A METHODOLOGICAL PROPOSAL FOR IMPROVEMENT OF DIGITAL SURFACE MODELS GENERATED BY AUTOMATIC STEREO MATCHING OF CONVERGENT IMAGE NETWORKS

J. García-León [a, *], A. M. Felicísimo [b], J. J. Martínez [a]

[a] Expresión Gráfica Arquitectónica, Universidad Politécnica de Cartagena, 30202 Cartagena, Spain – (josefina.leon, juanjo.martinez)@upct.es

[b] Ingeniería Cartográfica, Geodesia y Fotogrametría, Escuela Politécnica, Universidad de Extremadura, 10071 Cáceres, Spain - amfeli@unex.es
Session code PS, WG V/1

KEY WORDS: Cultural Heritage, Architecture, Statistics, Reliability, Method.

ABSTRACT:

A Digital Surface Model (DSM) generated by automatic stereo matching of convergent image networks includes a great number of 3D-points that come from diverse combinations of stereo-pairs. This points can have a very different accuracy and reliability, in addition to a great and nondesirable spatial redundancy.
We analized different methods to generate several synthesis DSM whose points are the result of a statistic process. The aim is to obtain a regular mesh of points whose Z coordinates are estimated from the whole set of data over the interpolating function. We choose the best of them using a random mesh of points whose coordinates were measuredby multiple direct intersection.

1. INTRODUCTION

The purpose of photogrametric methods basing on automatic correlation is to generate massive clouds of points (figure 3). García-León et al. 2003 is an example of the use of a convergent geometry (figure 2), from which a great deal of information has been drawn. This paper also demonstrates that these data can undergo selection regarding the value of the correlation coefficient. Selection eliminates bad quality data and simplifies matters, in spite of which, the amount of resulting points is still huge. In this paper, a method to filtrate these points is introduced, in order to achieve a model of synthesis surface without appreciable loss in accuracy.

Several methods have been used; for example, Kriging, broadly used in other disciplines and based upon sound statistical principles, since it ensures an optimal interpolating function. The aim is to obtain a regular mesh of points whose Z coordinates are estimated from the whole set of data over the interpolating function.

2. DATA

This work was carried out on one of the churches of the historical centre: San Mateo Church, sited in Cáceres (Western Spain, city declared World Heritage by UNESCO in 1986). The Southern façade has a complex design due to the presence of one tower and some relieves that frame the main gate. All these elements make this church ideal for our study (Figure 1).

Figure 1. Southern façade of San Mateo Church.
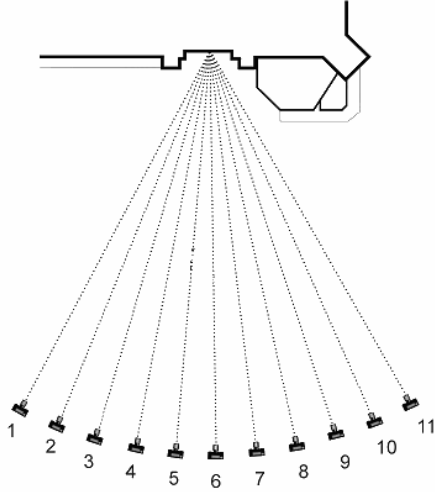
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* Corresponding author.
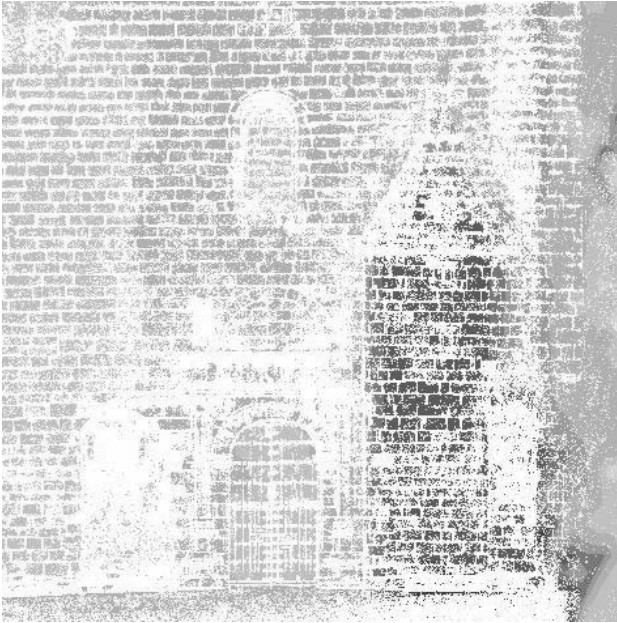
Figure 2. Design of the convergent geometry

Figure 3. Correlated clouds of points.

3. METHODS

Different estimates have been given, all of them validated afterwards, letting us know the mean square error and compare models' accuracy.

3.1 Inverse Distance Weighing (IDW)

The z coordinates of the point to interpolate are estimated allocating weights to environment data in inverse relation to distance; nearest points thus getting more weight in calculations. It is an exact method that estimates the value of the variable for a point not belonging to the sample, using the following expression (1):

$$z_j = \frac{\sum_{i=1}^{n} \frac{1}{d_{ij}^{\rho}} \cdot z(x_i)}{\sum_{i=1}^{n} \frac{1}{d_{ij}^{\rho}}} \qquad (1)$$

where d_{ij} is the Euclidean distance between each data item and the point to interpolate, and p is the weighting exponent. The least mean square error of the prediction (RMSPE) is calculated in order to determine the optimal exponent value. The optimal power (p) value is determined by minimizing the root mean square prediction error (RMSPE). The RMSPE is the statistic that is calculated from cross-validation. In cross-validation, each measured point is removed and compared to the predicted value for that location. The RMSPE is a summary statistic quantifying the error of the prediction surface (Johnston et.alt.
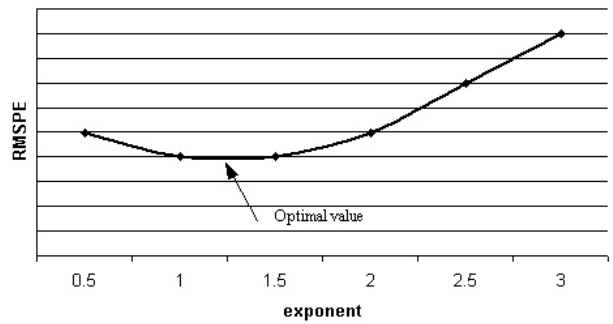

Figure 4. Optimal exponent determination graph.

3.2 Radial basis function (RBF)

Radial base functions comprise a wide group of exact and local interpolators that use an equation with its base dependent on distance. Generally speaking, the value of the variable is given by the following expression (2):

$$z_j = \sum_{i=1}^{n} a_i \cdot F(d_{ij}) \qquad (2)$$

where F(dij) is the radial base function, with d being the distance between points; a_i, the coefficients that will be calculated solving a linear system of n equations, and n, the number of neighbouring sample points involved in obtaining z_j.

In this case, we will use a radial base multiquadratic-type function (3)(Aguilar et. al, 2001), which comprises an r parameter: the softening factor. This value should be previously tested according to the data in each case; a very high value will generate a very softened surface, far from the real surface.

$$F(d_{ij}) = \sqrt{d_{ij}^2 + r^2} \qquad (3)$$

3.3 Kriging

It is an exact and local interpolation method (Moral, 2003) that sets the weight of each sample point according to the distance between the point to interpolate and the sample points.

Kriging's procedure estimates this dependence over the semivariance, which takes different values according to the distance between data items. The function that relates semivariance to distance is called semivariogram and shows the variation in correlation among the data, according to distance. The basic expression is (4):

$$\gamma(h) = \frac{1}{2n}\sum_{i=1}^{n}(z_i - z_{i+k})^2 \qquad (4)$$

where n is the number of value pairs separated by a distance h.

Theory demands the semivariogram to be of general validity for the whole digital model's area. This means that data interdependence should be the exclusive function of the distance among them, and not of its absolute space location, because of which it doesn't allow for the treatment of discontinuities that lead to abrupt changes, such as slope ruptures.

4. RESULTS

To evaluate the effectiveness of the interpolation methods, the data were validated through a random mesh of points (figure 5), whose coordinates were measured using multiple direct intersection by classic topography.

Figure 5. Distribution of the validation points.

For the statistical evaluation of the effectiveness of each method, the model we obtained was checked with the real model, using the root mean square error (RMS) over the 72 validation points, which is defined by the following expresion(5) (Felicísimo, 1994):

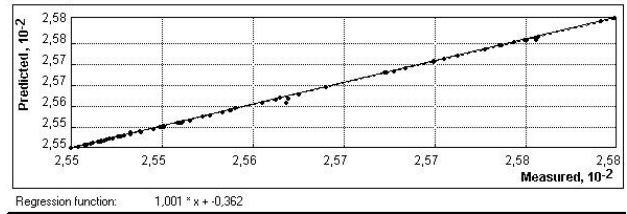$$RMS = \sqrt{\frac{\sum_{i=1}^{n}(z_i^{estimated} - z_i^{real})^2}{n}} \qquad (5)$$

Figure 6. Result of points' validation

There are different search types among which we must choose to select those neighbouring sample points that will take part in the numeric determination of the "non-sample" point. This can be performed taking quadrants, octantes or the whole circular sector into account. So as to research the influence we performed the IDW interpolation using the three types of neighbour selection for 30 neighbours of which at least 12 within a search circumference of a 10cm radius, obtaining the following final RMS (table 7):

Selection	RMS (m)
all	0.025
quadrants	0.028
octantes	0.030

Table 7. Model's error according to different search types by sectors.

4.1 Optimal number of neighbouring points

The number of neighbouring points that take part in the interpolation was calculated evaluating the RMS, using IDW as a method.The method without quadrants has been selected for being the one with best results, as seen in the previous section.

Number of neighbours	Minimum number of neighbours	RMS (m)
45	15	0,026
30	12	0.025
15	10	0.026
8	8	0.032
6	4	0.033

Table 8. RMS according to the number of neighbours selected

According to the table 8, there is a certain threshold above which the interpolated model's precision doesn't improve, no matter how high the number of points considered. For this reason, the options of 30 neighbours with at least 12 within and that of 15 neighbours with at least 10 are considered valid, since having more points without improvement in precision only increases the volume and time of calculations.

4.2 Determination of search radius

Tests were carried out choosing neighbours within a circular area of variable radius, keeping the number of neighbouring points fixed at 30 with at least 12 within, using selection without quadrant, over the whole sector (table 9).

Method	Semiaxis	RMS
IDW	0.50	0.025
	0.10	0.025
	0.05	0.025
	0.01	0.028
Kriging	0.5	0,041
	0.1	0.041
	0.05	0.042
	0.01	0.021

Table 9. RMS according to neighbours' selection radius.

In the light of results, we can affirm that the method most homogeneous to the selection circumference is IDW, knowing that varying the radius, the model's mean square error remains constant.
It can be due to the fact that all points that take part in the interpolation have already been selected within a 5-cm radius; thus an increase in radius doesn't alter the interpolation at all. Hence the RMS varies when the radius decreases to 1 cm.

4.3 Choice of optimum exponent

The use of the IDW method implies choosing the optimum exponent of the weighting functions. In our case -having analysed all the data- the exponent with minimum RMSPE (i.e. the optimum) has a value of 1.257; which not only means that it is not a linear relationship, but that more importance is given to far away points than is this exponent is quadratic.

4.4 Statistical evaluation

Comparing among models using the value of a 10-cm radius without quadrants, we obtained (table 10):

Method	RMS (m)
IDW	0.025
RBF	0.046
Kriging	0.041

Table 10.. Comparison among the different models.

4.5 Visual evaluation

Visual evaluation shows little differences between three analized methods. The model using IDW method (figure 11), the model with RBF method (figure 13) and the model generated by kriging method (figure 8).

Figure 11: IDW model

Figure 12: RBF model

Figure 13. Kriging model

5. CONCLUSIONES

Results have shown that these methods can be used to accomplish an effective filtering of massive clouds of points generated by means of automatic photogrametry. The values of accuracy are reasonable for the model studied, although different methods yield different results. It is remarkable that the simplest method (IDW) is also the one that reaches smaller RMSE values of just 2.5 cm. There is therefore no need for more sophisticated methods, which have almost duplicated the previous RMSE in the cases analysed. Likewise, the IDW method is more robust in the face of changes in selection area and in the number of points used in the interpolation.

Los resultados han mostrado que los métodos utilizados son útiles para realizar un filtrado eficaz de las nubes masivas de puntos que se generan mediante fotogrametría automática. Los valores de exactitud son razonables para el modelo estudiado aunque los métodos dan resultado diferentes. Es interesante que el métodos más simple (IDW) es también en que alcanza menores valores de RMSE, de apenas 2.5 cm. No es necesario, por tanto, acudir a métodos más sofisticados, que en los casos analizados casi han duplicado el RMSE anterior. Asimismo, el método IDW es más robusto ante cambios en el área de selección y el número de puntos usados en la interpolación.

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