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The role of morphometric parameters in Digital Terrain Models interpolation accuracy: a case study

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Abstract
In the present study different algorithms, usually available in GIS environment, are analyzed in order to spot an optimal interpolation methodology and to define, by classification techniques, which morphological variable affects the interpolation quality. The investigated dataset is a helicopter-borne laser scanner survey carried out on a mountain slope. It has been interpolated at various resolutions, and a percentage of the entire set has been employed to evaluate the interpolation accuracy. The analysis has highlighted, among the tested interpolators, the Natural Neighbour as the best one. The classification has drawn the attention to the total curvature and slope as the main factors affecting interpolation accuracy. The next goal is the mapping of such classification results.

Keywords: CART, laser scanner, terrain morphology.

Introduction
Digital Terrain Models (DTM) have been employed for decades as a support in several analyses, such as watershed analysis [Collins, 1973], morphometric parameters computing [Anselmo and Godone, 1976] or as support layers in remote sensing processes [Guindon et al., 1981]. Although DTM are a valuable data source, they are characterized by several issues that can prevent or hamper the fulfilment of an analysis process, if not correctly handled and faced. In fact DTM computing process is affected by different error sources. Firstly, input data measured by, generally speaking, topographical [Brasington et al., 2000] or photogrammetrical means [Poon et al., 2005] are affected by errors that will have an effect on the final DTM’s accuracy. DTM are also obtainable, as derived products, from existing maps digitizing [Carter, 1988; Weng, 2002] with similar accuracy issues. The advances in the laser scanner technique [Baltsavias, 1999; Wehr and Lohr, 1999] have introduced a new data source for DTM [Lohr, 1998]. Moreover, in the last years, the
development of high resolution sensors has renewed the importance of DTM, as they are the main result of the survey [Liu et al., 2007; Pfeifer et al., 2009]. The large amount of data allows a better description of the measured terrain and the dataset splitting in order to perform validation procedures on the dataset without excessively reducing its informative content [Bater and Coops, 2009].

The availability of these products has allowed to extend the DTM employment in several fields of application. E.g. Jaboyedoff et al. [2010] or Ventura et al. [2011] have exploited DTM capabilities in landslides analysis. Researches on landform maps and channel network extraction have also been carried out [Pirrotti and Tarolli 2010]. Beyond geomorphometry, lidar DTM have been employed in studies concerning vegetation and its detection for urban planning [Höfle and Hollaus, 2010] and forest management [Korpela et al., 2010] purposes.

In order to obtain the DTM output, after input data collection, an interpolation procedure is performed with the purpose of computing a continuous surface from the discrete measurements [Heritage et al., 2009]. The interpolation algorithm choice covers a key role in DTM generation as interpolators behave in different ways depending, for example, on the cellsize, landform types and data density [e.g. Fisher and Tate, 2006; Mitas and Mitasova, 1999; Chaplot et al., 2006] and can thus induce errors in the output DTM [Smith et al., 2004]. Wise [2012] suggest the employment of the Shannon theory, or information theory [Shannon, 1948] in order to measure the information loss when a DTM is aggregated to a coarser scale. As previously stated, DTM accuracy is also influenced by the measured terrain morphology inducing errors and uncertainties both in the survey phase and in the interpolation one [Aguilar et al., 2005; Bater and Coops, 2009; Guo et al., 2010].

Errors in DTM interpolation affects further processing, as DTMs are often used to derive terrain derivatives and it has been shown that small errors in elevation can lead to large errors in these derived values [Wise, 2011]. In viewshed analysis, errors in steeper terrains will have great impact on results [Fisher, 1998], on the other hand small errors in flat areas will have a greater influence on runoff and flood modelling than in steeper areas [Burrough and McDonnell, 1998].

In this paper the authors focus on the interpolation algorithms usually available in GIS packages and on their employment in a “black box” approach, i.e. leaving parameters as suggested by software estimation [Mitas and Mitasova, 1999]. The investigation is oriented to quantifying, by statistical procedures and evaluations, the influence of terrain characteristics in interpolation quality. The further aim is to employ such quantifications, obtained from classification algorithms and decision trees, in a cartographical representation with the purpose of outlining critical areas drawing the attention of the final user. Such data should acts as weighting parameters while employing the interpolated model as an input data in further processing or as a preliminary evaluating layer, perhaps computed from a previously surveyed elevation model, in order to forecast the quality of a planned survey.

**Materials and methods**

**Study area**

The study area is located in Aosta valley - North western Italian Alps (45°51’6”N; 7°50’30”E) in the ski resort named Monterosa Ski (Fig. 1). Particularly, the test site is located on a mountain slope near the arrival of a cable car of the resort.
The site has been surveyed by helicopter borne laser scanner (Tab. 1) with the purpose of measuring its morphology, as a preliminary step in a wider experimental context concerning avalanche triggering and monitoring [Ceaglio et al., 2010; Maggioni et al., 2013]. The slope, with an altitude difference of about 300 m (from 2300 to 2570 m asl), has a mean inclination of about 28° and a NNW aspect. The width varies from about 80 m at the top near the ridge to 40 m in the middle of the avalanche track, to more than 100 m in the deposition zone. The ground roughness is very high, being covered by debris of different sizes, with single rocks up to 4 m of diameter.

Table 1 - Survey parameters.

| Survey area        | 1 Km²          |
|--------------------|----------------|
| Survey resolution  | 20 points/m²   |
| Orthoimage resolution | 10 cm       |
| Vertical accuracy  | 10 cm          |
| Horizontal accuracy| 18 cm          |
| Datum              | ED1950         |
| Projection         | UTM Zone 32    |
| Orthometric model  | ITALGEO2005    |
Data collected from the helicopter-borne sensor have been processed in ArcGis environment. The first step was the extraction of a sub dataset (250 x 250 meters) located in the upper sector of the slope, characterized by highly variable morphology (Fig. 2). The resulting dataset has been split into a training dataset (95% of the original data), employed for the computations and the interpolation procedures, and a test dataset (5%) to be used as an independent dataset for the validation procedures.

Interpolation techniques
Interpolation tools available in geographical information systems are useful and allow the operator to easily perform different kind of elaborations and to display them graphically in order to show the results in a way intelligible also to non-skilled subjects.
Interpolators are divided in two typologies [Hartkamp al., 1999]:
1. Deterministic
2. Stochastic
these interpolators use a linear combination of known values with different weighting and neighbouring search schemes. Every interpolator assumes spatial continuity: data that are closer to interpolation point have more influence (weight), during the computations, in comparison with faraway ones, according to the First Law of Geography [Tobler, 1970].
Interpolators could be defined as weighted average methods, with similar processing concept; the operator, in fact, needs to compute an unknown value, at an unsampled
location, given a set of neighbouring sampled values, collected at locations neighbouring the unknown one; the quantity of neighbouring points included in the search radius affect directly the final surface smoothing and the computing time. The interpolation procedure, then, acts as follows: i.e. by the definition of the search area or neighbourhood around the unknown point, the detection of the observed data points within the previously defined neighbourhood and, finally, the assignment of appropriate weights to each of the observed data points. The interpolation methods differ in the way of computing samples’ weights [Wong et al., 2004]. In the following paragraph, interpolators employed in the work are briefly described.

**IDW**

IDW (Inverse Distance Weighing) interpolator is an automatic and easy to use technique, as it requires few decisions from the operator, such as search neighborhood parameters, exponent and eventually smoothing factor, from the operator [Hessl et al., 2007]. It’s particularly suitable for reduced dataset, where other fitting techniques may be affected by errors [Tomeczak, 2003]. The process is highly flexible and allows estimating dataset with trend or anisotropy, in search neighborhood shaping. Anyhow interpolator’s output may be affected by “bull’s eyes” or terraces [Burrough and McDonnel, 1998; Liu, 1999].

IDW directly implements the assumption that a value of an attribute at an unsampled location is a weighted average of known data points within a local neighborhood surrounding the unsampled one [Mitas and Mitasova, 1999], as the following formula:

\[
Z_j = \frac{\sum_{i=1}^{n} \frac{Z_i}{(h_{ij} + \delta)^\beta}}{\sum_{i=1}^{n} \frac{1}{(h_{ij} + \delta)^\beta}}
\]  

[1]

Where \(Z_j\) is the value at an unsampled location, \(Z_i\) are the known values, \(\beta\) is the weight and \(\delta\) is a smoothing parameter.

The separation distance \(h_{ij}\) between a known and unknown point is measured with is euclidean distance:

\[
h_{ij} = \sqrt{(\Delta x)^2 + (\Delta y)^2}
\]  

[2]

where \(\Delta x\) and \(\Delta y\) are the distances between the unknown point \(j\) and the sampled one \(i\) according to reference axes.

**Spline**

Splines [Johnston et al., 2001] are interpolators that fit a function to sampled points. The algorithm uses a linear combination of \(n\) functions, one for each known point.
\[ \hat{Z}(s_0) = \sum_{i=1}^{n} \omega_i \phi(\|s_i - s_0\|) + \omega_{n+1} \quad [3] \]

Where \( \phi(r) \) represent the interpolation function, \( \|s_i - s_0\| \) the euclidean distance \( r \) between an unknown point \( s_0 \) and a measured one \( s_i \), while \( \omega_i \), with \( i = 1,2,...n+1 \), are weights. Weights are assigned according to the distance of known points, under the constraint that the function, in their locations, must give the measured value. This conditions lead to the computation of a system of \( N \) equations with \( N \) unknowns with a unique solution. Splines include different kinds of functions:

**Thin-plate Spline function:**

\[ \phi(r) = (\sigma \cdot r)^2 \ln(\sigma \cdot r) \quad [4] \]

**Multi-quadric function:**

\[ \phi(r) = \left[ r^2 + \sigma^2 \right]^{1/2} \quad [5] \]

**Inverse Multi-quadric function:**

\[ \phi(r) = \left[ r^2 + \sigma^2 \right]^{-1/2} \quad [6] \]

**Completely regularized Spline function:**

\[ \phi(r) = -\sum_{n=1}^{\infty} \frac{(-1)^n \cdot r^{2n}}{n! n} = \ln \left[ \frac{\sigma \cdot r}{2} \right]^2 + E_1 \left[ \frac{\sigma \cdot r}{2} \right]^2 + C_E \quad [7] \]

**Spline with tension function:**

\[ \phi(r) = \ln \left( \frac{\sigma \cdot r}{2} \right) + K_0 \left( \sigma \cdot r \right)^2 + C_E \quad [8] \]

Where:

- \( r \) = distance between the point and the sample
- \( \sigma \) = tension parameter
- \( E_1 \) = exponential integral function
- \( C_E \) = constant of Euler (0.577215)
- \( K_0 \) = modified Bessel function.

Splines function are slightly different, every one has a different smoothing parameter depending on the \( \sigma \) parameter. In every method, the higher is the value of \( \sigma \), the higher will be the gradualness.
of the variation, except for the “Inverse multi-quadric” where the opposite condition is true.
In the following analyses only two Splines were available, according to the selected GIS
package: the Regularized and the Tension one. The Regularized Spline creates a smooth,
gradually changing surface with values that may lie outside the sample data range: the
regularizing parameter is in fact employed to achieve a smoother solution e.g. a small value
results in a close approximation of the data, while a large one results in a smoother solution
[Gousie and Franklin, 2005]. The Tension Spline creates a less smooth surface with values
more constrained by the sample data range: changing the value of the tension parameter
tunes the surface from a stiff plate into an elastic sheet [Mitas et al., 1997].

Natural neighbours
Natural neighbour interpolation finds the closest subset of input samples to an unknown
point and applies weights to them based on proportionate areas in order to interpolate a value
[Sibson, 1981]. The natural neighbours of any point are those associated with the neighbouring
Voronoi polygons. Initially, a Voronoi diagram is constructed from all given points, and a new
Voronoi polygon is then created around the interpolation point. The proportion of overlap
between this new polygon and the initial polygons are then used as weights.
Natural Neighbours is local, using only a subset of samples that surround the unknown point,
and assuring that interpolated values are within the range of the samples. It does not infer
trends and will not produce peaks, pits, ridges or valleys that are not already represented by
the input data. The surface passes through the input samples and it is smoothed everywhere
except at the locations of the input samples. It adapts locally to the structure of the input
data, requiring no input from the user pertaining to search radius, sample count, or shape. It
works equally well with regularly and irregularly distributed data [Watson, 1992].

DTM quality assessment
The train dataset has been interpolated by the four different algorithms (IDW, Natural
Neighbors, Tension and Regularized Spline), available in ArcGis extensions Spatial Analyst
[McCoy and Johnston, 2002] and 3D Analyst [Booth, 2000], thus computing rasters at 1
metre grid spacing, and then aggregating, by simple averages, the resulting grids at 2 and
5 metres grid spacing with the purpose of investigating the role of varying estimators and
output grid resolutions in the interpolation processes performance. The interpolations have
been accomplished by leaving every requested parameter value as suggested by the software
in order to avoid the operator influence in the process, i.e.: IDW (Power = 2, Search radius
= variable, Maximum number of points = 12), Splines (Weight = 0.1, Maximum number of
points = 12), Natural Neighbours (No parameters). According to this choice, geostatistic has
been discarded, considering that it is mathematically similar to Spline when its modeling
capability is not exploited [Cressie, 1991].
The validation has been carried out by extracting from each interpolated grid the elevation
value at the location of the test dataset, and comparing these values with the measured ones by
computing residuals, on which descriptive statistics (Root Mean Square Error - RMSE, Mean
Absolute Error - MAE, Mean Error - ME) have been calculated in order to point out the best
algorithm at each resolution.
To test the role of surface morphology on interpolation, a TIN has been computed from the whole
dataset (Training + Test), and by the employment of spatial analysis tools, several grids have
been obtained at 1 m resolution. Different morphometric parameters have been computed: slope (maximum rate of change in elevation over each cell and its eight neighbours), total curvature - computed on a cell-by-cell basis considering a 3x3 moving window approach [Moore et al., 1991; Zeverbergen and Thorne, 1987], pulse density [Lane et al., 1994; Lane, 1998] and roughness - or rather “roughness index” computed as the standard deviation of residual topography computed in a 5x5 window, i.e. the difference between the elevation values and their mean values calculated by a 5x5 cells moving window [Cavalli et al., 2008; Cavalli and Marchi, 2008] in order to have a suitable measure of roughness and to avoid the large scale effect (i.e. slope effect: high roughness in high slope area) affecting previous computing methodologies, as the standard deviation of elevation in a 3x3 cells moving window proposed by Gloersen et al. [2004]. In order to perform the test, data from each grid have been extracted in the test dataset locations, with the same previously explained procedure, and analyzed by employing R [R Development Core Team, 2010] provided with the Tree package [Ripley, 2011], by the CART analysis.

The CART (Classification and Regression Tree Analysis) analyzes the performance of a dependent variable as a function of other independent variables [Breiman et al., 1984]. It is a robust method that requires no special assumptions such as normal distribution of data; it is also capable of processing categorical and continuous variables in a single analysis. The output of the procedure is a tree diagram that divides the dataset, iteratively, in subsets of increasing homogeneity [Urban, 2002]: the algorithm finds a value in the individual variables, called “split”, which allows the division into two subgroups adequately significant; thus creating the described diagram, where each branch is associated with an independent variable and a certain threshold value [Michaelsen et al., 1994]. In order to avoid subdivision of the diagram in scarcely significant ramifications, it is possible to define a threshold (tree pruning) below which the algorithm does not split further branching [Kittler and Devijver, 1982]. In the described processing, no pruning threshold has been selected according to the resulting tree dimension.

The Tree package has been employed in order to define a classification tree describing morphometric parameter’s influence on residuals and, then, the Modelmap package [Freeman and Frescino, 2009] has been employed, for a further processing, with the aim of computing a map, predicting the residuals according to the same inputs.

The package analyzes the input data and performs a classification by employing the Random Forest approach [Breiman, 2001] and then plots the results in a grid containing the fluctuation of the dependent variable’s value. The map has been produced by processing the morphometric parameter rasters (roughness, total curvature, slope) and the pulse density one with the classification model defined by the CART analysis and a congruent grid structure. In order to check the ModelMap output a set of 250 random points have been generated and employed to sample, at their location, the pixel values of the map and other grids. Extracted values have been compared in order to hypothesize morphometric parameter relation with the predicted residuals.

**Result and discussions**

The test carried out on the LIDAR data has led to different results according to the processing phase. Firstly each interpolator has produced the grids, at various resolutions, without evident artifacts, mainly due to the abundance of input data.

The algorithm comparison, at different interpolation resolution, has allowed to define the best one among those available in common GIS packages. Then the morphological analyses, combined with the statistical evaluation, have defined several parameters inducing different
interpolation accuracies inside each DTM. Moreover, parameters importance has been quantified according to the different resolution.

**Interpolators’ evaluation**

The comparison, between the training and the test dataset, for each interpolator and at each resolution, has returned residual values. They have mean near zero and show quite symmetrical behaviour, when examining minimal and maximal values, allowing the employment of such data in further analysis. The analysis of residual descriptive statistics highlights that the better performance at 1 metre cellsize is given by the Natural Neighbour interpolator, followed by the Tension and Regularized Splines (Fig. 3). At 2 metres cellsize the Natural Neighbours shows, in every statistics, a worsening, on the other hand the other interpolators show similar behaviour as compared to previous resolution. At 5 metres cellsize the Natural Neighbours resumes acceptable values in descriptive statistics.

At every resolution, the IDW interpolator shows the highest values in each descriptive statistic.

![Figure 3 - RMSE, MAE and ME for each interpolator (NN = Natural Neighbours; RSPLINE = Regularized Spline; IDW = Inverse Distance Weighing; TSPLINE = Tension Spline) and resolution (1, 2, 5 metres).](image-url)
**Morphometric parameters and DTM quality assessment**

The three dimensional processing of the data has allowed the computation of several analysis grids - roughness, total curvature and slope (Fig. 4), employed in the following phases of the work as independent variable in the statistical analyses. Each one represents a facet of the vast topic of morphological analysis and it quantifies a characteristic of the investigated area.

![Figure 4 - Grids representing the morphological variables (a = roughness, b = total curvature, c = slope).](image)

The residual values computed in each interpolation have been tested against morphological variables and against the pulse density. The CART analysis has given a tree diagram for each test, subdividing the dependent variable (residuals) in homogeneous subgroups, according to independent variables split values (Fig. 5).

![Figure 5 - Tree diagram (Nearest Neighbour interpolator, cellsize 1 meter).](image)

The CART has highlighted the role of slope and total curvature in affecting interpolation quality. In fact the first split in the tree is due to the upwardly convex areas, another branching variable is the slope; areas characterized by high values of these parameters are influenced by high residual values. On the other hand flat or upwardly concave sectors are
characterized by, respectively, low or moderate residual values. The ModelMap package has computed the behaviour of the investigated variable, i.e. interpolation residuals. The main result is an ASCII grid congruent with the input variable grids (slope, total curvature, roughness and pulse density) containing, in its cells, residuals computed as a function of the previously stated variables and that can be considered as a map of the DTM quality (Figure 6). Sampling points characterized by high predicted residual values are located in areas with high or moderate slope, confirming the findings of Toutin [2002] and Hodgson and Bresnahan [2004] and remarkable roughness index values; pulse density seems irrelevant while, concerning total curvature, extremely, upwardly convex areas are characterized by, negative, high residuals; on the other hand, high, positive, values are located in concave areas (Tab. 2). The detected influence is in accordance with the work of Carlisle [2005], which highlighted a significant correlation between residuals and curvature values.

Table 2 - High residuals values and morphometric parameters.

| X (m)   | Y (m)        | Residual (m) | Slope (°) | Roughness | Density (pulses/m²) | Total curvature |
|---------|--------------|--------------|-----------|-----------|---------------------|-----------------|
| 410035  | 5078397      | -3.14        | 89.19     | 2.19      | 33.10               | 535.33          |
| 410118  | 5078418      | -2.91        | 89.03     | 1.64      | 27.06               | 763.92          |
| 410033  | 5078398      | 2.96         | 60.81     | 2.43      | 26.42               | -1384.72        |
| 410260  | 5078486      | 3.00         | 49.80     | 2.95      | 31.83               | -1466.72        |
| 410040  | 5078404      | 3.00         | 88.62     | 3.03      | 27.69               | -2491.77        |
| 410037  | 5078404      | 3.12         | 88.32     | 2.71      | 26.42               | -1538.55        |
| 410245  | 5078457      | 3.20         | 88.51     | 2.46      | 27.37               | -1431.30        |
| 410245  | 5078454      | 3.24         | 86.62     | 2.64      | 35.65               | -1651.83        |
| 410042  | 5078403      | 3.46         | 88.18     | 2.43      | 31.83               | -1022.93        |
| 410252  | 5078387      | 3.64         | 36.72     | 1.95      | 19.42               | -1124.02        |

The informative content of such layer is a valuable reference for the operator while employing the DTM in further analyses; it can help the interpretation of results or help forecasting anomalous outputs from the analyzed variable, probably due to low quality interpolation.

Figure 6 - DTM quality mapping (left) and orthoimage of the investigated sector (right). The white circles highlight areas with higher residuals.
Conclusions

The employment of laser scanner in terrain analysis provides a high resolution dataset which can be exploited by several investigation techniques and tools. The studied area, 62500 m², has been measured by 1718408 laser pulses thus giving an equal number of survey points. This huge amount of data allows the interpolation of high resolution DTMs. At the same time, the data set can be split without reducing its informative content, in order to extract validation points with the purpose of validating interpolated grids.

The use of statistical analysis provides different techniques to quantify interpolation quality, and consequently it allows to compare a set of interpolation algorithms. In case of these comparisons, their different approaches should be carefully taken in account, as each interpolator requires a different set of decisions by the operator and results may vary substantially.

According to the algorithm comparison, Natural Neighbour has resulted as the best one at the original 1m cellsize and at lower resolutions, but at higher cellsizes its residuals show uneven behaviour, with high values at 2 metres and, again, low values at 5. No explanation for this has been deduced, also because other interpolators behave completely different, i.e. without abrupt fluctuations in their values. According to the classification analyses the parameters that cover a main role in DTM quality are slope and total curvature, confirming previous findings in literature [e.g. Su and Bork, 2006].

Classification trees or similar techniques allow focusing the investigation on external parameters that may affect the interpolation quality. The choice of such parameters is highly subjective and should be carefully done in order to avoid taking in account non meaningful variables in the analyses. Research’s future goal is, in fact, the in-depth examination of such techniques and their contribution in the evaluation of significant variables input in order to define a methodological approach.

The employment of, local, spatial variability indexes helps in summarising investigated terrain’s parameters for the following analyses; however the processing can be refined by the computation of more complex indexes, allowing the in-depth representation of spatial variability, and consequently a better investigation of its effects on interpolation residuals. Terrain’s variability can be modelled by the employment of geostatistics [Trevisani et al., 2012], fractal analysis [Sharma et al., 2011], segmentation procedures [Lucieer and Stein, 2005], wavelets analysis [Booth et al., 2009] or by combining different approaches. The detection of textural features is achieved, for example, in geostatistics by analysing spatial continuity [Trevisani et al., 2009] or by interpreting the variogram, summarised by fractal dimension [Lloyd and Atkinson, 2002a], as a measure of spatial variation [Burrough, 1981]. These approaches have to cope with the issues of trend estimation and selection of moving window size, that may lead to misinterpretation of the dataset and consequently inducing errors in the processing [Lloyd and Atkinsons, 2002b; Olea, 2006].

The segmentation approach applies image analysis techniques to morphological analysis in order to extract information stored in the DTM. The analysis is carried out by computing indexes - e.g. Local Variable [Woodcock and Strahler, 1987; Drăguț et al., 2011] - describing levels of organization in the structure of data or pattern elements that can be classified as different morphometric parameters [Gessler et al., 2009]. On the other hand the use of wavelet analysis is aimed to locally filter elevation data and to detect thresholds in topographic parameters for defining landforms and other descriptive indexes [Kumar and Foufoula-Georgiou, 1997; Lashermes et al., 2007].
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