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Automatic Segmentation of 3D Point Clouds of Rubble Masonry Walls, and its Application to Building Surveying, Repair and Maintenance

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Abstract – Changing climatic conditions are contributing to faster deterioration of building fabric. Increasing number of heavy rainfall events can particularly affect historic and Cultural Heritage (CH) buildings. These evolving and uncertain circumstances demand more frequent survey of building fabric to ensure satisfactory repair and maintenance. However, traditional fabric surveys have been shown to lack efficiency, accuracy and objectivity, hindering essential repair operations. The recent development of reality capture technologies, together with the development of algorithms to effectively process the acquired data, offers the promise of transformation of surveying methods.

This paper presents an original algorithm for automatic segmentation of individual masonry units and mortar regions in digitised rubble stone constructions, using geometrical and colour data acquired by Terrestrial Laser Scanning (TLS) devices. The algorithm is based on the 2D Continuous Wavelet Transform (CWT), and uniquely it does not require the wall to be (nearly) perfectly flat or plumb. This characteristic is important because historic structures, in particular, commonly present non-negligible levels of bow and waviness and out-of-verticality.

The method is validated through experiments undertaken using data from two relevant and highly significant Scottish CH buildings. The value of such segmentation to building surveying and maintenance regimes is also further demonstrated with application in automated and accurate measurement of mortar recess and pinning. Overall, the results demonstrate the potential of the automatic segmentation of masonry units towards more comprehensive and accurate surveys.

Keywords: point cloud processing, heritage science, masonry, stone, surveying, segmentation, continuous wavelet transform

1. Introduction

One fifth of all buildings in Scotland are characterised as being historic. This includes more than 400,000 buildings that were constructed before 1919 [1]. It is intuitive that the repair and maintenance of these aging structures is becoming increasingly onerous due to degradation processes and the sheer age of the materials employed. Compounding this, it is well recognised that climate change is placing significant performance strain upon the existing built environment, ostensibly due to increased intensity and frequency of rainfall events in the UK [2] [3]. Within the context of a northern maritime climate, these buildings are wetter for longer and are often situated in environments with low potential evaporation [4]. Increased and accelerated deterioration of porous building materials subjected to saturated conditions is correlated with higher incidence of high and low order magnitude spalling associated with frost, increased biological activity, and salt related damage [5] [6] [7] [8].

Aging fabric, twinned with increasingly aggressive environmental conditions, necessitates greater levels of contextualised building survey for effective targeted remedial intervention. Protocols and
processes currently employed support conservation activities, ideally creating an objective datum for intervention. Nevertheless, these can be costly to undertake and place significant economic strain upon individuals and organisations entrusted with satisfactory building upkeep. These protocols are principally traditional in nature, adopting visual / manual evaluation of masonry elements, down to individual units. Additionally, inability to effectively record rubble masonry creates communication problems for those developing repair strategies, specifying remedial works or undertaking fabric intervention.

Attempts to record via hand drawing is cost prohibitive and is therefore only traditionally undertaken for buildings of the greatest significance or in the case of specialist studies focusing upon archaeological analysis or for academic purposes (see [9]). Furthermore, hand drawing is prone to inaccuracy due to its inherent complexity, resulting from a lack of uniformity, roundness and regularity of masonry units. Given this, a default of generic hatching (labelling) of the material is applied to approximate areas to be highlighted. This is clearly insensitive in capturing and reflecting the reality of the as-built materials confronting the evaluator, hindering attempts to specifically identify areas requiring further assessment. In these situations, recording is therefore practically reduced to narrative description of the masonry wall area (in m²) and cannot effectively reflect the complexity of the build. Importantly, such recording does not offer the ability to readily locate individual stones in what could be described as a ‘sea of stones’, causing communication problems for current and future information retrieval.

Attempts to enhance reporting uniformity have led to the utilisation of system-based approaches or protocols to survey [10] and whilst helpful, they cannot discount the inherent variation in surveyors’ experience [11].

The use of state-of-the-art remote sensing technologies offers the promise of enhanced survey accuracy with the logical benefits that flow from primary characteristics such as cost, safety and objectivity. Reflecting this, various researchers have cumulatively progressed the body of knowledge on the value of these new technologies to support building surveying and maintenance activities.

In 1995, Ogleby [12] undertook a comprehensive review of techniques and technologies that existed for the generation of information adopted for the historic interpretation of monuments and sites of cultural significance. In that paper, the author focused on photogrammetric applications and the subsequent generation of CAD models. Further geospatial data acquisition technologies, and more specifically Terrestrial Laser Scanner (TLS) and photogrammetry, have revolutionized the recording and documentation aspects of historic buildings. Within the context of historic buildings surveying, Wilson et al. [13] illustrated the benefits of TLS contextualised upon complex UNESCO World Heritage sites, adopting a case study approach. Similar advances have been made using photogrammetry, taking advantage of rapid progress in photographic technology and computer vision. High-resolution cameras are now widely available at a relatively low cost, and the development of robust automated feature detection and matching in digital images, (e.g. SIFT [14] or SURF [15] features), as well as dense matching approaches [16] have considerably improved the image processing stage, enabling entirely automated processing pipelines. More recently, strategic use of Unmanned Aerial Vehicles (UAVs) for reality capture has been providing a new platform for photogrammetry to partially solve access issues. The value of UAVs to surveying has already been demonstrated in various contexts such as for ecological [17] or structural surveys [18]. These works illustrate how to obviate the use of scaffold and are therefore clearly beneficial in reducing acquisition time and cost. In the context of historic monuments, UAV-based photogrammetry has been shown to provide alternative solutions to TLS. For example, Puschel et al. [19] proposed the use of terrestrial and UAV pictures to capture and create an accurate 3D model of Castle Landenberg. Koutsoudis et al. [20] similarly proposed a photogrammetric
system combining UAV and terrestrial pictures, and compared the resulting reconstruction with TLS, obtaining promising results.

These technologies have proven to be effective, delivering accurate 3D and colour measurements. However, the outcome obtained by the mentioned devices are in raw data form (point clouds) and require further processing to produce understandable semantically-rich information that can be interpreted by experts.

With respect to the analysis of geospatial data, initial identification of primary building volumes or entities can be considered as a 1st order structure tier, with 2nd order tiers including subdivisions into principal building components such as walls, roofs, etc. The segmentation of the individual masonry units can be considered as 3rd order structure tier. But, as noted earlier, such segmentation is rarely conducted, let alone systematically successfully achieved, due to the sheer number of stones, the lack of uniformity in the materials, and the subjectivity of the individual surveyors observing the structures. Yet, whilst difficult to achieve, this is an essential component of other tangible processes (i.e. effective costing of the works and the development of repair strategies).

Within this context, objective and cost-effective data processing methods are required to facilitate reporting and analysis. Automatic segmentation and further processing of data from modern reality capture technologies (i.e. TLS and photogrammetry) would facilitate surveying operations undertaken by surveying experts, enabling them to focus on value-adding activities such as conducting building pathology from identified defects, and developing in-depth repair strategies. Various research teams have been specially working on advancing this field. Most prominently, a semi-automatic delineation and masonry classification was developed by Oses and Dornaika [21] who used Artificial Intelligence techniques (k-NN classifiers) to identify stone blocks in 2D images. Additionally, Cappellini et al. [22] proposed a semi-automatic approach to semantically label 2.5D data (colour and depth information) of brick and stone walls obtained using photogrammetry.

Whilst data segmentation and subsequent calculations, in both visual and computer-based surveys, are relatively easy to achieve in brickwork, squared coursed rubble and ashlar, these calculations are inherently more complex in the case of random rubble masonry due to variability in stone and mortar dimensions. The objective of this paper is to present a novel approach to deal with the segmentation of masonry walls made of irregular rubble or ‘random’ rubble. The method, detailed in the next sections, is based on the analysis of 2.5D wall data (acquired by means of TLS) in the spatial frequency domain, by means of the 2D Continuous Wavelet Transform (CWT). This mathematical tool, as shown in [23], allows a detailed analysis at local level and is not sensitive to more global levels of flatness, waviness, curvature and plumbness of walls, which are commonly encountered in historic buildings.

The rest of the paper is structured as follows: Section 2 contains an introduction to the CWT. Section 3 describes the method designed for stone/mortar segmentation. Section 4 presents how such segmentation can effectively further analysis of value to building surveying and maintenance, with the example of mortar regression from the masonry surfaces. Section 5 introduces the experiments carried out to test the developed technique and reports the obtained results. Section 6 concludes the works and offers directions for future works.

2. 2D Continuous Wavelet Transform for Stone Walls Segmentation

The Wavelet Transform is a signal analysis method that is based on the convolution of the input signal with a wavelet function at different locations along the signal and at multiple scales. This enables the detection of the signal pattern of the wavelet function at potentially any scale and at any location [24].
The Continuous Wavelet Transform (CWT) is one of the several variants of the Wavelet Transform that is commonly considered for pattern or frequency detection in a signal. This can be applied to solve the problem of surface waviness characterization [24]. It is important to highlight that CWT is not only applicable to 1D signals, but also to 2D signals, as presented in [25].

Applying the CWT, like any other WT, requires the selection of the mother wavelet. One common CWT wavelet is the Mexican Hat wavelet, as shown in Figure 1. This 2D wavelet is composed of one main undulation with centre frequency $f_c$ that is the same for both dimensions. The centre frequency of the Mexican Hat wavelet is $f_c=0.252$. By convolving an input 2D signal with the Mexican Hat wavelet at a given scale $a$, undulations of characteristic frequency $f$ can be detected; $f$ is calculated as:

$$f = \frac{f_c}{\delta_p a}$$

where $\delta_p$ is the point sampling period in the input signal along the given dimension.

Figure 1: 3D view of the 2D Mexican Hat wavelet

In the case of the point cloud of a wall or any other structural surface, the 3D dataset can be transformed into a depth map (i.e. a 2.5D dataset) with cell size $\delta_p$. The 2D CWT can then be applied to the transformed data to detect and precisely locate the stones on the wall. Importantly, the stone walls, constituted of both ashlar and/or random rubble components, may vary in shape and size, especially in the case of walls containing rubble. Therefore, the dimension of the stones cannot be used as a reference scale $a$ for the CWT. However, joints between stones are relatively regular in width. This expected width can be used to set the scale $a$ at which the CWT must be applied so that it responds strongly in mortar regions.

3. Method for stone segmentation and labelling

This section is dedicated to illustrating how the CWT is used to segment individual stones in a 3D point cloud. Data acquisition and pre-processing of the data, corresponding to the aforementioned 1st and 2nd order structure tier classification (wall segmentation), lead to coloured point clouds of the wall face such as the one depicted in Figure 2. This data is inputted into the segmentation algorithm, which is summarised in Figure 3. The region highlighted in Figure 2 is used as an example to illustrate the segmentation process described below. Figure 4 shows the results obtained for that section of wall at each stage of the process, with Figure 4(a) showing the initial 3D point cloud of that region.
Figure 2: West wall of Linlithgow Palace courtyard. The highlighted area is used in Figure 4 to illustrate the data processing stages.

Figure 3: Overview of the proposed stone segmentation pipeline. The section in the green box includes the operations performed on each individual stone segment and shadow boxes correspond to 3D data

First, the data is converted into a 2D depth map (also called 2.5D map) by means of an orthogonal projection on a (vertical) surface grid defined with a regular sampling $\delta_p$. This grid is calculated following a strategy based on the RANSAC algorithm [26] in the case of walls whose two principal curvatures are close to zero (i.e. planar walls). If one of these curvature values is not close to zero, such as with round tower walls, a cylinder is instead calculated as a reference geometry [27]. The value of each grid depth map pixel is then calculated as the mean distance to the fitted surface, of the set of points that fall within it by orthogonal projection. In the case of the use of a cylindrical reference surface, this is achieved by unwrapping the point cloud using the approach described in [28]. An example of a depth map is shown in Figure 4(b).

The 2D CWT is applied to the depth map using an estimate of the mortar joint width to define the scale of interest $\alpha$. The CWT process delivers a scalogram, showing the CWT responses at each pixel in the depth map. Angular values corresponding to scalograms for three different frequencies below the characteristic frequency $f$ (i.e. defined scale $\alpha$) are shown in Figure 4(c); the angular values obtained for the characteristic frequency $f$ are shown in Figure 4(d). With the objective of avoiding under-segmentation, a conservative strategy is followed when defining the width of mortar joints, i.e. the scale $\alpha$. The value of $\alpha$ used in this method is 1.2 times a coarse average width of the mortar joints estimated by the surveyor.

Note that, whilst no value is given for the width of a rubble masonry joint due to the variability of the masonry deployed (See [29]), certain physical characteristics in the associated use of lime mortars direct us towards a nominal width dimension of approximately 15-20mm [30]. More specifically, the relative slow set of lime mortars makes it vulnerable to moisture related shrinkage during curing. This phenomenon is reduced by adopting a ‘well graded’ aggregate and, in situations where the joint is wider the utilisation of suitable pinning stones (off cuts or small stones that are pushed or built into
the mortar joint) are adopted. It is therefore empirically essential to keep the overall volume of mortar in the joint to a minimum, by packing with suitable pinnings, and to thoroughly compact the mortar. Deviation from this heuristic could result in materials failure. However, it must be noted that such modern practice did not apply in historic rubble masonry wall, and it is common in such contexts that the width of mortar joints be 30-40mm. Therefore, in this work, we ask that the surveyor provides as input an estimate width of mortar joints according to the evaluated façade (which will typically be either 20mm or 40mm).

The binary image delivered by the 2D CWT contains an approximated segmentation of the stones. However, as illustrated in Figure 4(d), such irregularities of the surface profile of the rubble stones can generate concavities that lead to strong responses of the CWT (see small black areas inside the white segments in Figure 4(d)). To correct this, we make the observation (and assumption) that rubble stones are normally contained exactly within their convex hull. Thus, we replace each white segment with its convex hull. Figure 4(e) shows the result.

As previously mentioned, a slightly higher value for the scale \( \alpha \) is used as input for the CWT. While this increases the performance of the segmentation, it also leads to stone segments that are moderately smaller than their actual size (and conversely mortar joints moderately wider than their actual width). To correct this effect, an iterative dilation process (1 pixel per iteration) is performed for each stone segment, considering colour information from the associated point cloud.

At the end of the dilation process, 2D stones segments are considered to be properly defined, as illustrated in Figure 4(f). Figure 4(g) shows the final segmentation results re-mapped on the 3D point cloud.
Figure 4: Illustration of the stone segmentation process. a) Input wall 3D point cloud, b) depth map, c) 2D CWT scalogram for the selected scale a, d) 2D stone segments after convex hull step, e) 2D stone segments after the final dilation step; and f) final segmentation re-mapped onto the 3D point cloud.

Importantly, we note that the CWT response is not sensitive to frequencies that are much lower than the characteristic frequency. This means that variations in the flatness, waviness and curvature of walls with such low frequency (i.e. large wavelength) do not impact the response of a wavelet used to detect high frequencies representing mortar joints. Figure 5 illustrates planarity disparities typically observed in historic masonry walls. This particular wall is used in our validation experiments for which the results are presented in Section 5.

Figure 5: Local depth values in a rampart of Craigmillar Castle (Scotland)
4. Application of the stone segmentation through further analysis

The segmentation achieved with the described algorithm can be used for the evaluation of materials and their associated construction technologies. Additionally, when utilised in repeated survey operations it can move beyond ‘static’ determination of condition and enable analysis of progressive defects. More specifically, stone segmentation can be used to evaluate changes in individual stones (e.g. erosion or movement) and record those changes down to individual stone level. Segmented mortar joint regions can be further analysed to deliver valuable information on their conditions and, by extrapolation, the effect of deterioration on surrounding masonry.

To demonstrate this, we present an additional data processing algorithm that analyses the mortar region segments outputted by the previous algorithm to report the mortar region linear measurement and calculate depth profiles along the mortar centre lines. This constitutes important information to detect recessed zones, and accurately estimates the quantity of repointing to be undertaken. In addition, depth of joint recess is a primary mechanism for highlighting vulnerable areas of masonry that may be subject to progressive loosening of the material if left unattended. The system can also automatically estimate the mortar region width, which can inform on the need for pinning (a.k.a. gallets). The following explains the developed algorithm. Figure 6 summarises the approach and Figure 7 illustrates each of its steps.

![Figure 6: Overview of the proposed mortar region analysis pipeline. The objects coloured in orange represent the operations performed on each individual stone segment](image)

The depth and binary maps for the mortar region(s) obtained from the segmentation process are used as inputs in this process. A skeleton operation [31] is first applied to the binary map to obtain the centre lines of the mortar areas (Figure 7(a)). For each point along the centre line of the mortar regions, its depth value is compared to those of the neighbouring stones, delivering the depth difference between stones and mortar (Figure 7(b)). This mortar relative-depth map can be used to identify recessed regions.

In a similar manner, the orthogonal distance between each point along the centre line and the neighbouring stones is calculated to obtain a mortar width map, (Figure 7(c)). The depth and width maps can be employed jointly to calculate the volume of mortar required for repair and determine areas where pinning stones may be required. This is illustrated in Figure 7(d) that has been produced by assuming that pinning is required where mortar width is larger than the scale α used in the 2D CWT).
5. Experimental results

The algorithms presented in the previous sections have been tested with dense point clouds acquired from several walls at two significant Scottish Cultural Heritage buildings, namely: Craigmillar Castle and Linlithgow Palace. In the case of Craigmillar Castle, a Faro Focus 3D Laser Scanner digitised the scene, providing 3D and colour information, with a resolution of 3mm. In Linlithgow Palace, a Leica P40 Terrestrial Laser Scanner was used for data acquisition, delivering colour and geometric information, with a resolution of 2mm.

In this section, two different experiments are presented, at both small and large scale, to illustrate: first, the accuracy of the proposed system and secondly, the potential of the tool to be used for maintenance, repair and interpretation works in complete walls (i.e. building elevations).

5.1. Quantitative assessment of the segmentation method

In this subsection, a quantitative evaluation of the method’s accuracy is presented. Three rectangular sections of masonry with approximate area 30m² from a Craigmillar Castle rampart wall were selected (see highlighted areas in Figure 8). Note the presence of blocked-up windows, with stones laid in different planes, is challenging.

The three regions are at different heights (ground level, 2 and 5 meters) and have been selected for the diversity of wall conditions they present.
First, for each selected region, a manual segmentation of the stones’ boundaries is performed on the colour/depth maps. The resulting segmentation maps (see binary maps in Figure 9) are then used as ground truth. The results of the automated segmentation achieved by the proposed algorithm is also shown in Figure 9.

The manual segmentation delivers an area covered by the segmented stones of 18.61 $m^2$. The proposed algorithm reports that 17.76 $m^2$ is covered by the segmented stones. The difference results in an error of 4.6%. With respect to the mortar regions, the algorithm estimates 325.37 $m$ of mortars, whereas the manual segmentation led to 312.06 $m$, which gives an error of 4.26%.
Figure 9: Wall segmentation results. a) Section 1, b) Section 2 and c) Section 3. For each section, top: 3D point cloud of the wall section; middle: manual segmentation of the orthographic projection of the wall; bottom: orthographic projection of the labelled segments.
The difference between manual and automatic segmentations is primarily due to four factors (see Figure 10):

- **a)** Under-estimation: some stones are detected as a combination of smaller stones;
- **b)** Over-estimation: some stones are segmented as a unique stone;
- **c)** False stone: some mortar areas are labelled as stone; and
- **d)** Missing stones: some small stones have not been identified.

![Figure 10: Issues in the segmentation of stones and mortar](image)

These factors, and their influence on the labelling of the automatically segmented stones are presented in Table 1. In this table, the ‘One-to-One’ column corresponds to stones in the ground truth that have been identified as a single stone by the algorithm. The other columns report the statistics for the four error cases presented above (Figure 10). As can be seen, most stones are successfully identified as one stone by the algorithm. Under-estimated stones are usually large units that, due to the irregularity of their face, are wrongly detected as several stones. Over-estimated stones are, on the contrary, small stones that, because of their close proximity, are labelled as a unique unit. Finally, missing and false stones, even if relevant in number, noticeably present small areas.

**Table 1: Distribution of the differences between manual and automatic segmentations**

<table>
<thead>
<tr>
<th></th>
<th>One-to-one</th>
<th>Under-estimated</th>
<th>Over-estimated</th>
<th>Missing stones</th>
<th>False stones</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Number of stones</td>
<td>219</td>
<td>84</td>
<td>6</td>
<td>22</td>
</tr>
<tr>
<td></td>
<td>Median area</td>
<td>53</td>
<td>231</td>
<td>85</td>
<td>11</td>
</tr>
<tr>
<td>2</td>
<td>Number of stones</td>
<td>178</td>
<td>67</td>
<td>59</td>
<td>36</td>
</tr>
<tr>
<td></td>
<td>Median area</td>
<td>48</td>
<td>249</td>
<td>28</td>
<td>11</td>
</tr>
<tr>
<td>3</td>
<td>Number of stones</td>
<td>291</td>
<td>92</td>
<td>35</td>
<td>40</td>
</tr>
<tr>
<td></td>
<td>Median area</td>
<td>75</td>
<td>204</td>
<td>52</td>
<td>14</td>
</tr>
</tbody>
</table>

Figure 11 further illustrates the segmentation performance by reporting segmentation quality at ‘pixel’ level. In this figure ‘false negatives’ are regions of stone that are labelled as mortar by the algorithm, and ‘false positives’ are mortar regions labelled as stone.
Figure 11: Pixel-level labelling performance results are shown for section 1 (a), section 2 (b) and section 3 (c). Black and magenta regions are pixels that are correctly recognized as stone (True Positive) and mortar (True Negative) respectively. Yellow regions are ‘false positives’, i.e. mortar areas that are incorrectly labelled as stone. White regions are ‘false negatives’, i.e. stone areas that are incorrectly labelled as mortar.

As can be appreciated in Figure 11, an important part of false negative areas come from the frame of blocked-up windows. These stones are architectural dressed stones. They are not rubble and impact the results mainly because of the sudden but small change in the local surface plane. Regarding false positives, these are fundamentally produced when the space between some stones is narrower than expected (i.e. areas with particularly narrow mortar joints or pinning stones close to a bigger stone).

From a more analytical perspective, several metrics, widely used for image segmentation evaluation, have been considered to estimate the performance of the proposed algorithms.

Considering the labelling of regions as True Positive (TP), True Negative (TN), False Negative (FN) and False Positive (FP), the performance of the segmentation of each stone can be given by the correctness of this labelling. Similar to the metrics presented in [32], True Positive Area Fraction (TPAF) and True Negative Area Fraction (TNAF) represent the area properly labelled. TPAF measures, for each stone, the fraction of the stone area that has been properly segmented by the algorithm. On the other hand, TNAF quantifies the area of mortar correctly identified in the surroundings of each stone. These parameters are calculated as seen in (1) and (2).

\[
TPAF = \frac{TP}{TP+FN} \quad \text{with} \quad TPAF \in [0,1] \quad (1)
\]

\[
TNAF = \frac{TN}{TN+FP} \quad \text{with} \quad TNAF \in [0,1] \quad (2)
\]

Tanimoto coefficient (Tc) [33] represents a similarity ratio between two images. In this paper, this coefficient measures the similarity of each manually segmented stone \(S_A\) and its corresponding segment (or segments) identified by the algorithm \(S_B\) as detailed in (3),

\[
Tc = \frac{\sum_{i=1}^{n} S_{Ai}S_{Bi}}{\sum_{i=1}^{n} S_{Ai}^2 + \sum_{i=1}^{n} S_{Bi}^2 - \sum_{i=1}^{n} S_{Ai}S_{Bi}} \quad \text{with} \quad Tc \in [0,1] \quad (3)
\]
where \( n \) is the number of pixels of the bounding box containing \( S_A \) and \( S_B \), and the value of \( S_{AI} \) (and \( S_{BI} \)) is 1 if the pixel is labelled as stone, and 0 otherwise.

Note that \( T_c \) can also be represented by using the labelling illustrated in Figure 11 as shown in (4).

\[
T_c = \frac{TP}{TP+FP+FN} \tag{4}
\]

Table 2 shows the median, mean and standard deviation values of the aforementioned metrics for all the stones on the evaluated wall sections. Note that, while \( T_c \) and TPAF deliver information about the performance of stone segmentation, TNAF evaluates the labelling of mortar regions. The relatively high values of \( T_c \), and TPAF mean that stones areas have been segmented well. On the contrary, the lower value of the coefficient TNAF implies that mortar regions have been underestimated in size in some parts, mostly due to the effect of regions with narrow mortar joints (under the aforementioned scale \( a \)) which are not properly segmented. This means that the algorithms classify mortar areas as stone when stones are too close to one another, increasing the FP coefficient and decreasing TNAF.

Table 2: Segmentation performance parameters

<table>
<thead>
<tr>
<th></th>
<th>( T_c )</th>
<th>TPAF</th>
<th>TNAF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Median</td>
<td>0.68</td>
<td>0.83</td>
<td>0.60</td>
</tr>
<tr>
<td>Mean</td>
<td>0.63</td>
<td>0.77</td>
<td>0.58</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>0.20</td>
<td>0.20</td>
<td>0.22</td>
</tr>
</tbody>
</table>

5.2. Applying the developed tool to complete ‘planar’ walls

The previous section shows the promising performance of the algorithm proposed for rubble stone wall segmentation. In this section, the value of such automated segmentation is demonstrated at larger scale, for complete walls. Results for the west wall of Linlithgow Palace courtyard (Figure 12(a)) and the rampart facing the east garden of Craigmillar Castle (Figure 13(a)) are detailed in the following paragraphs.

In both cases, different architectural components, such as windows, doors, buttresses and crenellations, have been manually removed from the point cloud, as these elements are not meant to be processed by means of the method proposed in this paper; they are not ‘wall’ components. Only the points corresponding to the building component ‘wall’ were processed by the algorithm detailed above.

Figure 12(b) and Figure 13(b) show the stones detected in the walls, and Figure 12(c) and Figure 13(c) the mortar regions with their calculated depth. Figure 12(d) and Figure 13(d) show locations where pinning may be required. Table 3 summarises information automatically obtained for both walls. Even though ground truth (i.e. manual) segmentations for the large datasets have not been generated, visual inspection suggests that the segmentation performance is similar to that reported above for the smaller section of the Craigmillar Castle wall.
Figure 12: Linlithgow Palace courtyard west wall. a) 3D coloured point cloud, b) Segmented and labelled stones, c) mortar depth map and d) Potential pinning stone locations

Figure 13: Craigmillar east garden rampart. a) 3D coloured point cloud, b) Segmented and labelled stones, c) mortar depth map and d) Potential pinning stone locations

Table 3: Quantitative parameters extracted after the automatic stone segmentation of Craigmillar and Linlithgow walls

<table>
<thead>
<tr>
<th></th>
<th>Craigmillar Castle</th>
<th>Linlithgow Palace</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wall area</td>
<td>21.3 x 6.3m (= 128.42m² without buttress area)</td>
<td>21.5 x 13.5m (= 196.75m² without windows and doors)</td>
</tr>
<tr>
<td>Detected stones</td>
<td>2952</td>
<td>3056</td>
</tr>
<tr>
<td>Area covered by stone</td>
<td>70.74m²</td>
<td>128.83m²</td>
</tr>
<tr>
<td>Stone size (mean)</td>
<td>239.63 cm²</td>
<td>421.56 cm²</td>
</tr>
<tr>
<td>Linear measurement of mortar</td>
<td>1.18km</td>
<td>1.44km</td>
</tr>
<tr>
<td>Area covered by mortar</td>
<td>57.68m²</td>
<td>67.95m²</td>
</tr>
<tr>
<td>Depth of centre line of mortar (mean ± std)</td>
<td>0.92cm ± 8.2mm</td>
<td>1.05cm ± 8.2mm</td>
</tr>
</tbody>
</table>
As can be noticed in Table 3, the number of stones and the length of mortar is similar in both walls, although the façade of Linlithgow Palace is twice as large as the one at Craigmillar. This suggests, and this is computationally confirmed thanks to the automated segmentation, that the Linlithgow stones are approximately twice as large. These results are interesting from the point of view of estimations for maintenance and repair works. It shows that rules-of-thumb for estimating the amount of mortar based on the wall size could easily lead to incorrect results if stone sizes are incorrectly estimated, which is particularly difficult in cases where stone sizes vary significantly.

5.3. Applying the developed tool to curved walls

As presented in Section 3, the proposed approach for ‘planar’ walls can be easily applied to ‘cylindrical’ walls by using a point cloud unwrapping procedure (instead of a planar projection method). In this last section, we show visually the working of this approach with real-life data acquired from a turret of Craigmillar Castle. Figure 14 shows the original data (a; b), the unwrapped coloured data (c), the result of the segmentation applied to the unwrapped data (d), and the final segmentation results re-mapped onto the point cloud (e).

6. Conclusions

This paper has presented a new tool to help conservation and construction professionals better understand and more objectively evaluate historic rubble masonry during survey operations. The results obtained demonstrate that reasonably complete and reliable information can be attained by means of a fast, cost-effective and safe survey strategies adopting these technologies.

Although this approach delivers added value to current surveying techniques and provides important information for historic interpretation purposes, further works will be conducted to perform analysis of relevant geometric and colour-related information from stones and mortar. This future research encompasses the detection and identification of defects on the fabric to keep track of the records and create a powerful tool for building surveying.

This valuable information will be stored in structured and semantic models, by integrating the presented method in a holistic solution harnessing Building Information Modelling (BIM) and Geographic Information Systems (GIS) technologies.

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Figure 14: Stone segmentation for surfaces for a cylindrical turret of Craigmillar Castle (Scotland). a) Region of interest, b) Input 3D point cloud, c) unwrapped data, d) 2D segmentation map, and e) final segmentation re-mapped onto the 3D point cloud.


