, such as low contrast of terrain textures, improper calibration of instruments, weak laser intensity, and bad weather condition (Sun et al., 2009; Aguilar et al., 2010). Furthermore, for areas with sharp and complex terrain features, outlier detection is especially challenging (Fleishman et al., 2005). Nevertheless, some methods have been developed to deal with spatial outliers. Among them, the robust Mahalanobis distance-based method has been widely adopted. For example, Chen et al. (2008) used this method to detect spatial outliers in a data set of West Nile virus, and Giménez et al. (2012) employed it to detect multivariate outliers in positioning data from Real Time Kinematic (RTK) Global Navigation Satellite System (GNSS) Networks. Nurunnabi et al. (2015) proposed a diagnostic principle component analysis (PCA) combined with Mahalanobis distance to detect outliers of LiDAR point clouds. Similarly, Gharibnezhad et al. (2015) introduced three types of robust PCA as a detector of outliers. However, the robust Mahalanobis distance-based method only uses a simple linear interpolation to assess the relationship between

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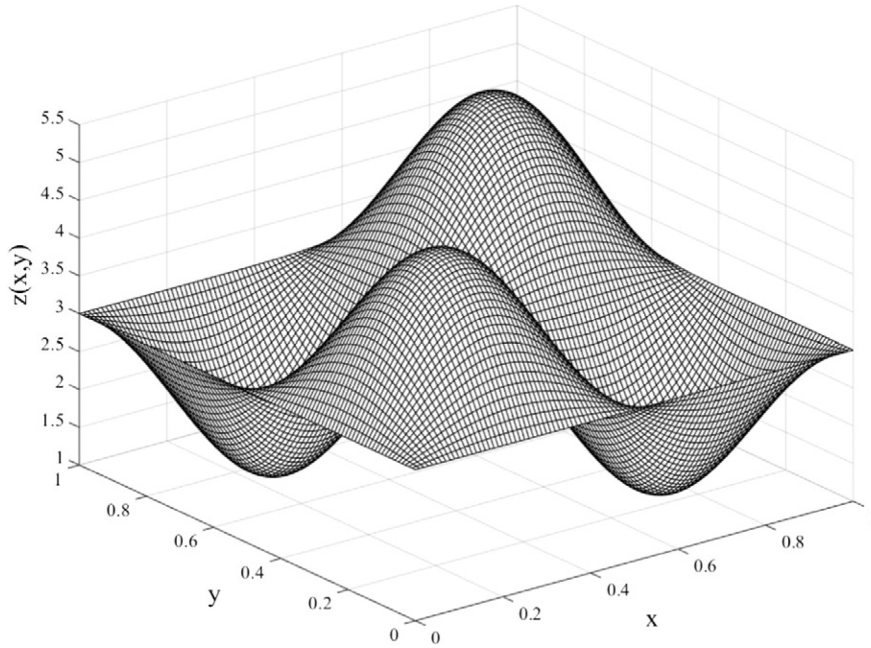

Fig. 1. The mathematical surface used in the numerical test. Its formulation is: $f(x,y) = 3 + 2\sin(2\pi x)\sin(2\pi y) + \exp(15(x-1)^2 - 15(y-1)^2)$.

neighborhoods. Thus, its performance is not assured for DEM construction especially in areas with steep slopes.

For DEM construction, a robust interpolation method is often needed. Some robust methods for planar surface fitting have been presented. For example, Fleishman et al. (2005) presented a robust moving least square technique based on forward search methods for piecewise smooth surface construction. The random sample consensus (RANSC) algorithm (Fischler and Bolles, 1981) has been improved for surface fitting to point clouds under the presence of outliers (Torr and Zisserman, 2000; Schnabel et al., 2007). Nurunnabi et al. (2014) employed a fast PCA based on minimum covariance determinant for robust surface fitting. However, the aforementioned methods are all for planar surface modeling, and their effect on producing DEMs with complex terrain characteristics requires further assessment.

Some classical interpolation algorithms including natural neighbor (NN), ordinary kriging (OK), Australian National University DEM (ANUDEM) and multiquadric method (MQ) have been widely used to derive DEMs from remote sensing data (Lloyd and Atkinson, 2002; Lloyd and Atkinson, 2006; Bater and Coops, 2009). A series of tests indicated that MQ is excellent in terms of required time, storage, accuracy, visual pleasantness of the surface, and ease of implementation (Franke, 1982; Aguilar et al., 2005). However, spatial outliers seriously affect the performance of MQ, since it is an exact interpolator sensitive to outliers.

In statistics, several robust estimators have been developed to decrease the influence of non-normal data distributions, such as L-estimators, R-estimators and M-estimators (Huber, 2004). The M-estimators appear the most useful because of their generality, simplicity, and efficiency (Huber, 2004). Based on the M-estimators, this paper employs an adaptive weight function for MQ with three parts: null for large errors, one for small errors, and quadric for others. The aims of this paper are to: (1) develop a robust algorithm of MQ based on the M-estimators (MQ-M) for DEM construction under the presence of outliers; (2) assess the robustness of MQ-M for surface modeling with simulated data sets; (3) compare the performance of MQ-M with those of the classical interpolation methods; and (4) evaluate the contribution of MQ-M.

Table 1
RMSE values of MQ-M, MQ-L and the classical MQ under different error distributions in the numerical test.

Error distribution	MQ-M	MQ-L	MQ
$N(0,0.1^2)$	0.0237	0.5653	0.0244
$L(0,0.1)$	0.0220	0.0302	0.0234
$(1-\theta)N(0,0.1^2)+\theta N(0,3^2)$ $\theta = 0.1$	0.0255	0.0446	0.1251
$(1-\theta)N(0,0.1^2)+\theta N(0,3^2)$ $\theta = 0.2$	0.0302	0.0688	0.1575
$(1-\theta)N(0,0.1^2)+\theta N(0,3^2)$ $\theta = 0.3$	0.0384	0.0723	0.1729
$C(0,0.1)$	0.0441	0.0621	0.3727

2. Methods

2.1. Formulations

MQ is an analytical interpolator of representing irregular surfaces that involve the summation of equations of quadric surfaces located at significant topographic points (Hardy, 1990). Suppose that a surface is a graph of a function $z = f(x,y)$, in terms of MQ, it can be expressed as,

$$f(x,y) = \sum_{j=1}^{m} \alpha_j p_j(x,y) + \sum_{j=1}^{n} \beta_j q(r_j) \tag{1}$$

where m is the degree of the polynomial; $p_j(x,y)$ and α_j are the j-th basis and coefficient of the polynomial; r_j is the distance from the interpolated point (x,y) to the j-th data point; $q(r)$ is a basis function; and β_j is the j-th weight of the basis function. For MQ, $q(r) = \sqrt{r^2 + c^2}$, where c is a shape parameter. Its optimal value depends on the number and the distribution of data points, the data vector and the precision of the computation (Rippa, 1999). In our paper, the optimal value of c is determined by the k-fold cross-validation (CV) technique (e.g. $k = 10$). More detailed information can be found in Section 2.2.

The matrix formulation of Eq. (1) can be expressed as,

$$\mathbf{f} = \mathbf{P}\boldsymbol{\alpha} + \mathbf{Q}\boldsymbol{\beta} \tag{2}$$