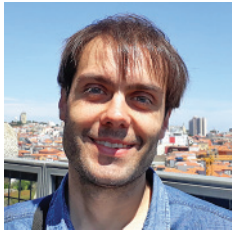
ISSN 1828-5961



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Point cloud optimization based on 3D geometric features for architectural heritage modelling

The present article shows a novel methodology to classify 3D point clouds related to architectural heritage elements based on dimensional features, and using open source software. The 3D point cloud is the key element for the extraction of semantic and/or vector information, as well as the meshing step for architectural heritage modelling. A point cloud classification that optimizes the point cloud while preserving the relevant information will improve the subsequent operations. The present methodology is based on the extraction of the geometric properties of the 3D point clouds on the basis of the 3D covariance matrix. Among all the possible dimensional features, the omnivariance (Ω) is considered the most suitable for the variety of situations of the architectural heritage elements. For a study case of the Niculoso Pisano Portal of the Monastery of Santa Paula of Seville (Spain), three clusters are defined according to the different level of details. As a result, and in comparison, to a standard spatial sampling of 1 cm, the proposed clustering allowed a weight spatial sampling within the interval 20 – 1 cm, achieving an 85%-point reduction, keeping 3D points in the complex areas, whereas the low detail areas, like planes, were considerably reduced in size for the next steps of parametric modelling. The error of the optimized point cloud, by the comparison with the original point cloud has a mean value of 0.3 mm and a standard deviation of ± 4.6 mm.

Keywords:
Classification; optimization; cultural heritage; point cloud; geometrical features

DOI: https://doi.org/10.20365/disegnarecon.26.2021.18

1. INTRODUCTION

The digital documentation processes are becoming an essential element in conservation tasks and decision making, and in this regard, geoinformatics provide a wide set of techniques for the documentation, conservation, and promotion of cultural heritage (CH) (Xiao et al., 2018). While it is possible to achieve high precision and spatial resolution values, the obtained 3D point clouds are usually too heavier for the required tasks to transform the raw data into useful products for the conservation and management of CH assets. A drawback is the fact that it depends on the characteristics of the scanning area to obtain a point cloud that guarantees a homogenous result. But the major drawback is the need to have a sufficiently light point cloud to be able to manage the data with a minimum of agility, but either in many cases it will be necessary to work with the fragmented point cloud, or key details will be lost in the decimation process.
Currently, the 3D measurement and consequent creation of virtual models (CH buildings, assets, scenarios, architectural environments, etc.) is a key tool increasingly employed due to the continuous improvement of the geoinformatics techniques and instruments involved (both software and hardware). The range of applications is widening from the mere 3D digitalization to 3D visualization for augmented, virtual, and/or mixed reality (Bekele et al., 2018); preservation and safeguarding (Remondino and Stylianidis, 2016); data sharing and web visualization (Boutsi et al., 2019); and creation of integrated information systems for management or analysis (Soler et al., 2017), being the common requirements the completeness and precision, so the CH professionals can employ these models efficiently.
The 3D point cloud is the key element for the extraction of semantic and/or vector information, as well as the meshing step for architectural heritage modelling. To define a faithful model of a CH element, the current 3D measurements play a key role to carry out the multi data fusion of all the relevant historical and documental information. Therefore, a point cloud classification that optimizes the point cloud while preserving the relevant information will improve the subsequent operations (Rodriguez-Gonzálvez et al., 2017). Therefore, the aim of the present manuscript is to present a methodology to classify the 3D point clouds related to architectural heritage based on dimensional features. The approach is based on open software, to ease its application among CH professionals. As a result, an optimized point cloud will be generated, preserving the details while decreasing the model size, thus this product will ease the next steps of parametric modelling, since the 3D mesh deliverable obtained will serve as a basis for preservation, consolidation, valorisation, and/or divulgation of the CH element.
The proposed workflow takes advantage of the geometric properties of the 3D point clouds to extract the key parameters that characterized the irregular areas, namely, the areas where the processing has to be more careful to avoid any loss of detail. The 3D geometrical features encapsulate the geometrical relationship between 3D points for a local neighbourhood (Weinmann et al., 2013), and can be computed from the 3D covariance matrix (Jutzi and Gross, 2009). The geometrical features have been applied to complex tasks as LiDAR point cloud segmentation (Xu et al. 2017) or the semantic classification of submilimetric photogrammetric point cloud (Rodriguez-Gonzálvez and Rodríguez-Martín, 2019).

2. MATERIALS AND METHODS

In this section, the study case analysed and the proposed classification approach are described. The methodology is structured in three phases: 3D feature extraction, clustering, and weighted sampling. The complete methodology is summed up in the following figure (Fig. 1):

2.1. Study case

The Monastery of Santa Paula is located in the historic neighbourhood of San Julián in Seville (Spain). It was built for the cloistered Order of Saint Jerome in 1473 and was the first monastery in the city to be declared as a historic monument (listed as Good of Cultural Interest (BIC - Bien de Interés Cultural)). The religious building, which is occupied by the cloistered nuns continuously since five centuries, includes a church that was built between 1483 and 1489. It is accessed from a modest entrance brick doorway that opens the way to a landscaped atrium. The greatest important structure in this atrium is the entryway to the church, known as the Niculoso Pisano Portal (Fig. 2). The construction of the Portal was carried out by sculptor Pedro Millán and Francisco Niculoso Pisano in 1504. The Portal, which is the study area for the proposed methodology, is composed by an impressive brick-and-tile structure where its sole design integrates

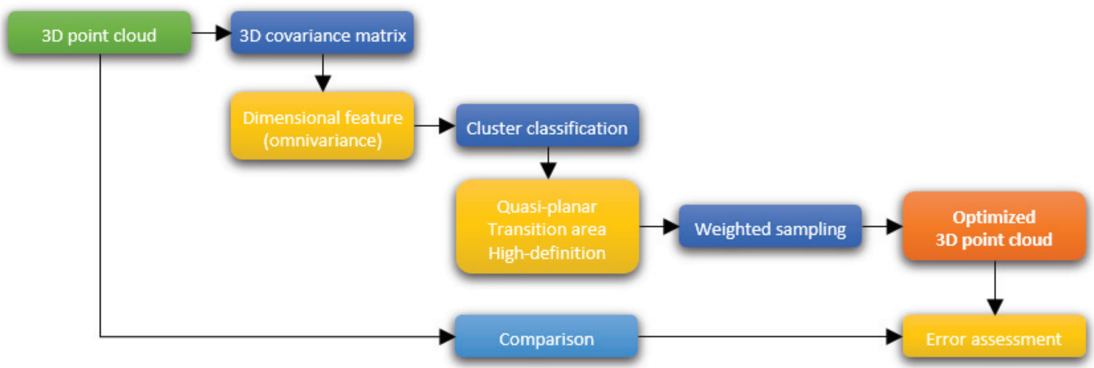

Fig. 1 - Workflow of the proposed methodology.

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Gothic and Mudéjar style with Renaissance components. The panel of ornamental tiles is decorated of complex figures and tondos with a plateresque crowning, all covered with polychrome glazed tiles. This study case was selected as an example of complex architecture with a mix of planar and smooth surfaces, and non-parametric shapes and ornaments, as normally happens in heritage buildings. Therefore, the present study case is representative one the architectonic heritage to assess the proposed point cloud optimization algorithm.

2.2. Methodology

The present subsection is devoted to the semantic classification of the point cloud, to generate subregions thanks to the analysis of 3D dimensional features. The input is a 3D point cloud, which does not require any specific consideration since it will be analysed only its geometry. The geometric features are extracted according to the eigenvalues of the covariance matrix of a local neighbourhood for each 3D point in the input point cloud. This subset of points can be selected based on k-nearest neighbours or points within of a sphere of a pre-defined radius. For this subset is it possible to compute the optimal plane, but since it is an overdetermined system, a least-square system is written (1):

$$\mathbf{A} \cdot X = 0 \qquad (1)$$

where the matrix A (2) contains the k points with coordinates x, y, z relatives to the neighbourhood centroid (x_0, y_0, z_0), and the vector X contains the coefficients of the normal vector of the plane.

$$\mathbf{A} = \begin{pmatrix} x_1 - x_0 & y_1 - y_0 & z_1 - z_0 \\ \vdots & \vdots & \vdots \\ x_k - x_0 & y_k - y_0 & z_k - z_0 \end{pmatrix} \qquad (2)$$

Fig. 2 - Monastery of Santa Paula Seville (Spain): (left) Laser scanner recording of the main entrance brick doorway to the landscaped atrium and (right) detail of the Niculoso Pisano Portal.

The least-square solution of the equation (1) is computed by the principal component analysis (PCA) of the matrix A^TA, or covariance matrix (Cov). The 3D covariance matrix encapsulates the geometrical relationship between 3D points for a local neighbourhood, and therefore its geometrical properties (Demantké et al., 2012). The covariance matrix (Cov) has the values of the variance in the principal diagonal (3). By the diagonalization process of matrix Cov, the eigenvectors of the covariance matrix are obtained, and as a result, the three eigenvalues (λ_1, λ_2, λ_3).

$$\mathbf{Cov} = \frac{1}{k}\mathbf{A}^T\mathbf{A} = \begin{pmatrix} \sigma_{xx} & \sigma_{yx} & \sigma_{xz} \\ \sigma_{yx} & \sigma_{yy} & \sigma_{yz} \\ \sigma_{zx} & \sigma_{zy} & \sigma_{zz} \end{pmatrix} \qquad (3)$$

The eigenvalues correspond to the principal components of the spatial distribution of the points; they are sorted as $\lambda_1 \geq \lambda_2 \geq \lambda_3$ and employed to compute the 3D features, which can be grouped as dimensional features (Weimann et al., 2013) (Blomley et al., 2014): linearity (4), planarity (5) and sphericity (6), and other measures such as omnivariance (7), anisotropy (8), eigenentropy (9) and surface variation (10), also called the change of curvature.

$$L = \frac{\lambda_1 - \lambda_2}{\lambda_1} \qquad (4)$$

$$P = \frac{\lambda_2 - \lambda_3}{\lambda_1} \qquad (5)$$

$$S = \frac{\lambda_3}{\lambda_1} \qquad (6)$$

$$\Omega = \sqrt[3]{\lambda_1 \lambda_2 \lambda_3} \qquad (7)$$

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$$A = \frac{\lambda_1 - \lambda_3}{\lambda_1} \quad (8)$$

$$E = -\sum_{i=1}^{3} \frac{\lambda_i}{\Lambda} \log\left(\frac{\lambda_i}{\Lambda}\right) \quad (9)$$

$$C = \frac{\lambda_3}{\lambda_1 + \lambda_2 + \lambda_3} \quad (10)$$

where Λ is the sum of the eigenvalues. The aforementioned dimensional features are global features that reflect the common characteristics of point cloud geometry. They characterize the degree of change in the surface of the point cloud according to different criteria. So, the selection of the dimensional feature that best reflects the surface changes is critical to carry to the guided spatial sampling. In order to facilitate the understanding of the dimensional features, and to exemplify the selection of the dimensional feature employed in the proposed approach in Figure 3 is shown their computation over a real-case of a sandstone with an irregular surface and shape. Please note that the sandstone is not part of the Niculoso Pisano Portal, but it has been selected to exemplify the capacity of each dimensional feature due to the different surfaces present. The computation and representation of the results were carried out with the opensource software CloudCompare (Girardeau-Montaut, 2021).

It can be appreciated how the dimensional feature that best captures the surface variability is the omnivariance (Fig. 3.e), since takes into account the three eigenvalues, which are highest in areas with changes in the three axes. Moreover, the obtained values are better distributed between the minimum and maximum values, so they can be thresholded easily. Therefore, among all the possible features (Blomley, et al., 2014), the omnivariance (Ω) is considered the most suitable for the variety of situations of the architectural heritage elements.

In order to illustrate the relationship between the shapes, their geometric complexity level, and the

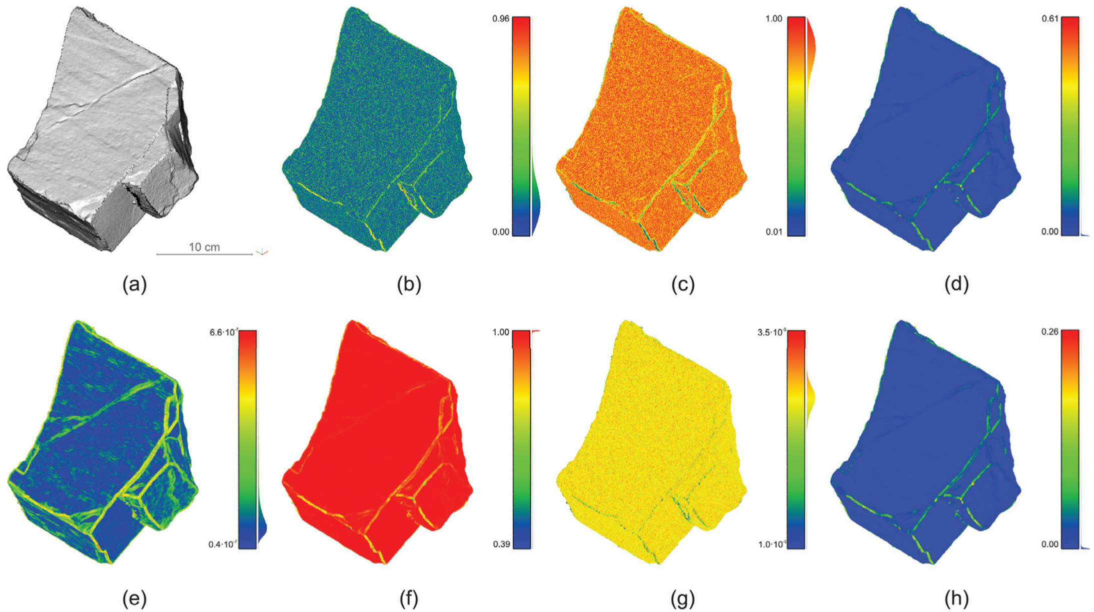


Fig. 3 - Simulation results of different dimensional features: (a) Original 3D point cloud of a sample rock; (b) linearity; (c) planarity; (d) sphericity; (e) omnivariance; (f) anisotropy; (g) eigentropy; (h) surface variation. Please note that the colour palette and the distribution of the histogram values (all dimensionless, except the omnivariance expressed in m^2) are shown to the right of each subimage (b to h).

selected dimensional feature (omnivariance), in Figure 4 is shown its computation over an ideal profile of a column shaft with a mix of linear, curve, and transition lines. The profile was generated using CAD software, and extruded orthogonally to create a continuous mesh; next, the mesh was sampled to obtain a uniformly distributed point cloud.

On the basis of the computed omnivariance values, a classification on different clusters is generated, which will allow a guided spatial sampling.

By the approximate knowledge of the main geometrical primitives anticipated it is possible to specify a set of thresholds to define a discrete number of clusters according to similar omnivariance values, being the higher values related to high detailed features, as borders, corners, and/or surface discontinuities. Therefore, three clusters are suggested; the aforementioned high detailed

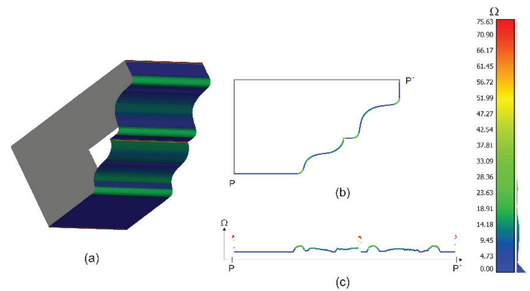


Fig. 4 - Simulation results of the omnivariance computation over a column shaft: (a) 3D view of the 3D point cloud colorized with the omnivariance values; (b) cross-section of the 3D point cloud; (c) unroll of the visible part of the column shaft. Please note that all the subimages share the same colour palette expressed in mm^2.

DOI: https://doi.org/10.20365/disegnarecon.26.2021.18

ISSN 1828-5961

areas, the quasi-planar features which are areas closer to planes and/or smooth surfaces where the highest sampling will be carried out; and finally, the transition areas which encompass the intermediate areas that are difficult to assign to any of the both clusters.
Once the clustering is completed a guided spatial sampling is applied to all the points inside the cluster based on their associated geometrical features. In the highly detailed areas (highest omnivariance cluster) the lightest decimation is applied since it encloses the areas where the ornaments are located, thus for subsequent meshing tasks it is necessary to keep all the details. So, two objective values are established, the maximum spatial resolution to be preserved (T_1), and the minimum one to retain all the features (T_2). The areas without any significant feature, enclosed in the cluster with the lowest omnivariance values, can be idealized as a planar surface, so the final number of points could be severely reduced. For this cluster, two objective spatial resolution values are defined, firstly the minimum sampling value (T_4), which cannot be lowered, to avoid committing a great simplification; and secondly the sampling value for the boundary areas between the intermediate and low detail clusters (T_3). To sum up, four spatial sampling resolutions are established:

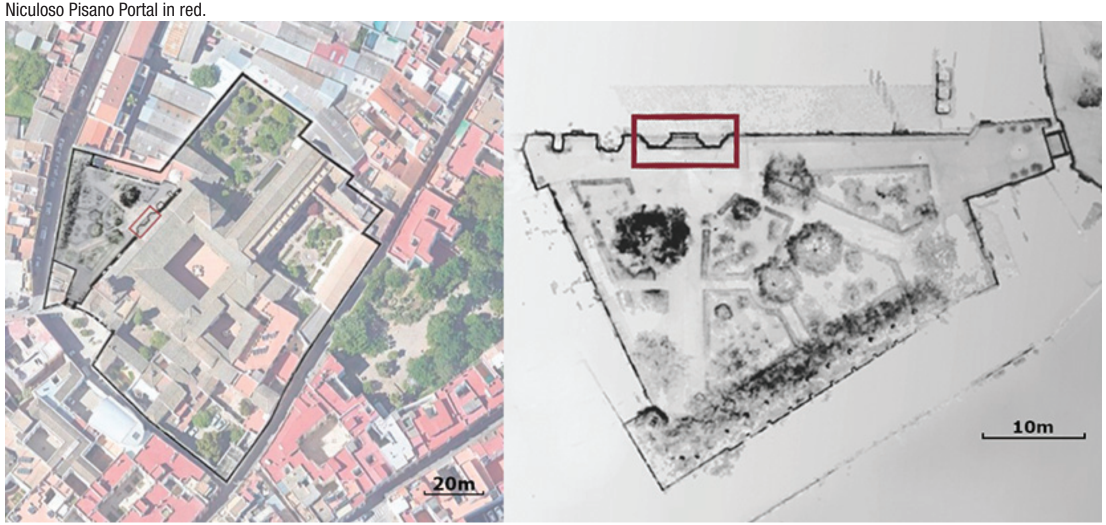
- T_1: maximum spatial resolution of the 3D point cloud. This value is established on the basis of the technical specification of the input sensor and expected error, so the preserved 3D points are significant, whereas computational overloads are avoided.
- T_2: minimum spatial resolution of the high-detailed areas. This value should be similar to T_1, or equal to T_1 if the number of high detail areas is low in relation to the scene size.
- T_3: the threshold between the transition and low-detailed areas, that functions as a break-point in the subsampling, being the representative value of the scene, assessed globally.
- T_4: minimum spatial resolution of the low-detailed areas.

Among each threshold value, a weighted spatial sampling will be applied on the basis of a linear function. As a result of the process, a final 3D optimized point cloud is generated, which, although lightweight, retains all the key geometrical features. This weight reduction improves subsequent tasks as meshing, vectorization, information management through Heritage Building Information Modelling (HBIM), or even web visualization. Please note, that the HBIM, as the integration of 3D models and databases works as a support in the decision-making processes for the restoration and refurbishment of the CH asset (Bruno et al., 2019). As a side note, the stated thresholds for sampling distance do not relate to the omnivariance, namely, they can be adapted for each study case.

3. RESULTS

A point cloud obtained from a Terrestrial Laser Scanner (TLS) is used to exemplify the methodology, however, it can be applied to 3D data coming from Mobile Mapping Systems (MMS), photogrammetry, etc.
The study case is the Niculoso Pisano Portal of the Monastery of Santa Paula in Seville (Spain). The fieldwork was carried out in October 2018. The campaign was focused on the digital recording of the main entrance to the atrium as well as the facade of its church, with special interest in the Niculoso Pisano Portal. The data acquisition was carried out using a TLS Faro Focus^{S} 350 which reaches a resolution of 0.6 - 350 m, with a measurement speed of ca. 1 million of points by second and a distance error of ± 1mm. The 3D data of the structures were surveyed with a sub-centimetre spatial resolution (6 mm at 10 m) and furthermore, with the aim to create photo-realistic 3D models, HDR images (High Dynamic Range 5x) were collected. Altogether 13 stations were necessary to capture the main features of the area, avoiding obstacles due to vegetation. In order to test the proposed methodology, the church portal

Fig. 5 - Study case: (a) Location in Google Maps of the Monastery of Santa Paula; (b) and detail of the 3D point cloud of the atrium and the situation of the Niculoso Pisano Portal in red.



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ISSN 1828-5961

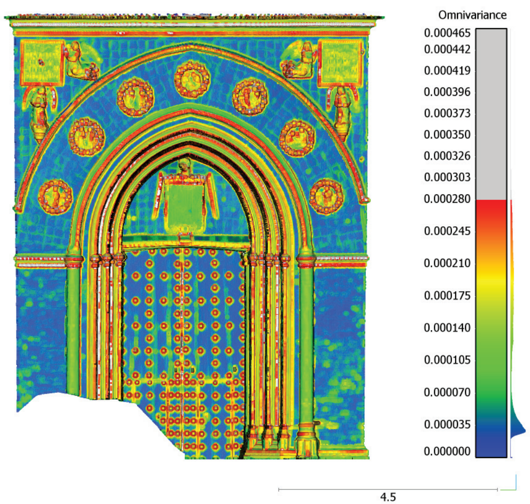

Fig. 6 - Representation of the selected dimensional feature (omnivariance). The scale is in meters.

Fig. 7 - Result of the classification. The scale is in meters.

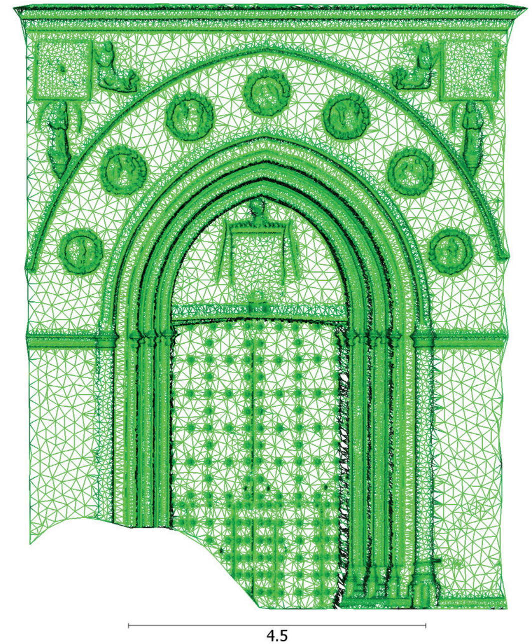

Fig. 8 - Global view of the mesh from the optimized point cloud. The scale is in meters.

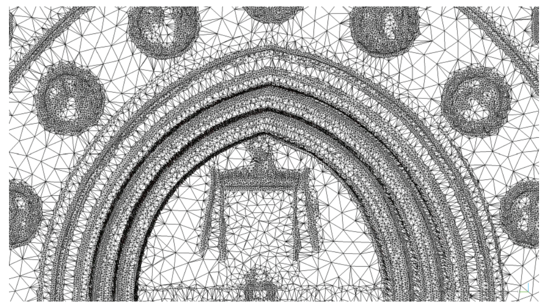

Fig. 9 - Detailed view.

(Fig. 5) of Niculoso Pisano was chosen, due to its geometric complexity. The example point cloud of the Portal has 1.05 million points and an average spatial resolution of 8.3 mm.

For the computation of the 3D geometric features, the open-source software CloudCompare is used, since it has in-built the computation function. In Figure 6 is shown the result of the omnivariance computation. The histogram has been modified to show the points which encompass 95 % of the points to improve the visualization.

According to the omnivariance values is possible to establish three pre-established clusters, as shown in Figure 7: quasi-planar features ($\Omega < 1 \cdot 10^{-4}$ m^2) in purple colour; transition areas ($1 \cdot 10^{-4}$ m$^2 < \Omega < 2 \cdot 10^{-4}$ m^2) in green colour; high detailed features ($\Omega > 2 \cdot 10^{-4}$ m^2) in yellow colour.

Thanks to the clustering it is possible to apply a weighted sampling for each cluster. If over the original point cloud is set a 1 cm resolution, the point cloud will be reduced to 515062 points. The 1 cm resolution was chosen since the 3D data acquisition was carried out with sub-centimetre resolution. By means of the proposed methodology is possible to set two thresholds of 2 cm (T_2) and 10 cm (T_3) in the change between the clusters, and a minimum resolution of 20 cm (T_4). The threshold T_1, or maximum spatial resolution, is set a 1 cm. As a result, the final point cloud is composed of 73808 points, a reduction of 85.7%. The result is shown in Figures 8 and 9.

The error of the optimized point cloud, by the comparison with the original point cloud has a mean value of 0.3 mm and a standard deviation of ± 4.6 mm.

In order to illustrate the subsampling process automation, according to the different clusters of points, a comparison between the presented methodology and a direct subsampling is shown. Please note that the direct subsampling is carried

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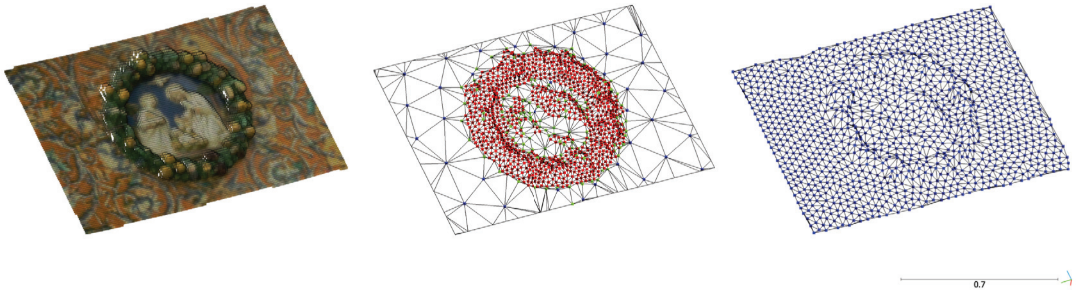

Fig. 10 - Central medallion above the arch of the Portal.

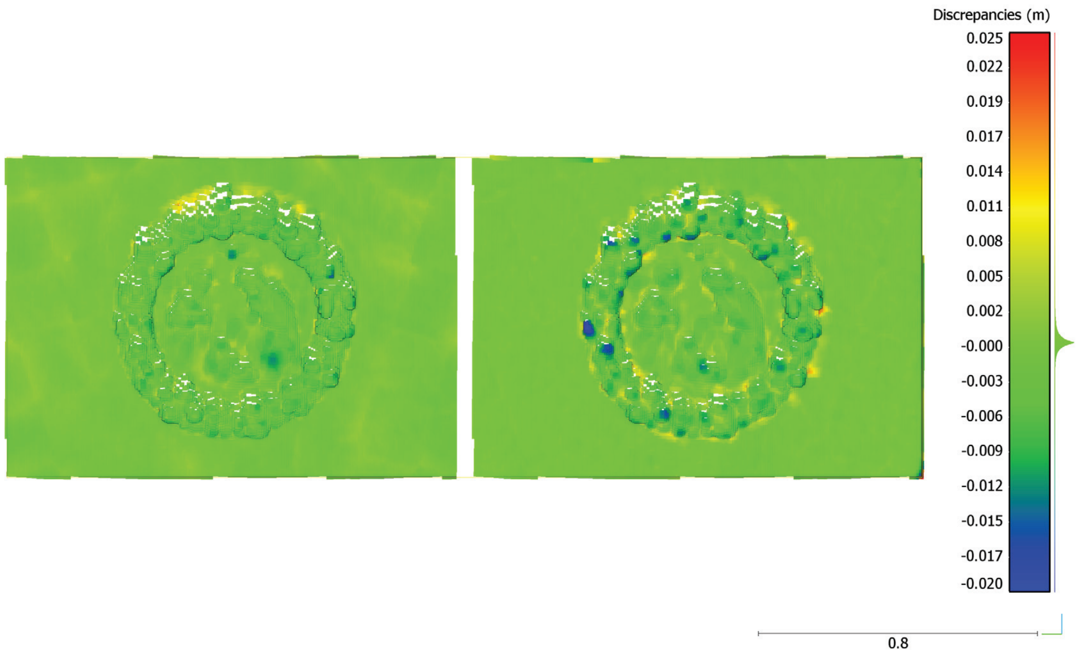

Fig. 11 - Discrepancies values between the original point cloud and the meshes shown in Figure 10 (left) and 10 (right). The units are in meters.

out with the in-built function of CloudCompare. The central medallion above the arch was selected since it has very detailed characteristics (Fig. 10) encompassing 18765 points. In the figure 10 is shown the result of the proposed workflow using the aforementioned thresholds (maximum spatial resolution of 1 cm), with a reduction of 93.9% (1140 points). To compare to the usual procedure, the original point cloud is spatially subsampled at 3 cm to achieve a similar number of points, being the result shown in Figure 10.

Visually, in Figure 10 is clearly that the proposed methodology distributes the 3D points in the key characteristics of the medallion. To assess them quantitatively, the error between the original point cloud and the meshes derived from both subsampling approaches are computed and shown in Figure 11. The proposed approach, for the selected area, has a mean discrepancy value of 0.1 mm and a standard deviation of ±2.0 mm, being the minimum and maximum discrepancies -16 mm and 14 mm respectively. In comparison the direct approach has no bias (mean value of 0.0 mm), but a higher standard deviation (±2.9 mm), as well as higher discrepancy range (from 20 mm to 25 mm).

As similar assessment is carrying out in low detailed areas, as the Portal's door (Fig. 12). This area is pretty simple and planar, but there are present several rivets that create to a certain geometrical complexity and an alternation of shapes. The original point cloud encompasses 31048 points, and the present methodology reduced up to 749 points (Fig. 12). This heavy reduction (97.6 %) is favored but planar area of the door which encompasses almost all the analyzed fragment. To achieve a similar number of points, a 5 cm direct subsampling is applied (Fig. 12) resulting a total of 761 points.

As in the previous example, or the proposed methodology, the optimized point cloud of the door area has a mean discrepancy value of 0.1 mm and a standard deviation of ±1.2 mm, while the direct approach (5 cm subsampling) has a mean value of 0.5 mm and a standard deviation of ±2.4 mm. The effect of these higher error can

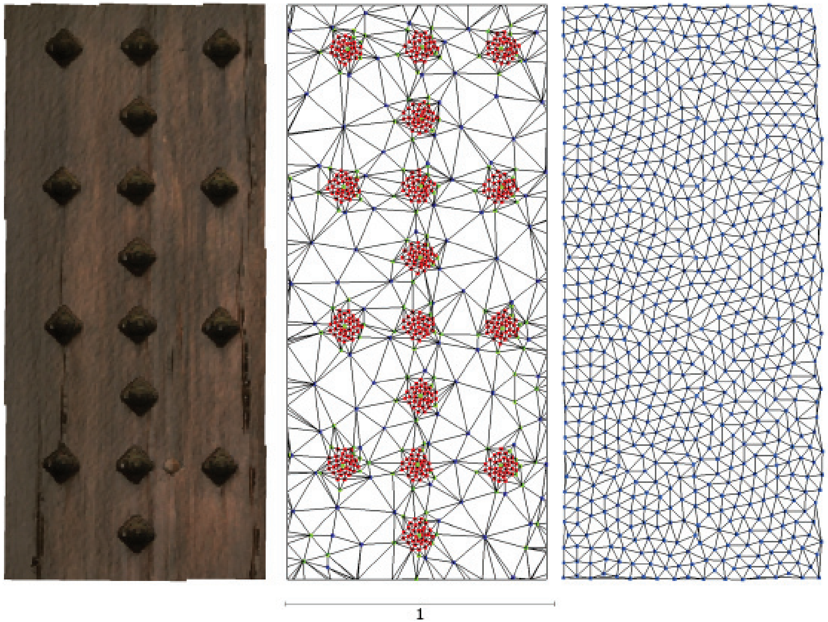

Fig. 12 - Left door of the Portal.

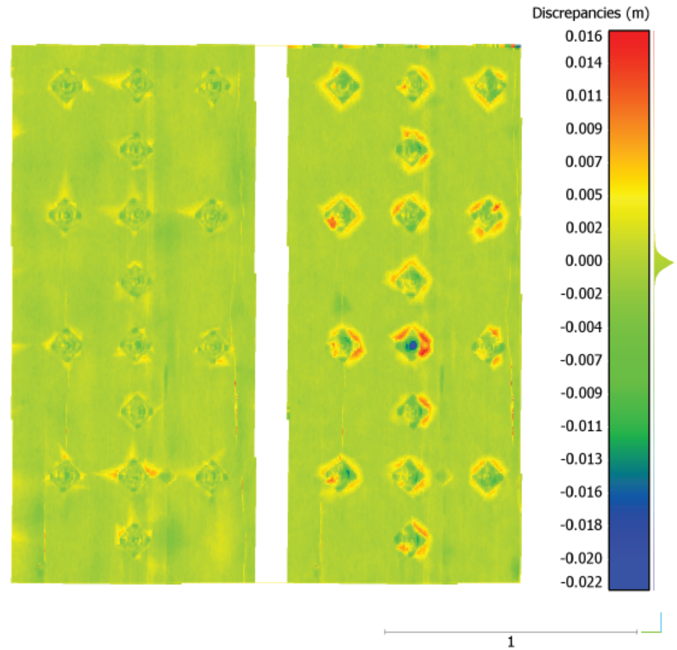

Fig. 13 - Discrepancies values between the original point cloud and the meshes shown in Figure 12 (left) and 12 (right). The units are in meters.

be appreciated in Figure 13, where all the sixteen rivets are not correctly modelized and does not preserve the shape. The error ranges between -8 mm to 15 mm for the Figure 12; and between -22 mm and 16 mm for the Figure 12.

4. CONCLUSIONS

A novel process for point cloud optimization, focused on the context of architectural heritage was presented. It allows optimizing the point cloud thanks to a classification based on the omnivariance feature while preserving the geometry. Despite there are other dimensional features, like planarity, they do not allow an adequate clustering of the point cloud. It was achieved an 85% point reduction for the study case while keeping 3D points in the complex areas. The low detail areas, like planes, were considerably reduced in size for the next steps of parametric modelling. For the proposed thresholds, the final geometrical error is lower than the input spatial resolution. As future research lines, a comparison with other point cloud optimization algorithms would be addressed.

As far as Cultural Heritage is concerned is of vital importance that the information obtained through the presented optimization methodology maintain high resolution geometric details in the complex areas while the size has been drastically reduced, allowing a manage and visualization in real time of complex models and facilitating their dissemination.

To conclude, the presented methodology allows the automation of parametric modelling using the three-dimensional information provided by the different Geomatic instruments.

5. ACKNOWLEDGEMENTS

The authors appreciate and acknowledge the support of the cloistered Order of Saint Jerome of the Monastery of Santa Paula in Seville and Prof. Salvatore Barba of the Department of Civil Engineering (DICIV) of University of Salerno, Italy, for the support on the surveying campaign.

DOI: https://doi.org/10.20365/disegnarecon.26.2021.18

ISSN 1828-5961

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