

A Self-interpolation Method for Digital Terrain Model Generation

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Abstract. This work presents an iterative method for obtaining a digital terrain model (DTM) from a digital surface model (DSM) given as input. The novel approach is compared to a state-of-the-art method from the literature using three case studies that represent diverse situations and landscapes including a coastal region composed of dunes, a mountain region, and also an urban area. The proposed method was revealed to be a promising alternative in terms of a better root-mean-square error. Input surface artifacts are successfully removed with the adoption of the proposed method.

Keywords: Digital terrain model · Digital surface model · Interpolation

1 Introduction

Topographic data are widely adopted as supporting information for research and civil applications, both in the context of environmental management, as well as in landscape and urban planning. Advances in remote sensing techniques and computational methods in the recent decades led to the widespread adoption of elevation data in several domains such as hydrological modeling, forest modeling, among others [11].

A Digital Elevation Model (DEM) is a digital representation of the Earth's surface, usually as a digital image that represents elevation values. The type of sensor used to collect elevation data determines the quality of the final result [12]. Data collected with surveying equipment, such as GPS, theodolites, and total

© Springer Nature Switzerland AG 2021
O. Gervasi et al. (Eds.): ICCSA 2021, LNCS 12949, pp. 352–363, 2021.
https://doi.org/10.1007/978-3-030-86653-2_26

stations, collect topographic elevations of the terrain precisely. However, the cost of the final product and time spent to obtain the information might be higher, therefore the number of data points collected might be smaller. Those factors usually restraint the adoption of this type of equipment for large-scale data collection [12]. In that sense, remote sensing techniques such as LiDAR (Light Detection and Ranging), orbital sensors, UAVs (Unmanned Aerial Vehicles), and radar type sensors such as SAR (Synthetic Aperture Radar) and InSAR (Interferometric Synthetic Aperture Radar) are some of the alternatives available for the collection of topographic data. Those approaches, however, collect land surface information instead of terrain information purely [12].

A grid DEM represents a continuous regular surface interpolated through the elevation points (discrete points). Generally, this grid is a set of data that builds up an image, where each pixel value corresponds to an elevation. A triangular irregular network (TIN) represents an irregular surface composed of non-overlapping triangles that connect at irregularly spaced measurement points, these triangles are represented as vector data structures.

When a DEM includes structures above the ground, such as trees, houses, and other buildings, it should be referred to as a Digital Surface Model (DSM) which represents the "first" measured surface. A DSM, therefore, models the reflective response of the terrain and also all objects and surfaces above it.

Digital Terrain Models (DTMs), on the other side, digitally represent the terrain's ground surface without any objects or constructions. This differentiation between ground and non-ground elevation data is of wide interest due to the high applicability of terrain data for environmental and civil construction purposes. DTMs are often adopted in topographic analysis, flood models, urban planning, among other applications [9]. A DSM, on the other hand, is useful when the aim is to represent and analyze surfaces above the ground, such as a 3D map of a city, for instance [2].

A DTM can be obtained as a refined version of a DSM, resulting from specific processing and/or filtering which aim to represent more accurately bare earth without the artifacts or objects on the surface [14]. Several DTM-from-DSM filtering algorithms have been proposed, which are built upon diverse numerical and analytical approaches. The choice of a method depends, among other factors, on the type of data structure considered. Typically, for point cloud data, filtering is used to make this separation between terrain and surface [10].

Under existing DTM-from-DSM methods the user must set a small to moderate number of parameters, which are at least three, typically. This work proposes a simple DTM-from-DSM filtering algorithm that relies on the iterative interpolation of the elevation values in the DTM. The number of parameters of the novel method is smaller when compared to other approaches, which might place the novel method as an easier-to-use alternative for practitioners from diverse areas. We show the applicability of the novel approach by comparing it to a state-of-the method from the literature for three test sites.

The paper is organized as follows. Related works are briefly reviewed in Sect. 2. The proposed approach is presented in Sect. 3. The evaluation

methodology is proposed in Sect. 4. The resulting model is evaluated and compared to a state-of-the art method in Sect. 5. Section 6 concludes the paper.

2 Related Work

Several filtering methods for obtaining the DTM from grid-type DSMs. In [6] a DTM-from-DSM method is proposed, which is especially applicable in steep, forested areas where other filtering algorithms typically have problems when distinguishing between ground and off-ground elements. Some methods rely on the extraction of morphological characteristics of the terrain [5,8,13]. In [7] a method is proposed which relies on extracting the most contrasted connected components from LiDAR data to remove non-ground objects. Recently in [1] a method based on the interpolation matrix of the weighted thin-plate spline is proposed.

The Terra (Terrain Extraction from elevation Rasters through Repetitive Anisotropic filtering) filtering method [9] adopts the terrain aspect to guide the direction of anisotropic filtering, maximizing the preservation of the terrain edges. A smoothing operation is locally directed along the terrain slope. Initially, the slope direction (aspect) at a node $Z_{i,j}$ is computed from a set of nodes inside a squared window centered at (i, j), which contains $\eta \times \eta$ nearby nodes. Later at each step of the iterative process, the smoothing itself occurs considering only the upstream grid nodes within a smaller $\lambda \times \lambda$ filter window centered at (i, j). The process is repeated M times, where M is a parameter. Higher values for M lead to smoother surfaces. The iterative update for each node at each step m is performed as:

$$Z_{i,j}^{m} = min(Z_{i,j}^{m-1}, mean(\{u | u \in U((i,j), \eta, \lambda)\})) \tag{1}$$

where the window U contains the upstream grid nodes as mentioned above, determined for the neighborhood of each (i, j), iteratively at step. Other kernel averaging functions could be used, as mentioned in the paper[1].

3 Proposed Self-interpolation Method

A simple iterative interpolation approach is proposed for the generation of a DTM from a DSM given (denoted as S). Elevation values at coordinates (i, j) in S are successively replaced by the result of the interpolation computed from the elevation values nearby. The iterative process starts at step $m = 0$ with the initial version of the DTM set as $T^{m=0} = S$, which corresponds to the DSM given. Successive refined versions of the DTM are represented as $T^0, T^1, \cdots T^M$, where M represents the number of iterative steps. Theoretically, all the remaining nodes apart from (i, j) itself could be adopted for the computation of the interpolation

[1] The R source code of Terra is available at: https://www.umr-lisah.fr/?q=fr/scriptsr/terra-script-r.

at (i, j). Therefore, the updated elevation value for each node $t_{i,j}^m \in T^m$ at each step m could be computed as the minimum between the previous value $t_{i,j}^{m-1}$ and its interpolated value as:

$$t_{i,j}^m = min(t_{i,j}^{m-1}, \mathcal{M}((i,j), T^{m-1} - \{t_{i,j}^{m-1}\})) \tag{2}$$

where $\mathcal{M}(p, V)$ represents the interpolation computed from input nodes in $V = T^{m-1} - \{t_{i,j}^{m-1}\}$ for the output coordinates given by $p = (i, j)$. However, majorly for the purpose of computational efficiency, only a subset of the nearby nodes will be adopted for the computation of the interpolation $\mathcal{M}$ at each node (i, j). A squared filter window $W((i, j), \lambda)$, centered at (i, j), containing $(\lambda \times \lambda) - 1$ nodes, is defined as the neighborhood of a node at coordinates (i, j). The filter window W is therefore defined as:

$$W((i,j),\lambda,m) = \left\{ t_{a,b}^{m-1} \text{for } a \in \left[i - \left\lfloor \frac{\lambda}{2} \right\rfloor, i + \left\lfloor \frac{\lambda}{2} \right\rfloor \right], b \in \left[j - \left\lfloor \frac{\lambda}{2} \right\rfloor, j + \left\lfloor \frac{\lambda}{2} \right\rfloor \right] \right\} - \{t_{i,j}^{m-1}\}$$

which leads to expression for the iterative process of the proposed method as:

$$t_{i,j}^m = min(T_{i,j}^{m-1}, \mathcal{M}((i,j), W((i,j),\lambda,m))) \tag{3}$$

Algorithm 1 illustrates the novel approach[2].

Algorithm 1: Self-Interpolation Method (SIM)

Input: A DSM matrix S
Input: The number of iterations M
Input: The window size λ
Output: The DTM Z

1 $T^0 \leftarrow S$;
2 **for** m = *1, 2, ⋯, M* **do**
3 **for** *all* $t_{i,j}^m \in T^m$, (i, j) = *the coordinates of all nodes in* S **do**
4 $W' \leftarrow \{$all $t_{a,b}^{m-1}$ in a $(\lambda \times \lambda)$ filter window centered at $(i, j)\}$
5 $W'' \leftarrow W' - \{t_{i,j}^{m-1}\}$
6 $t_{i,j}^m \leftarrow min(t_{i,j}^{m-1}, \mathcal{M}((i, j), W''))$;
7 $Z \leftarrow T^M$
return Z

The method $\mathcal{M}$ adopted in the step 4 of Algorithm 1 could be any point interpolation of choice. Here in this study the Inverse Distance Weighting (IDW) method was used, which is widely adopted in the spatial context and provides

[2] The R source code of SIM is available at https://github.com/emmendorfer/sim.

a computationally efficient approach [4]. The IDW method computes the interpolation $\hat{y}_{new}$ for a given location new from a set of n given values $y_{l_1}, y_{l_2}, \cdots, y_{l_n}$ at locations $l_1, l_2, \cdots, l_n$ as:

$$\hat{y}_{new} = \sum_{k=1}^{n} w_{k,new} \times y_{l_k} \tag{4}$$

where the weights $w_{k,new}$ for input data point at l_k are given as:

$$w_{k,new} = \frac{D_{l_k,new}^{-\alpha}}{\sum_{k=1}^{n} D_{l_k,new}^{-\alpha}} \tag{5}$$

where $D_{l_k,new}$ is the Euclidean distance between nodes at locations l_k and new. In this work, $\alpha = 2$ is assumed, which is the most commonly adopted value.

4 Methodology

Two test sites were considered for the evaluation of the method, which provided three distinct application scenarios due to multiple topographic situations covered. The first corresponds to a low-altitude UAV photogrammetric survey using a DJI Phantom 4 PRO drone[3]. The aerial survey, which occurred during the years 2018 and 2019, covers a 424ha urbanized coastal area in southern Brazil with an overlap of 80/60, frontal and side percentage respectively. The photogrammetric bundle consisted of 3096 photos properly calibrated and adjusted through 68 control points acquired by GNSS-RTK [7]. The 1 m *Dunes* DSM corresponds to a 100 × 100 m squared region centered at 32° 11'10"S 52°09'13"W, which is composed by sand dunes covered with very low vegetation.

Also from the same site, an urban area was considered. It corresponds to a 100 × 100m squared region centered at 32°11'20"S 52°09'49"W which is denoted here as the *UrbanRG* DSM, also with 1 m resolution.

Finally, a 5 m resolution DSM derived from interferometric synthetic aperture radar (IFSAR)[4] was also included. This 2017 data corresponds to an area in Alaska, USA. A 500 × 500 m area centered at 61°15'00"N 157°16'39"W was denoted here as *Alaska*. Elevations in this area vary from 115 m to 130 m.

A quantitative evaluation was performed for the *Dunes* and *Alaska* DSMs, as follows. Since both cases correspond to low vegetation areas, we will consider both original DSMs as being the reference DTMs for the evaluation of the DSM-to DTM methods considered. From each DTM two noisy DSMs are obtained by performing the increment in the elevation values for a portion of the nodes. Two alternative percentages were adopted: 25% and 50%. This allows one to verify

[3] All ellipsoidal height coordinates obtained by the survey were adjusted to orthometric heights using the geoid heights provided by the MAPGEO2015 software, which were made available by the Instituto Brasileiro de Geografia e Estatística (IBGE).

[4] Available at: https://www.sciencebase.gov/catalog/item/5cc3ccd0e4b09b8c0b760969.

the robustness of the filter on varying levels of artifacts inserted. For each node that is randomly selected to be altered, a random increment uniformly sampled from the interval $[0\,m, 5\,m]$ is added to the corresponding elevation value.

Two DTMs are computed for each noisy DSM, from both Terra and SIM methods. Finally, the Root Mean Squared Error (RMSE) between the reconstructed DTM and the original reference DTM is computed using all the elevation values available. This type of evaluation differs from what is adopted in other works where the evaluation is based on "reference DTMs" which are DSMs that were processed using some reference method.

5 Results

Initially, we evaluate the effect of the parameters of the algorithms on the quality of the resulting DTMs. Figure 1 shows the RMSE computed from the resulting DTMs from both Terra and SIM as a function of the parameters M and λ, for varying proportions of nodes altered (25% and 50%), considering both *Dunes* and *Alaska* areas. The Terra algorithm, besides M and λ has also the parameter η to be set. Since η should be greater than λ, we adopted an ad-hoc rule where $\eta = \lambda + 2$, in this first set of quantitative evaluations. Odd values were adopted for both window sizes, which guarantees that the center of the windows is exactly at (i, j).

In general, the RMSE response surfaces obtained from SIM attained lower values when compared to the corresponding RMSE surfaces obtained from Terra. Table 1 shows the optimal RMSE computed for all cases, along with the corresponding parameter values.

Table 1. Optimal RMSE values from Terra and SIM applied to *Dunes* and *Alaska* areas. The best result for each case is shown in bold.

Area	% of randomized elevations	Method	Best parameter values		Optimal RMSE
			λ	M	
Dunes	25%	Terra	5	3	0.5897
		SIM	3	3	**0.1097**
Dunes	50%	Terra	5	3	0.9537
		SIM	3	6	**0.1451**
Alaska	25%	Terra	3	3	0.6533
		SIM	3	2	**0.1994**
Alaska	50%	Terra	3	7	0.9652
		SIM	3	5	**0.2684**

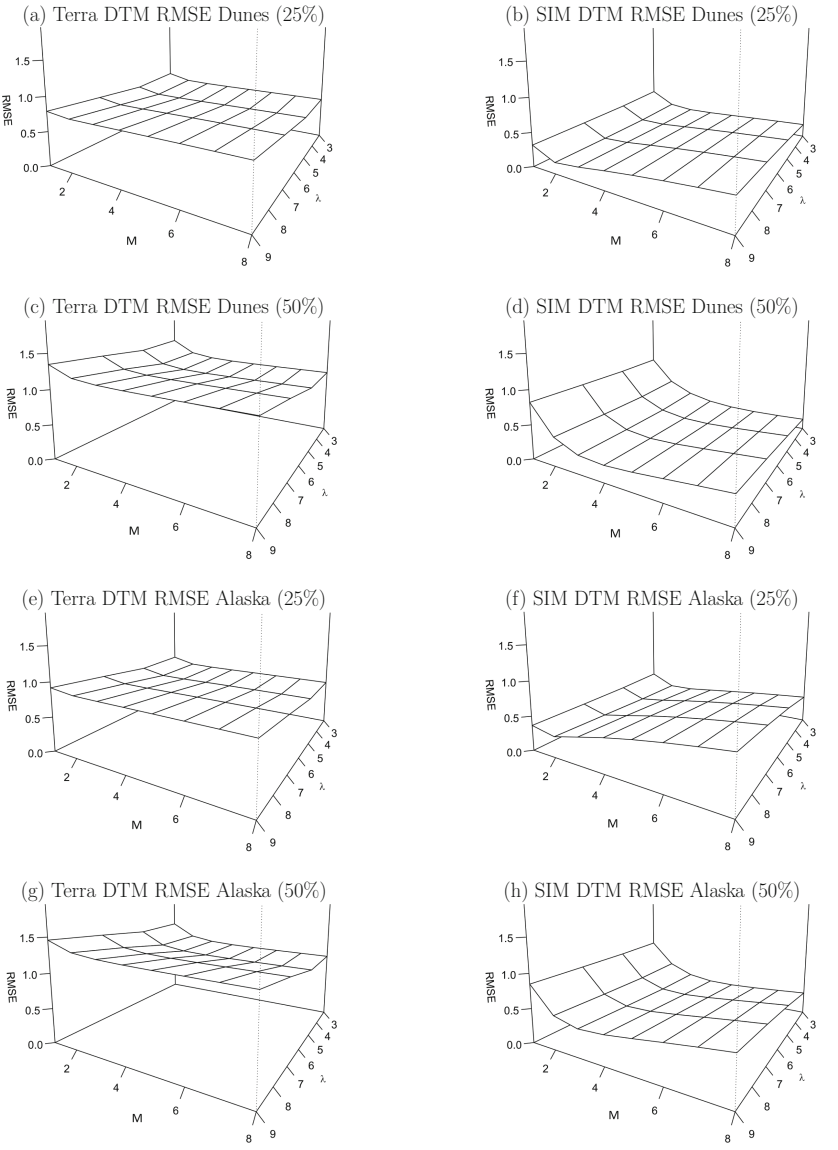


Fig. 1. RMSE computed from the result of Terra and SIM algorithms, as a function of the parameters M and λ, for varying proportions of nodes altered (25% and 50%), considering both the *Dunes* and *Alaska* areas.

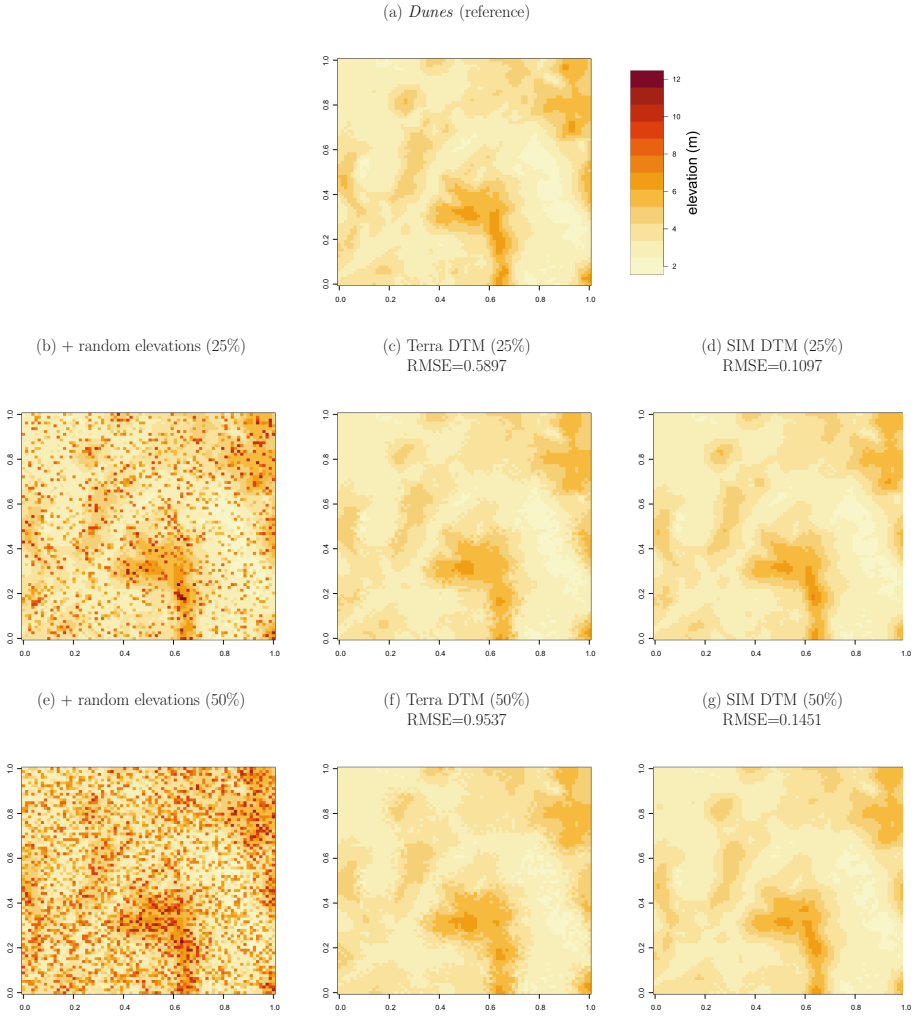


Fig. 2. Optimal results from Terra and SIM when applied to the *Dunes* area.

Figures 2 and 3 show the results obtained from both methods Terra and SIM using the optimal parameters shown in Fig. 1, applied to noisy DSMs. Figure 2 shows the results obtained for the *Dunes* region. The RMSE obtained from SIM was smaller than RMSE from TERRA. One can notice that the smoothing effect performed by the SIM method (Figs. 2d and 2g) preserves some dune features, while the TERRA method was not as conservative, resulting in a roughly "spotted" aspect, which makes certain dune features less evident in the reconstructed maps (Figs. 2c and 2f).

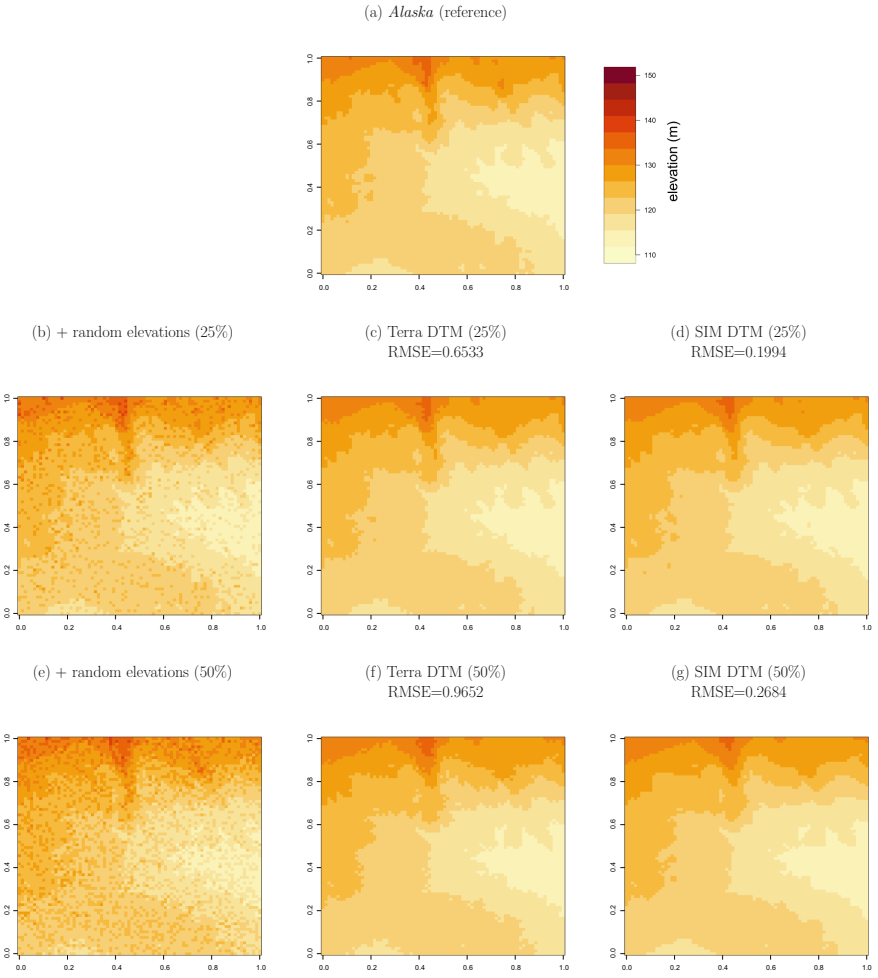


Fig. 3. Optimal results from Terra and SIM when applied to the *Alaska* area.

Figure 3 shows the reconstruction results obtained for the *Alaska* region. The RMSE values obtained from SIM were lower when compared to Terra, as in the previous case. The reconstructions obtained using the SIM filtering method (Fig. 3d and 3g) better preserve morphological characteristics of the original data when compared to the reconstructions obtained from Terra (Fig. 3c and 3f). The borders of an image are not affected by the Terra method, therefore border pixels were excluded from all images shown in the figures.

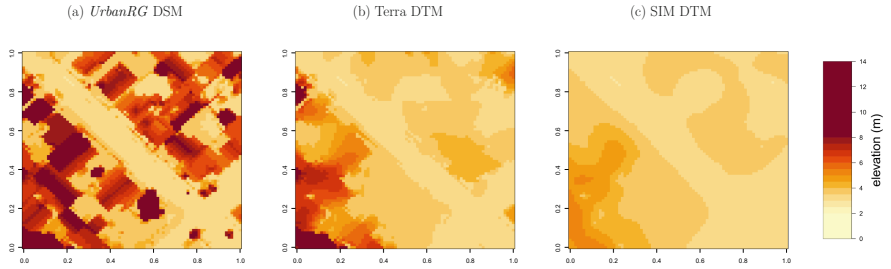


Fig. 4. Results from Terra and SIM when applied to the *UrbanRG* area.

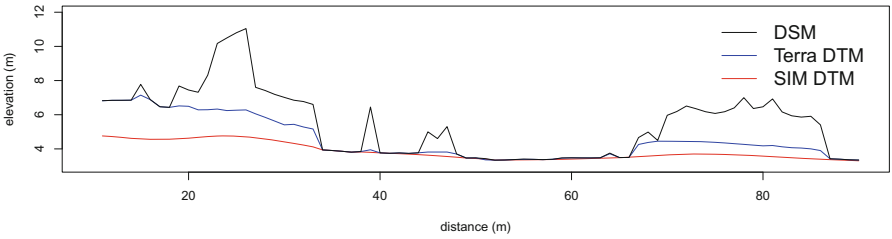


Fig. 5. A transect for *UrbanRG* area, considering the original DSM and resulting DTMs shown in Fig. 4.

To illustrate the adoption of the novel method in another context, Fig. 4 shows the DTM resulting from both Terra and SIM when applied to the *UrbanRG* area, which corresponds to an urban area. Parameters adopted for Terra in this case were $\lambda = 7$, $\eta = 10$. SIM was executed using $\lambda = 5$. For both methods, $M = 70$ was used. Other parameter settings for both methods led to worse results. Figure 5 shows transects for the same area, considering the original DSM and resulting DTMs. One can notice that SIM was able to achieve a further realistic result in this case when compared to Terra.

6 Conclusion

The choice of an appropriate method for generating a DTM given a DSM depends on the type of terrain, the type of objects to be removed, the amount of computational resources to be afforded, among other factors. Each method has its advantages and drawbacks: a method that fits well with some type of situation can be unsuited for another. This also motivates the improvement of existing methods and the search for alternatives. This paper described a novel DTM-from-DSM method which is very simple but rather effective when compared to a state-of-the-art reference approach. The method is evaluated on three scenarios that represent diverse situations that can be found in real applications. Optimal RMSE from the novel method was better when compared to the reference Terra method for all test cases considered, after performing an exhaustive search

on the parameter space for both methods. Results from Terra, however, could be improved since the number of parameters of the method is higher and the search was restricted to the two parameters that are common to both methods SIM and Terra. The method proposed here was revealed as an attractive initial alternative for practitioners since its parameter setting is easier to accomplish when compared to other methods from the literature.

Further work should explore other types of applications. Also, other DTM-from-DSM methods should be considered in further evaluations. Besides that, other alternatives could be considered for the interpolation method adopted in SIM besides just the IDW approach used here. For instance, variations of IDW itself such as the IDWR method recently proposed [3,4] could be used.

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