

# TECHNICAL PAPER 38

DIGITAL DOCUMENTATION, COMPUTER VISION AND MACHINE LEARNING FOR MASONRY SURVEYING AND MAINTENANCE



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Cover image: Detection of individual stones in a 3D laser scan of a masonry wall of Linlithgow Palace. Courtesy of Frédéric Bosché.

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# **EXECUTIVE SUMMARY**

Masonry structures constitute a significant proportion of the international traditional, and historic built environment. In Scotland alone, there are 500,000 pre-1919 traditional buildings mainly masonry-built, and more than two-thirds of the 300 properties currently in the care of Historic Environment Scotland (HES) are masonry-built.

Traditional masonry structures are clearly a highly valued part of the wider built environment and their maintenance is societally fundamental. Climate change projections for the UK suggest that the built environment in general, and the masonry-built historic environment in particular, is being placed under increasingly significant strain, which raises fundamental challenges to the monitoring and maintenance of those structures. Indeed, the impact of climate change upon their performance and upkeep, requires not just continuous, but more frequent inspection and maintenance. These activities logically have corresponding cost increases both financially and in terms of expended CO2 during interventions.

Inspection systems and more specifically provision of access constitute an important cost of reactive and proactive (planned) maintenance intervention. Worryingly, condition assessment has been widely reported to yield variable results due to subjective perceptions of inspectors, with the consequence of defects remaining undetected or inaccurately characterised. Such fundamental errors can result in unnecessary, and often costly maintenance being conducted. Clearly, processes that yield a more accurate, complete and objective inspection of building fabric would contribute significantly to the enhancement of maintenance and repair activities. In addition to the aforementioned, the cost of attaining and structuring survey data is often prohibitive and if not undertaken correctly can create significant problems with information processing, and exchanging data. Importantly, survey data acquisition is not risk-free and if not undertaken correctly can raise safety issues, particularly when working at heights.

The last decade has seen a rapid growth in the deployment of new technologies in the construction sector, from the use of remote sensing technologies for data capture to new powerful software and data-driven processes to obtain meaningful information. These novel operations are often captured under the umbrella terms of Building Information Modelling (BIM), and nowadays increasingly digital twinning (DT). In the context of building inspection and documentation, three-dimensional (3D) surveying technologies, like laser scanning (LS) and photogrammetry (PG), have seen great uptake under the leadership of organisations like HES. These solutions have the potential to transform inspection practice with time, cost and also safety benefits. However, while data acquisition and modelling have developed apace, the challenge remains on how to extract useful information from the data to support effective condition assessment and maintenance decision making.

This report summarises collaborative work conducted between HES, the University of Edinburgh and Heriot-Watt University since 2015. Whilst the team first assessed and contrasted the suitability of different 3D surveying techniques, its main effort has then focused on the processing of such data. This report particularly presents data processing solutions for: (1) segmenting 3D survey data (i.e. point clouds) of masonry walls into the individual stone units for both ashlar and rubble masonry; and (2) detecting and classifying visible defects on the surface of those units.

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In all cases, the solutions developed employ novel algorithms and their performances are presented and analysed using data acquired from actual properties under HES's care. The results have been shown to be informative and promising regarding the potential of such technologies; the rubble masonry segmentation tool has even been implemented as a free plugin for a widely used free software package for 3D point cloud analysis, namely CloudCompare. Whilst the fundamental research has shown great potential, the results also elude to where more work remains to be undertaken to increase the performance and robustness.

A final section of the report reflects on those results but also reviews wider developments in the areas of remote sensing and digitalisation that will, together with works like the ones reported here, will transform how the built environment is inspected and maintained.

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## INTRODUCTION

## I.I MASONRY STRUCTURES: THEIR UBIQUITY AND CHALLENGES PRESENTED IN THEIR **ASSESSMENT**

Masonry structures constitute a significant proportion of the international historic built environment. In 2018, HES estimated that in Scotland alone, there are 500,000 pre-1919 traditional buildings, many of them characterised as being of historic interest.

These are ostensibly constructed in masonry and lime-based materials, reflecting the prominence of these building technologies in Scotland. Among the various forms of masonry, ashlar is characterised as regular, squared or rectangular masonry blocks of stone finely dressed, and laid in courses, with tight joints of around 3mm (Davey, 1986). Such is their refinement of finishes that fine-tooling or polished visible faces are common (Warland, 1929). Ashlar is one of the most notable build types around the world and is associated with high-status architecture reflecting the time and cost associated with its construction. In contrast, rubble masonry is characterised by limited or undressed, rough stones coursed either dry (i.e. without mortar) or mortared (bound) with relatively thick mortar joints. These masonry forms tend to reflect cheaper construction and were often more readily used to act as a stable substrate for subsequent masonry finishes such as harls, renders, plasters etc. The prominence of masonry in high-profile construction is reflected in the fact that out of the over 300 HES properties in care, approximately 221 are masonry-built.

Whilst it is important to consider historic buildings, it must be re-emphasised that these numbers are extremely small when considering the almost innumerable unlisted buildings that could be argued to largely form the pattern of Scottish architecture - such is their scale that it has been calculated that masonry repair in Glasgow alone is in the region of £500 million (BGS, 2006). Beyond architectural form, it is important to recognise that infrastructural masonry plays an important role in supporting transport (road and rail) and delivering environmental services (sewage, waste water management and storage). Indeed, emphasising the scale, there are more than 70,000 masonry arch bridges in the UK, constituting over 40% of the country's bridge portfolio (Page, 1993).

Masonry structures have been shown to be exceptionally durable and are highly resilient when regular maintenance operations are upheld. Indeed, examples of masonry structure that are millennia old can be seen globally. External surfaces of masonry structures are exposed to the elements, and as a result, deterioration is accelerated by the severity of environmental climatic conditions that act as 'agencies of materials change' causing fabric weathering. Reflecting upon mechanisms of masonry deterioration when confronted with such climatically hostile environments (frequently wet and prone to frost, and increased incidence of severe climatic events), repair and maintenance expenditure for such structures can be correspondingly significant. Climate change thus constitutes a great challenge to the integrity and maintenance of masonry structures (HES, 2018). In the particular case of Scotland, the well-established increase in rainfall and increased frequency of severe climatic events (Hulme et al, 2002) have exacerbated these deterioration processes.

Inspection is paramount for the evaluation of deteriorated structures prior to maintenance or repair operations. Inspection systems and more specifically provision of access are an important cost of reactive and proactive (planned) maintenance intervention. It has been estimated that 10-20% of maintenance costs are associated with the provision of access for inspection. However, it is not unrealistic that complex scaffold solutions count for up to 40% of the total project cost. The challenge of access provision for maintenance is reflected in all types of construction, but is particularly important for historic buildings.

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This is due to the relative age and complexity of the fabric and associated degradation of the materials that may be many centuries old. Compounding this, the complexity of scaffold solutions that avoid physical anchorage and tying into masonry substrates (e.g. buttress and spire) can also be significantly greater than for newer structures that have considerations for access designed into them from 'first principles'. These solutions may be costly and, as with any working from height operation, create higher levels of risk for those erecting, maintaining, dismantling or using scaffolds. Alarmingly, from a health and safety perspective, almost half of construction fatalities and a quarter of non-fatal injuries result from falls from height (HSE, 2019), many of which are associated with scaffolding.

Compounding these difficulties, Straub importantly highlights that 'the practice of condition assessment by building inspectors yields variable results due to subjective perceptions of inspectors, [...] caused by a variety of factors such as previous experience, attitude to risk, and the use of heuristics' - i.e. rules of thumb or educated guesses (Straub, 2009). The cumulative effect of these forms of inaccuracies hinder the establishment of an objective starting point and ultimately the determination of suitable repair requirements (Forster and Douglas, 2010).

Clearly, cheaper and safer methods for accurate, complete and objective inspection of building fabric would contribute to a significant enhancement of maintenance and repair activities.

#### 1.2 THE VALUE OF DIGITAL DOCUMENTATION FOR MASONRY SURVEYING

The construction industry has seen a rapid growth in the deployment of new technologies for construction and maintenance, from the use of remote sensing technologies for data capture to new powerful software and data-driven processes to obtain meaningful information. These novel operations are often captured under the umbrella terms of BIM, and nowadays increasingly digital twinning.

As traditional approaches to masonry surveying are time-consuming, expensive, and impacted by subjectivity, there has been a growing interest in the use of remote sensing, non-destructive techniques in particular — and digitally-driven processes more generally (see Section 1.3) — to support more efficient, robust, safe and cost-effective digital documentation.

Remote, non-destructive sensing refers to the digital capture of physical characteristics of objects without making contact with it or damaging it. The obviation of traditional destructive testing is particularly important in historic buildings as destructive sampling logically debases the structure to be conserved. Remote sensing technologies encompass a number of solutions, including: visual imaging (i.e. standard photography), thermal imaging, multispectral and hyperspectral imaging, ground-penetrating radar (GPR), structure-from-motion photogrammetry and laser scanning. Many of these can be employed at ground level or airborne, i.e. mounted on drones, planes and even satellites. Current practice, reviewed in Section 2, is primarily based on digital pictures acquired at ground level. These do not provide detailed 3D information. But, using rectification and scaling, reasonably accurate dimensions along façade planes can be obtained. In contrast, laser scanning and structure-from-motion photogrammetry enable the acquisition of the 3D structure (and visible colour) of the surface of objects. For this reason, these technologies have been increasingly used for digital documentation, from small object, to buildings, to landscapes. HES have published the Short guide: applied digital documentation in the historic environment that provides a complete set of process guidance on reality capture and, in particular, the application of TLS and photogrammetry for digital documentation. The guide also discusses relevant applications (Frost, 2018).

Laser scanning (LS) constitutes a revolution to land and monument surveying. Modern laser scanners sweep their surrounding space with a laser beam to obtain dense and accurate 3D point clouds. While laser scanners can be used airborne, mounted on planes or helicopters to capture land elevation (in this case experts refer to the technology as LiDAR), in the context of monument recording it is more commonly used ground-based, in which case it is best referred to as static terrestrial laser scanning (TLS) and mobile laser scanning (MLS). TLS conducts scanning from fixed stations (e.g. on tripods) and requires the scanner to be moved to different locations to cover objects of interests. In contrast, MLS conducts scanning from moving platforms (e.g. backpack, trolley, or car), which enables faster scanning, but at the cost of lower accuracy.

Within the context of historic monument surveys, noteworthy examples of the use of LS include the work of Wilson *et al* who illustrate the distinct benefits of TLS for the survey of large and complex historic monuments via case studies of UNESCO World Heritage Sites and the Mackintosh building, the Glasgow School of Art (Wilson *et al*, 2013; Wilson *et al*, 2018). Nettley *et al* use TLS and LiDAR to obtain a photorealistic geospatial model of the historic quayside at Cotehele Quay, integrated in an accurate Digital Elevation Map (DEM) in order to assess the potential impact of rising sea levels resulting from climate change (Netley *et al*, 2013). Temizer *et al* show the value of TLS to survey underground structures like the Byzantine cistern situated beneath the court of the Sarnicli Han building (Temizer *et al*, 2013). De Matias *et al* employ TLS to study the geometry and damage of the Alcántara Bridge and Coria Cathedral in Spain (De Matias *et al*, 2013).

Photogrammetry (PG) is a well-established method for obtaining 3D records of historic monuments. Nonetheless, significant progress has been made in the last two decades, both in terms of hardware and software, to rapidly and accurately obtain such records. High-resolution and portable digital cameras are now widely available at a relatively low cost. Furthermore, the development of robust automated feature detection and matching in digital images (e.g. SIFT. See Lowe, 1999) for extracting structure from motion, as well as dense matching approaches have dramatically improved the image processing stage, enabling entirely automated processing pipelines.

Within the context of historic monument survey, noteworthy examples of the use of PG include the work of Cappellini *et al* who apply PG to produce 3D models of monuments that are used to generate 2.5D orthophotos of walls (Cappellini *et al*, 2012). Using the example of Roman walls, these orthophotos are used to conduct the semantic annotation of the opus of different sections of the wall.

The main limitation of PG systems is that they are not robust to varying lighting conditions and texture-poor or reflective materials. Furthermore, their accuracy quickly drops in comparison of that of laser scanners. Finally, single-camera PG systems provide 3D reconstructions only up to scale, and require the user to extract known dimensions in the scene to adequately scale the reconstructions.

#### 1.3 THE IMPERATIVE TO MOVE BEYOND DIGITAL DATA ACQUISITION FOR DOCUMENTATION

The above technologies are having a transformative effect on documentation and surveying practice, and are slowly becoming common practice – LS in particular. However, this transformation remains limited to data acquisition, with the subsequent complex tasks of building pathology (diagnosis, prognosis and therapy) remaining principally conducted manually with all the challenges already raised in Section 1.1. There is thus a clear need to develop methods and algorithms that can (semi-)automatically analyse the documentation data and effectively support those subsequent activities. Progressive implementation of reality capture and subsequent application of innovative data processing tools – such as Machine Learning

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(ML) algorithms - will altogether deliver a complete transformation of surveying, repair and maintenance practices (Valero et al, 2017; Bosché et al, 2015). Besides, digital survey information and pathology analyses have the benefit that they can be recorded in structured, semantically-rich data models, more specifically in connection with BIMs. Such information models will enable systematic monitoring of defects and prognosis, with a view to support more effective maintenance decisions and maintenance procurement processes. Besides, when aggregated at a regional or even national level, these information models will facilitate data-driven decision making for learning effective maintenance strategies and even for strategic financial planning of the conservation of masonry buildings and infrastructure.

This report presents results of a continuous collaboration between HES, the University of Edinburgh and Heriot-Watt University that has been aiming to deliver such innovations, in the particular but significant case of masonry structures. Following a first project where we principally assessed and contrasted the suitability of TLS, pole-mounted PG and UAV-based PG for the digital documentation of (rubble) masonry walls (Bosché et al, 2015), this report focuses on the analysis of such acquired data. In particular, we present results of innovative algorithms that we developed for the processing of TLS data of masonry structures to detect their individual stones (and mortar regions) (Section 3) and the detection and classification of masonry stone defects (Section 4).

# 2 MASONRY SURVEYING: FROM TRADITIONAL TO DIGITALLY-SUPPORTED PRACTICE

## 2.I CURRENT PRACTICE

Current practice for the survey of masonry structures may be divided into three stages. First, and of prime importance is to ascertain or analyse the client's requirements of undertaking a survey as this would dictate the breadth, depth and focus of the reporting (i.e. general condition, or targeted needs such as assessment of likelihood of falling masonry). Importantly, a well-considered survey should recognise the imperative of developing a relationship between ascertaining the client's requirements and reporting expectations, with the presentation of broader data utilisation, meaningfully-contextualised survey results and key findings that are understandable and of value to those commissioning the work – in essence, thinking what the client needs, and how to relay that information so it is of greatest value to them.

The second stage is a preliminary survey that is usually conducted from the ground. This often utilises a good quality digital camera (i.e. DSLR) that is used to capture each masonry elevation. The subsequent images can be 'rectified' to provide an elevation view that can be 'marked up'. The façade elevation is often the focus of much of the time and cost associated with a survey given the architectural importance and likelihood of decorative carved enrichment, relative to other elevations. From this image, a drawing showing each stone may be produced. This is onerous in terms of time, cost, and at times access, and is also prone to measurement error given the often large number of individual masonry units. Beyond the recording of each stone, additional information such as condition and defects can be marked in the drawing. This is attained via visual survey from ground level using binoculars or from working platforms. Damage to masonry and their levels of degradation may be recorded using Fitzner's Damage Index method (Fitzner et al, 2002). Figure 1 illustrates an example of resulting annotated image. Note that scaling of the image is obtained by measuring some elements on site, here the hatched doorway. This process is finely described the guide *Stonemasonry skills and materials: a methodology to survey sandstone building façades* produced by HES (Urquhart, 2007).



Key to colour coding on marked-up images

- Stone requiring immediate replacement
- Stone requiring replacement within 20 years
- Stone requiring replacement within 20 years unless urgent maintenance is carried out
- Stone showing some deterioration but will last more than 20 years
  - Stone requiring future replacement (>20 years) unless maintenance is carried out

Figure 1: Rectified image of façade with overlays showing stone decay codes and repair needs. Image reproduced from Stonemasonry skills and materials (2007).

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The outcome of this initial survey, or alternatively the implementation of a pro-active maintenance schedule, may then raise the need to conduct an additional more detailed survey to fully characterise the maintenance works that must be conducted. This supplementary work will typically require the erection of scaffolding. The detailed survey may include both destructive and non-destructive investigative techniques and additional sample removal (i.e. commonly, petrographic analysis of natural stone or intact samples of mortar for optical microscopy and wet chemical analysis to better understand the physical characteristics of the fabric). In addition, rudimentary assessments of stones may be undertaken by lightly tapping with a hammer or screwdriver handle to expose delamination that is denoted by an alteration of the sound generated (e.g. a ringing or dull sound). In addition, mortars may be scratched to assess their binding characteristics or 'hardness', although it is recognised that this often yields limited value over other more sophisticated methods. If ashlar stones are assessed to require replacement, then these must be precisely measured and the obtained values sent to the quarry for exact cutting. The accuracy of both measurement and cutting of the dimensional stone often leads to complications. If the stone is over measured, then the stone needs further reduction on site by the fixer mason. Conversely, if the stone is undersized then a new stone needs to be ordered or a larger mortar joint will be required.

#### 2.2 HOW CAN DIGITAL TECHNOLOGIES ASSIST MASONRY SURVEYING?

TLS has gained high prominence in the sector and its ubiquity, in particular its predictable performance, has potentially over-shadowed alternatives, such as PG. But the benefits of all digital reality capture technologies need to be better understood by the sector, predicated on rational and robust decision making that frames value centre stage.

Access is of prime importance and scaffolding will normally remain erected in place between the detailed surveying and the execution of identified maintenance and repair works. Whilst the decision to proceed with the works may be relatively rapid, a lag between the submission of measurements of the replacement dimensional stones to the quarry and their actual procurement (i.e. receipt of cutting schedules, sawing of six side, and delivery) will result in the scaffolding remaining unused. Ultimately, as discussed throughout, access provision often has a significant impact on overall project costs (i.e. including both inspection and repair expenses) which can meaningfully reduce the scope of works as money is directed away from fabric repairs to scaffolding. Secondary implications of long-term scaffold erection are associated with debasement of user/visitor experiences and safety concerns associated with unauthorised access by the public especially in the case of city centre works. With new digital technologies, the need for scaffolding during inspection (and potentially even repair) could be removed and, as result, overall inspection (and maintenance) costs could be reduced significantly and secondary impacts and risks reduced.

Another issue, whilst not often explicitly discussed, is the challenge to keep inspection and maintenance records co-located in order to enable us to effectively retrieve information from them and relate them to one another. For example, understanding the inspection 'history' (i.e. record) of a stone in a building façade may require a surprisingly convoluted information retrieval process composed of multiple reports with annotated measured line diagrams. Compounding this complexity, additional specialised forms of information associated with match stone numbers across diagrams or stone specific conservation treatments (e.g. consolidation and pinning) may need to be linked back to primary survey documents. It is clear that the nature of documentation, the way in which it is structured and retrieval capability have significantly reduced productivity and increased the probability of error.

With new digital technologies for surveying as well as information management (e.g. Historic BIM, as well as ontologies and linked data technologies), inspection documents could be recorded digitally and in structured ways so that information can be retrieved and analysed effectively.

Moving beyond relating digital records of individual buildings, the recording of inspection surveys and reports in digital and structured ways using industry standards would offer opportunities for digital records to be compared across buildings within organisational portfolios and beyond. The accessibility of data driven analysis at such scales has the potential to enhance our understanding of almost countless stone decay mechanisms, considering inherent materials properties and wider geographical and environmental factors (regional and national level). This can also help us improve our perception of repair demand and its evolution, for example to support budget allocations for maintenance or training. We refer the reader to *Stonemasonry skills and materials* (Urquhart, 2007) for a detailed discussion of the value of such data at a regional and national level.

# 2.3 CONSIDERATIONS FOR THE APPROPRIATE SELECTION OF DIGITAL SURVEY TECHNOLOGIES AND THE IMPORTANCE OF PLANNING FOR DATA ACQUISITION

The appropriate selection of technologies has always been an important factor in effective surveying operations. Whilst it is generally recognised by surveying professionals that digital data capture is beneficial on multiple levels (Forster *et al*, 2017), the understanding of the decision making that underpins the wide-ranging options that confront a practitioner is arguably little understood.

Depending on the nature of the project and the building under evaluation, a particular technology or a combination of these (including PG and TLS) will be used for data acquisition. As referred to previously, *Short guide: applied digital documentation in the historic environment* reviews various data capture techniques that can be applied to the recording, analysis, conservation and visualisation of the historic environment, and also discusses the whole data acquisition process, from planning to data management and dissemination (Frost, 2018).

In the following, we present some complementary results highlighting the challenges around adequate technology selection and planning for data acquisition of historic buildings envelopes. Figure 2 illustrates a comparative technology performance analysis conducted at Craigmillar Castle, with a focus on time (acquisition and processing) and cost of the operation, as well as the completeness of the generated point cloud. In accordance with traditional manual survey operations, thought must be given to the aim of the survey operation and how to acquire the data with the specified quality. An ill-considered survey of any type will lead to omission in data and extrapolating forward, inconclusive or misguided reporting.

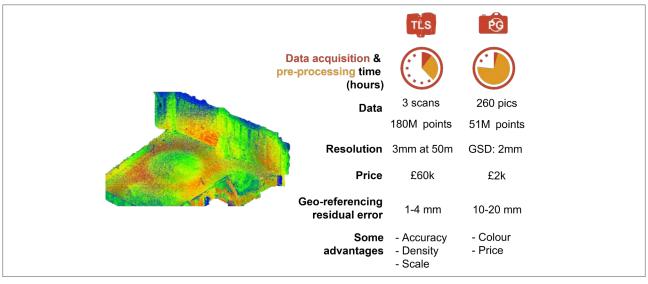


Figure 2: Comparison for TLS and PG technologies for the data acquisition and pre-processing of the east garden of Craigmillar Castle (Edinburgh).

These pre-survey considerations may be thought of as being largely circumvented in digital data acquisition, but, as was shown in the Craigmillar Castle example and illustrated in Figure 3, poorly planned digital surveys can lead to incomplete data debasing the survey findings. Within this context, minimising occlusions, ensuring the right level of point cloud density, and conducting surveys in favourable light conditions (if colour information is important) are part of the planning for scanning/photogrammetry strategy.

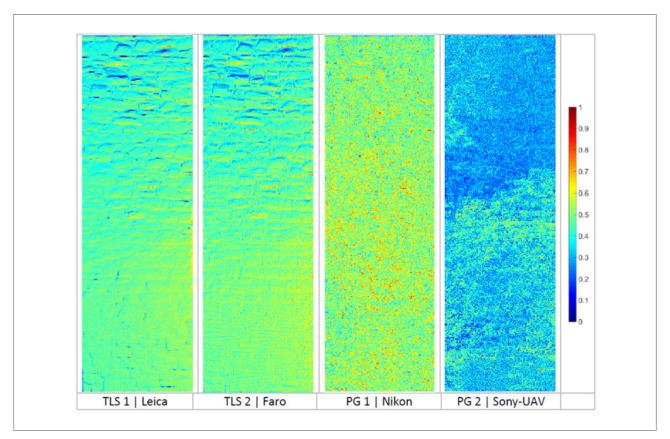


Figure 3: Point density [pt/cm²] for different data acquisition devices.

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# 3 SEGMENTATION OF DIGITISED WALLS

The importance of being able to identify individual masonry units is critical for many surveying, maintenance and repair activities (Urquhart, 2007). The isolation of individual masonry units facilitates the attachment of additional information such as dimensional data, materials properties and conservation needs (such as whether to replace or consolidate). This is common in all masonry forms whether composed of ashlar or rubble.

The segmentation of random rubble masonry forms was traditionally problematic to achieve. Indeed, an inability to accurately record and label individual random rubble masonry units ostensibly resulted in descriptive specifications being used to locate the region requiring intervention. Automatic segmentation allows for the attachment of other types of survey data to the individual units and the segmentation of larger 'global' areas of rubble masonry units creates opportunities for quantification of units which would have previously not been possible with traditional techniques.

Requirements for manual segmentation of ashlar masonry has always been required given the nature of the 'dimensional' stone requiring accuracy for replacement in repair operations. This was an excessively time consuming and often complex survey operation with high probability of inaccuracy in recording the individual stones. Ashlar stone surveys also formed a large part of conservation operations beyond replacement of individual masonry units such as pinning and doweling, surface consolidation and indenting.

#### 3.1 RUBBLE MASONRY WALL SEGMENTATION

The first and main contribution made in this research project is the development of an algorithm for automatically segmenting TLS point clouds of rubble masonry walls into their constitutive components, i.e. the individual masonry units and mortar regions. This task is challenging because, in contrast to ashlar masonry, the stones and mortar regions are very irregular in their size and the shape of their boundaries and face. To our knowledge, the method reported here is one of the first produced, and, as shown in the case study, it already delivers good results.

#### 3.1.1 Method

In this section, we briefly summarise the approach developed. For full details, we direct the reader to Valero et al (2018).

The approach is based on the observation that in rubble masonry the mortar regions are generally recessed in comparison with the stone faces. In other terms, if considering the rubble masonry wall face as an elevation map, the centre line of the mortar regions is often at the bottom of 'U-shaped' valleys that separate individual stones (i.e. the mountains). This is illustrated in Figure 6b that shows a point cloud of a rubble masonry wall (Figure 6a) is coloured with a gradient illustrating the depth with respect to the wall face. This observation led us to propose to employ the 2D Continuous Wavelet Transform (CWT) operation to detect those valleys.

The entire data processing pipeline is summarised in Figure 4 and the individual stages are briefly summarised below. Figure 6 shows the data obtained at each of those stages, using an example input 3D point cloud. Once again, for full details, we direct the reader to Valero et al (2018).

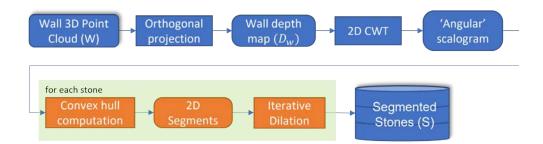


Figure 4: Data processing pipeline for the segmentation of point clouds of rubble masonry into individual stones and mortar regions. Reproduced from Valero et al (2018).

- Orthogonal projection: The input to the process is the 3D point cloud of a wall façade (Figure 6a). We fit a plane to that data and create a depth map image of the wall by projecting the 3D points on that plane (Figure 6b). In the depth map image, each pixel's value is the average orthogonal distance of the 3D points that orthogonally project into that pixel.
- **2D CWT:** The 2D CWT is a convolution operation that multiplies an input 2D image with a selected 2D wavelet operator that is translated across the input signal and also applied at different scales. Here, we propose to apply the 2D Mexican Hat wavelet (see Figure 5) to the depth map image with the aim to detect the above-mentioned valleys. The output of the 2D CWT applied to Figure 6b is shown in Figure 6c.
- Convex hull computation and morphological operation: As can be seen in Figure 6c, the stone face of rubble stones can have random shape and features and these may also respond well to the 2D CWT convolution. Therefore, while the stone regions can be seen quite clearly they also include incorrect mortar detections inside them. To remove those errors, we replace each stone region i.e. connected set of white pixels in Figure 6c with its tight convex hull. The convex hulls are then eroded and dilated with a view to remove the very small stone regions that are most likely incorrect. The output of this process is shown in Figure 6d where stones and mortar regions are clearly delineated. Figure 6e shows the same output but with each detected stone coloured distinctly. Finally, since it is known which original 3D point corresponds to which pixel in the depth map image, Figure 6f shows the final segmentation result back in the original 3D point cloud. Notice how the algorithm effectively deals with stones and mortar joints of various shape and profile.

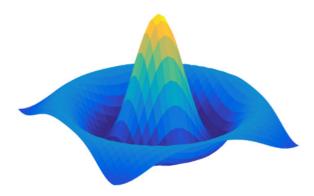
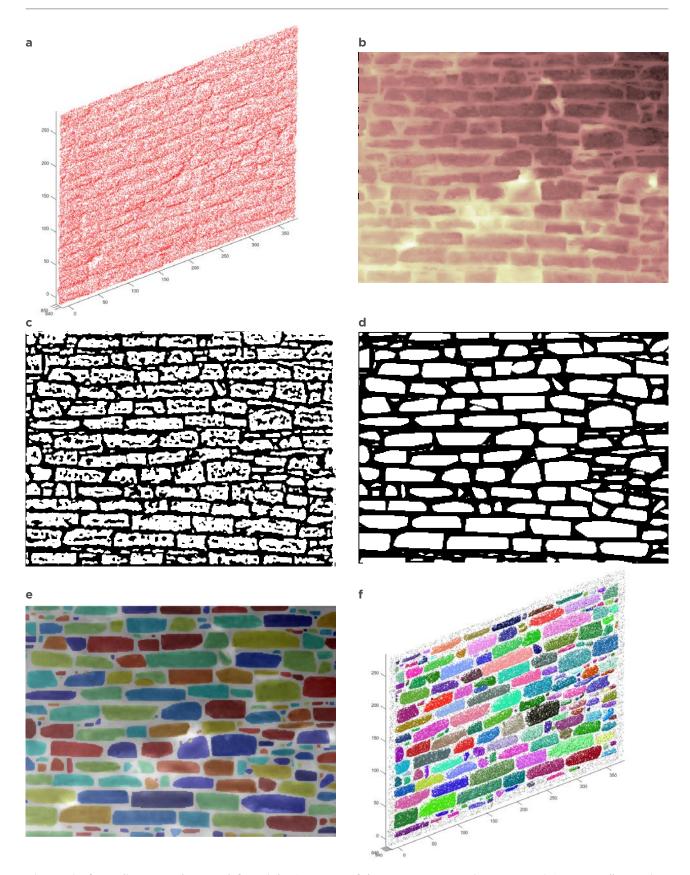


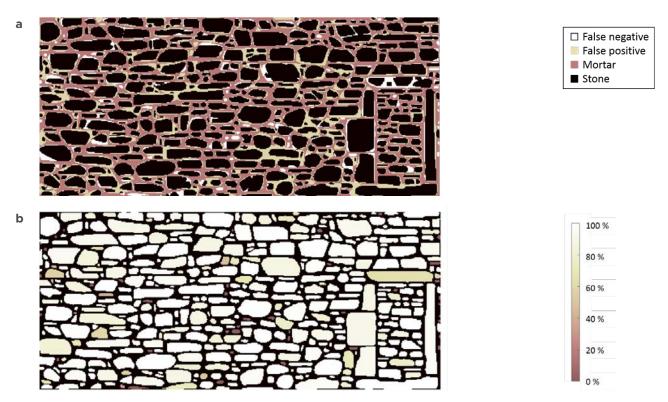
Figure 5: 3D view of the 2D Mexican Hat wavelet.



Figures 6a-f: Reading top to bottom, left to right. Summary of the stone segmentation process. 6a) 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.

A quantitative assessment of the segmentation accuracy has been undertaken by comparing the results obtained by the algorithm against those obtained through a meticulous manual segmentation in the section's orthophoto. Figure 7a illustrates the labelling performance results. It shows good overall results, although the size of the stones seems slightly over estimated by the current algorithm. Figure 7b further summarises the results of Figure 7a by colouring each stone according to the percentage of its area in the orthophoto that is correctly labelled as stone. As can be seen, the area of most stones is typically well segmented, with ratios over 75% for the majority of stones. The few errors appear for some (but not all) of the smallest ones.

In addition, once the mortar regions and stones are detected, the mortar centre line can be retrieved using a thinning procedure and the depth of mortar along that line retrieved from the 3D data. Deeper valleys could then indicate mortar recess. Figure 8 illustrates this for the same example as in Figure 6.



Figures 7a and 7b: Illustration of the assessment of the performance of the proposed wall segmentation algorithm. In a) the labelling performance results are shown. Black and magenta regions are pixels that are correctly recognised as stone and mortar 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. In b) each stone is coloured according to the percentage of its area (in the orthophoto) that is properly labelled as stone.

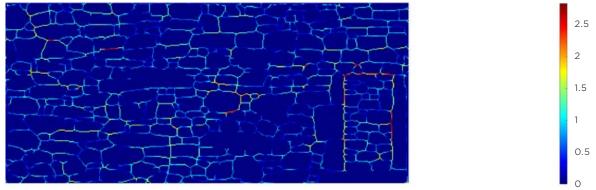


Figure 8: Depth of the mortar regions along their centre line.

The above algorithm for the automated segmentation of rubble masonry is demonstrated at a larger scale for the west wall of Linlithgow Palace courtyard (Figure 9). In that example, architectural components such as windows and doors, have been 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 the 'wall' component. Only the points corresponding to the building component 'wall' were processed by the proposed algorithm. Figure 9b shows the stones detected in the walls, and Figure 9c the mortar regions with their calculated depth.

In the case of rubble masonry, repair works are typically priced by square metres, and such information is readily provided by our method. It is nonetheless noteworthy that, in the case of mortar repair in rubble masonry, works are traditionally priced per metre square, while mortar repair is priced by linear metre in the case of ashlar masonry (see Section 3.2). The reason is that providing a linear metre measurement in the case of rubble masonry is challenging. But, as shown in Table 1, our method does provide linear metre measurements in such context. As a result, if such an approach to surveying were to be deployed in practice (following further validation of its efficacy), mortar repair pricing practice for rubble masonry could eventually be revised.



# **CASE STUDY**

### 3.1.2 LINLITHGOW PALACE

Table 1: Linlithgow Palace courtyard west wall.

Quantitative parameters extracted after the automatic stone segmentation			
Wall area	21.5m x 13.5m = 196.75m <sup>2</sup>		
Detected stones	3,056		
Area covered by stone	128.83m²		
Stone size (mean)	421.56cm <sup>2</sup>		
Linear measurement of mortar	1.44km		
Area covered by mortar	67.95m²		
Depth of centre line of mortar (mean ± std)	1.05cm ± 8.2mm		

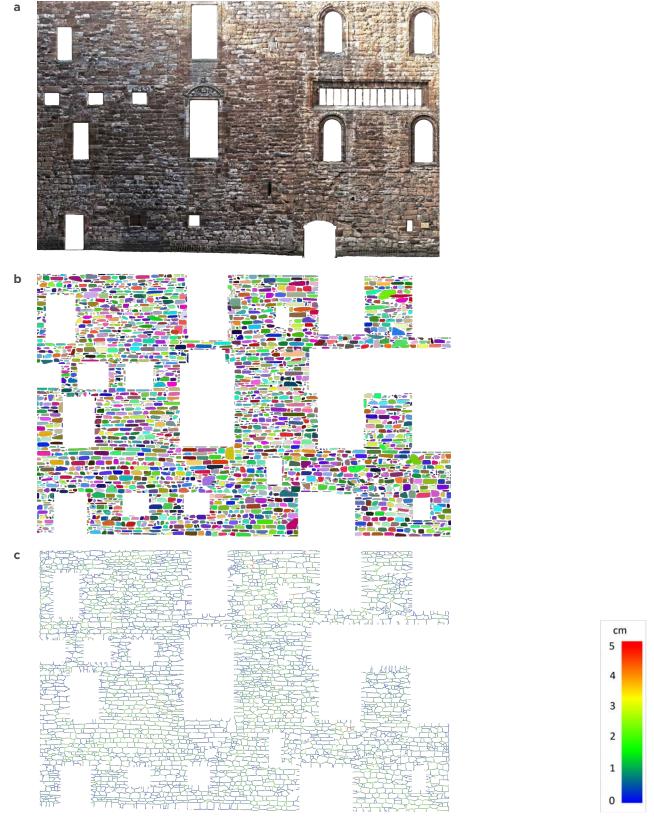


Figure 9: Linlithgow Palace courtyard west wall. 9a) 3D coloured point cloud; b) segmented and labelled stones; and c) mortar depth map.

#### 3.2 ASHLAR MASONRY WALL SEGMENTATION

The second contribution made by this research project is the development of an algorithm for automatically segmenting TLS point clouds of ashlar masonry walls into their constitutive components, i.e. the individual masonry units. While the advantage of ashlar masonry over rubble masonry is that the stones and mortar regions are ostensibly regular in their size and shape, mortar regions are very thin without much recess compared to the stone face (when not chamfered), so that they are potentially challenging to detect in point cloud data. In this context, a different approach has to be considered.

#### 3.2.1 Method

Similar to the case of segmentation of rubble masonry, the approach is based on the observation that mortar regions are generally recessed in comparison with the stone faces. However, the limited width of these regions, which can be on the order of magnitude of imperfections on the surface of the stone, and the resolution of the scans make a method based on CWT unsuitable to label mortar and stone areas. Therefore, the proposed solution is grounded on the analysis of histograms of colour (i.e. RGB) and intensity (of reflectivity of the laser beam) images, and takes advantage of the predominance of vertical and horizontal mortar joints in ashlar masonry as well as the different reflectivity of materials. For full details, we direct the reader to (Acas, 2021).

The data processing pipeline is summarised in Figure 10 and the individual stages are briefly summarised below:

- Orthogonal projection: the input to the process is the 3D point cloud of a wall façade. We fit a plane to that data and create intensity and colour images (i.e. maps) of the wall by projecting the 3D points on that plane. In both maps, each pixel value is the average intensity, red, blue, and green of the 3D points that orthogonally project onto that pixel.
- Window edge detection: this process takes as input the intensity map and identifies empty regions (where no 3D points have been projected) that correspond to openings in the wall. The bounding boxes of the areas without projected points are considered the boundaries of the windows.
- Horizontal mortar joint detection: this process takes as inputs intensity and grayscale maps (the

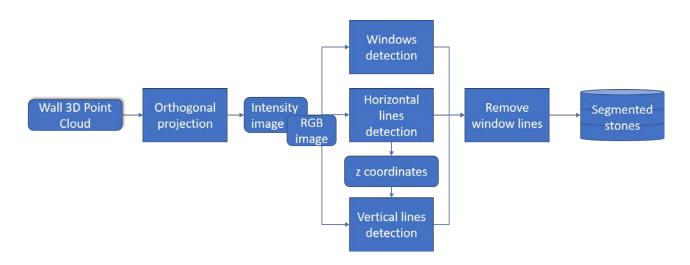


Figure 10: Data processing pipeline for the segmentation of point clouds of ashlar masonry into individual stones and mortar regions.

latter derived from the RGB values) and delivers the vertical coordinates of the horizontal mortar joints. To obtain these, median values of intensity and grayscale are calculated for each row of the map and compared with the median values of the adjacent rows, following a strategy based on the analysis of histograms (Acas, 2021). Those rows containing an important number of pixels with intensity/grayscale values considerably different to the adjacent rows are labelled as horizontal mortar joints.

• **Vertical mortar joints detection:** the vertical coordinates of the horizontal mortar joints are utilised to define horizontal strips (see Figure 11a) that represent each row of stones. These strips are then evaluated using a similar approach to now identify vertical mortar joints (Figure 11b).

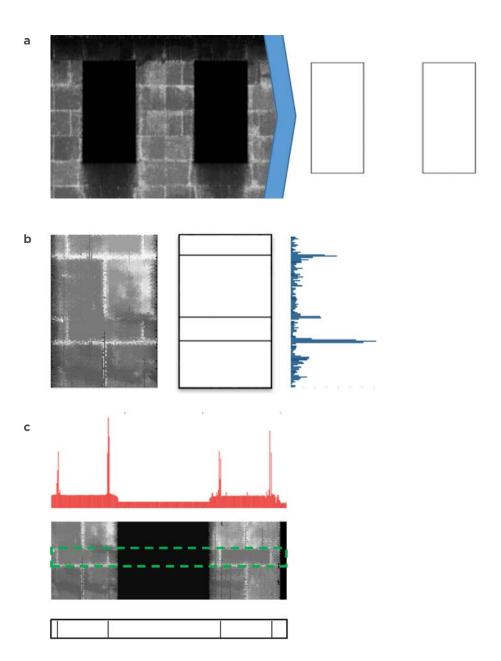


Figure 11: a) Windows; b) horizontal; and c) vertical mortar joints identified for ashlar masonry. See Acas (2021).

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Figure 12: South-eastern façade of St Andrew's house. The region of interest is highlighted in red.

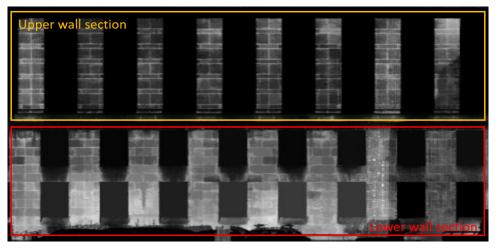


Figure 13: TLS intensity values for the upper and lower wall sections.

## **CASE STUDY**

## 3.2.2 ST ANDREW'S HOUSE

The algorithm for the automated segmentation of ashlar masonry has been tested at larger scale with data from the south-eastern façade of St Andrew's House, in Edinburgh (highlighted in red in Figure 12). As can be seen in Figure 13, due to varying wall patterns in terms of brick configuration, colouring, and window positioning, the point cloud has been divided into two trial datasets: the upper wall section and lower wall section. The significant height of the façade makes this division into the upper and lower sections useful to evaluate the potential effects of the inclination of the laser beam hitting the wall for capturing geometric data. Note that the bottom part of the lower wall section is occluded by parked cars, and therefore incomplete, so it has been removed from the cloud.

Figure 14 shows the result of the detection of the ashlar units of the upper section while results for the lower section are shown in Figure 15.

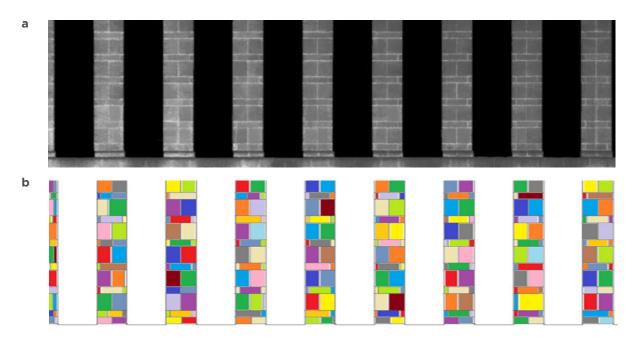


Figure 14: St Andrew's House south-eastern façade. 14a) Upper section intensity map; b) segmented and labelled stones for the upper section.

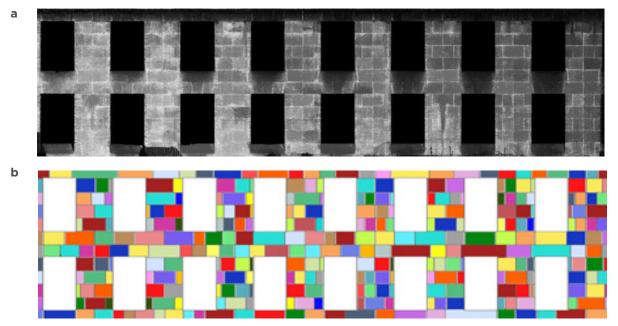


Figure 15: St Andrew's House south-eastern façade. 15a) Lower section intensity map; b) segmented and labelled stones for the lower section of the wall.

A quantitative assessment of the performance of the automatic segmentation has been undertaken by comparing the obtained results, for both upper and lower wall sections, with a manual segmentation of the wall, which is considered a ground truth.

Segmentation lines delivered by the algorithm that coincide with those provided by a manual segmentation are labelled as True Positives (TP), while those segments detected by the algorithm but not present in the manual segmentation are considered False Positives (FP). In contrast, real mortar lines not identified by the algorithm are considered False Negatives (FN). From this, the True Positive Rate (TPR), also known as *Recall*, is calculated as the fraction of manually segmented lines accurately detected by the algorithm (see *Eq. 1*) and the *Precision* is the fraction of segments correctly identified as lines between all those labelled as lines by the algorithm (see *Eq. 2*). Both *Precision* and *Recall* have values between 0 and 1.

Eq. 1 Recall = 
$$\frac{TP}{TP+FN}$$

Eq. 2 Precision = 
$$\frac{TP}{TP+FP}$$

Table 2 and Table 3 summarise the results obtained for the detection of horizontal and vertical lines respectively for both the upper and lower wall sections.

Table 2: Performance metrics of horizontal lines detection.

	True Positive (TP)	False Positive (FP)	False Negative (FN)	Recall	Precision
Upper wall section	15	0	0	1	1
Lower wall section	9	2	3	0.75	0.82

Table 3: Performance metrics of vertical lines detection.

	ТР	FP	FN	Recall	Precision
Upper wall section	144	28	36	0.80	0.84
Lower wall section	137	83	40	0.77	0.62

#### 3.3 SOFTWARE TOOL FOR THE SEGMENTATION OF 3D POINT CLOUDS OF MASONRY WALL

The rubble segmentation tool has been deployed as a free plugin to the open-source software CloudCompare (CloudCompare, 2020; Valero *et al*, 2020). CloudCompare is a freeware specialising in the manipulation and processing of point cloud data for various applications. It supports a range of open formats, including E57 format, which is an ASTM standard (Huber, 2011). The plugin includes a tool for the automated segmentation of rubble masonry point clouds along with another one to enable their manual corrections.

The plugin can support various applications, but in particular enables users to effectively produce detailed elevations of masonry walls. The tool is distributed freely under the GPLv2 license. The source code is available at github.com/CyberbuildLab/masonry-cc, and the plugin is now distributed with CloudCompare. Figure 16 shows a screenshot of CloudCompare with the developed tool being used to process the point cloud of a masonry wall.

At the time of writing this report, the plugin for automated segmentation only includes the algorithm to automatically segment point clouds of rubble masonry (Section 3.1). However, the team plans to further develop its algorithm for the automated segmentation of point clouds of ashlar masonry and will then integrate it to the plugin. Regarding the segmentation of ashlar masonry, it must however be noted that the existing algorithm principally designed for rubble masonry may in fact also be employed successfully in cases of ashlar masonry that present prominent faces, e.g. with chamfered faces.

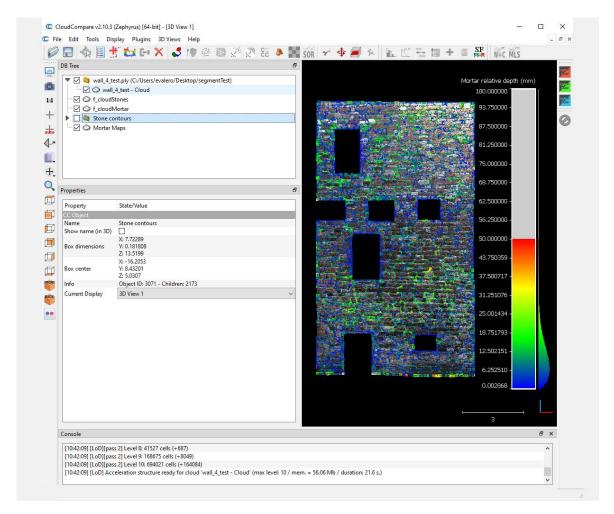


Figure 16: Screenshot of CloudCompare running the proposed plugins.

#### 3.3.1 Performance and usability study

The performance and usability of the plugin for automated segmentation has been evaluated using an experiment. For the experiment, which is reported in detail in Valero *et al* (2020), ten professionals working in architectural conservation at HES were invited to participate in a trial session. Eight of those ten participants had previous experience in working with point clouds, and six of those had previously worked with CloudCompare. The participants then completed two exercises. They first segmented part of a rubble masonry wall, sized 2mx2m, using the manual segmentation plugin only ('Manual'). Then, they applied the automated segmentation plugin to a different region with dimensions 3mx2m and corrected the obtained results with the manual segmentation plugin ('Auto+Manual'). Table 4 summarises the results.

As can be seen, the percentage of stone area properly labelled as stone is high in both 'Manual' and 'Auto+Manual' cases, with marginally better results for 'Auto+Manual'. The average distance from mislabelled points to their closest stone was also similar in both cases. Given this comparable quality performance, the time performance shows that the users are almost four times faster when using 'Auto+Manual'. This demonstrates the value of the automated segmentation algorithm we developed, in term of both segmentation process efficiency and efficacy.

Table 4: Results obtained for manual segmentation and correction after automatic segmentation.\*

	Manual	Auto+Manual
Average correct labels [%]	95.0	97.3
Average distance of mislabeled [cm]	1.95	1.94
Average time [min/m²]	8.6	2.4

<sup>\*</sup> The first row reports the average, for all the test subjects, of the percentage of points correctly labelled as stone in the point cloud. The second row gives the average distance from mislabelled points (i.e. false positives) to the closest stone. The third row reports the average time spent by the participants. As the dimensions of the patches were different, time values are per m².

## 4 DEFECT DETECTION AND CLASSIFICATION

The second facet of this research has focused on the detection and classification of defects in reality capture data (TLS and PG) from masonry structures. More specifically, the team aimed to assess the feasibility of employing machine learning techniques to detect masonry defects (or alterations) in such datasets.

In this section, we summarise the techniques developed and the results of our experimental results. A more detailed presentation of these can be found in Valero *et al* (2019). In this work, TLS and PG were combined to produce accurate point cloud coloured with reliable red-green-blue (RGB) information. In order to create these precise models, both point clouds were aligned and, subsequently, each point from the TLS cloud was coloured with the RGB information from its nearest neighbour from the PG model. The stone segmentation methods presented in Section 2 were then applied to the point cloud, and the point cloud of each stone was then assessed individually. The work described in this report has been conducted with focus on the analysis of defects in ashlar masonry, with stones having flat faces. While some of the methods described below would apply to other types of masonry, some do expect a stones with flat faces.

It is important to highlight that the assertion of simple 'changes' in fabric from the surface is all that can be expressed or objectively reported. Diagnosis, i.e. identifying the root cause of defects, is not covered here as this would require additional data inputs to target the likelihood of causal relationships to any particular defect.

Sections 4.1 and 4.2 summarise the methods developed for the detection and classification of defects, respectively. Section 4.3 then reports the results of the preliminary performance assessment conducted with real data.

#### 4.1 DETECTION OF DEFECTS AND BUILDING PATHOLOGY

Medically, pathology it is defined as 'the study of diseases or abnormalities'. The Royal Institution of Chartered Surveyors (RICS) define building pathology in their competency pathway for building surveying as 'the understanding of building defects and the appropriate remedies' (RICS, 2017). Building pathology is a specialist branch of surveying that is associated with the systematic study of deterioration in materials and fabric. In most basic terms it evaluates deterioration predicated on the concept of cause and effect.

Approaches to pathology should follow a systematic, scientific, staged sequence: manifestation (the showing of something abnormal), diagnosis (identification of issue by examination), prognosis (likely course/trajectory of situation), therapy (treatment of aliment or condition), and treatment (intervention to improve condition). Robust determination of each stage in any specific defect (defined as a shortfall in performance) can prove challenging especially within the study of masonry deterioration due to the inherent complexity of decay mechanisms in natural stone and often complex external weathering factors. Reflecting this the International Council on Monuments and Sites (ICOMOS) published a *Glossary on stone deterioration patterns* in an attempt to aid those evaluating defects in these materials and also to bring uniformity and universal definitions in stone decay mechanisms. Almost countless permutations in deterioration processes can be noted in natural stone but ICOMOS create major sub-groupings that include cracks, discolouration, mechanical damage, erosion, delamination, crusts and biological growth.

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Decay often manifests itself through alterations in the geometry and surface textures of the masonry units or the colour of their surface. Both 3D and RGB data, obtained with reality capture devices, can be processed to codify and quantify changes in material using different mathematical operations which can be used to detect and classify masonry defects.

The first step of such a process is to detect and highlight areas containing defect manifestations. For this, the segmented individual ashlar units are evaluated to identify regions potentially affected by deformation or loss of material and chromatic alterations. For this detection process, two characteristics are initially assumed: tooled faces of ashlar units are relatively (1) flat and (2) homogeneous in colour. Therefore, rougher or discoloured areas are considered outliers and are thoroughly analysed to identify defects. The homogeneity or heterogeneity of geometry and colour attributes can be defined by means of mathematical tools.

#### 4.1.1 Geometric defects

For deterioration associated to geometry, a plane is fitted to the surface of each ashlar stone. Areas containing outliers, characterised as being points far from the plane, can be considered potentially affected by decay (see Figure 17a and Figure 17b). Depending on the finishing of the ashlar, a threshold (i.e. distance point to plane) is set to identify the outliers. Aside from unique treatments, ashlar face tooling depth is normally below 2.5mm. We thus set the threshold to that value. The layout of the outlying points and how the regions are connected can subsequently help identify the nature of the defects.

Each masonry unit may present one or more defect. To detect different decayed areas, a binary map with a resolution of 1mm is created by projecting the above outliers onto the fitted plane, as illustrated in Figure 17c. Compact regions are then segmented from one another using a region growing algorithm. Finally, the original 3D points corresponding to each detected defective area are correlated, as shown in Figure 17d. The segments, enclosed by bounding boxes (i.e. Region of Interest or ROI), are stored as independent entities for which geometry-related metrics are subsequently calculated to characterise the deterioration patterns.

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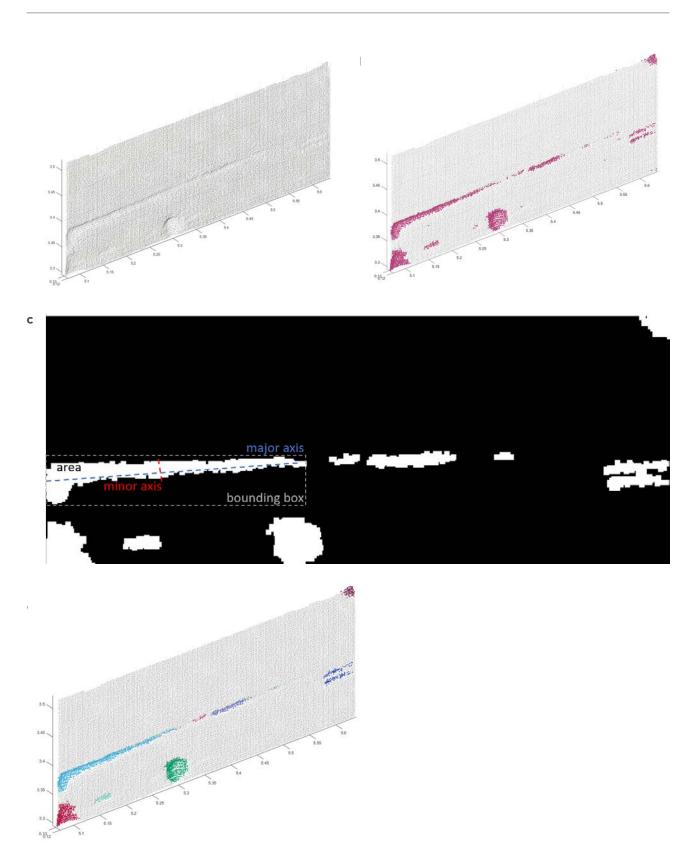


Figure 17: Process for the extraction of geometric parameters. 17a) Point cloud of an ashlar masonry wall; b) outliers, highlighted in pink; c) binary map after orthogonal projection of outliers; d) potential geometry-related defective areas  $highlighted \ in \ different \ colours. \ In \ subfigures \ including \ axes, \ values \ are \ in \ meters.$ 

#### 4.1.2 Chromatic alterations

With respect to chromatic alteration and potential colour-related defective areas, a similar approach based on the extraction of outliers is proposed. In this case, regions with some colour components far from the average for the stone face are potentially defective and are highlighted to be used as inputs in the subsequent classification process.

For this, we first transform the colour information from the RGB model commonly used in images to the hue-saturation-value (HSV) model. This model facilitates the analysis of the predominant *hues* (h) and darker and lighter areas can be identified by means of the *value* (v) channel. Following the RGB-to-HSV colour transformation, the mean and standard deviation of the v channel are calculated and *outlier* regions are defined as pixels/regions where the v channel is over mean(v) + std(v) or mean(v)-std(v). This is illustrated Figure 18b.

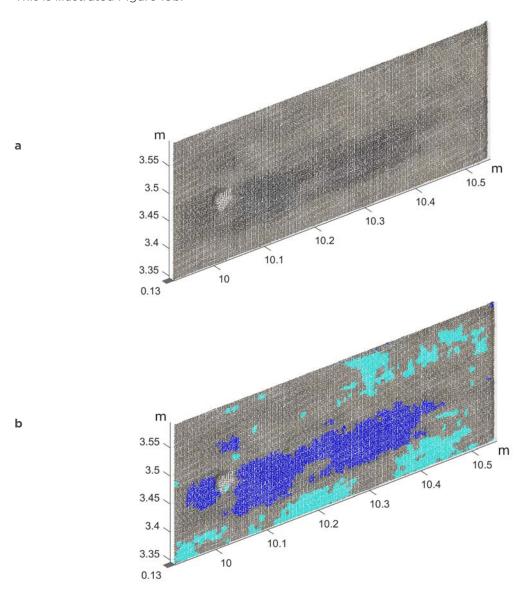


Figure 18: Areas with value components beyond a defined threshold. 18a) Original point cloud; b) areas in cyan are points where the v channel is over mean(v) + std(v) and areas in dark blue are points where the v channel is below mean(v)-std(v).

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#### 4.2 CLASSIFICATION OF DEFECTS USING MACHINE LEARNING

The above detections of manifestations of defect must then be further analysed to classify whether they are indeed defect and what kind of defect. To achieve, we employ a Machine Learning technique which learns from features of areas of defect manifestations. The process to develop a ML model includes the following steps:

- 1. Select parameters/features that are calculated from the input data as well as a ML model.
- 2. Create ground-truth dataset, i.e. dataset where defects are manually marked (as rectangles in our case) and classified.
- 3. Train and validate the selected ML model using the image dataset and simultaneously select the most reliable features.

The following sections summarise the first two of those process steps. More detailed presentations of all three steps can be found in Valero *et al* (2019). Section 4.3 reports the experimental results achieved with this approach.

#### 4.2.1 Features and ML model considered

We consider a number of material change parameters that we gather in two groups:

**Geometry-related parameters:** evaluating the deviation of the masonry surface to the expected original profile. Fourteen parameters are calculated and considered:

- · Ratio of outliers over inliers
- Roughness
- Median distance (from the outliers to the average plane)
- · Distribution of normal vectors
- Area
- Elongation
- Rectangleness
- Circularity
- · Number and area of unconnected defective areas within each ashlar unit
- · Texture parameters, including: Contrast, Energy, Correlation and Homogeneity.

**Colour-related parameters:** linked to colour alterations on the stone. Twenty-one parameters are calculated and considered:

- Dispersion of hue
- Dispersion of value
- Range of hue
- Range of value
- · Skewness of value
- Texture parameters (contrast, energy, correlation, and homogeneity) of hue
- Texture parameters of saturation
- Texture parameters of value
- Texture parameters of grayscale

The texture-related parameters are devoted to the study of repetitive patterns within the ROI. This ROI can be a whole face of an ashlar unit or a part of a face ('sub-unit').

Similar decayed regions will present common symptoms, with some of the parameters displaying comparable values. As a result, the representation of *n* parameters in an n-dimensional space is expected to show different data clusters which can be associated to analogous defects. To determine precise boundaries between these clusters, we employ a machine learning technique.

The selection of an adequate machine learning approach depends on the number and nature of samples in the studied dataset and evaluated features (Yang *et al*, 2020). In this work, after considering the number of available samples (around 3,000 for both geometric and colour analysis) and the extracted features (less than 20 in both cases), a supervised technique, more precisely a logistic regression multi-class classification algorithm, has been employed to categorise defective areas.

#### 4.2.2 Ground-truth dataset

For training the supervised classifier, deteriorated regions have been manually segmented and labelled by experienced building surveyors who specialise in stone, and following the criteria presented by ICOMOS (see Wilson *et al* (2018) and Figure 19). Each segment, which is marked as a rectangular ROI, is given a label indicating the defect observed in the area. The feature parameters described above are then calculated using XYZ and RGB data contained within each rectangular boundary.

Training is conducted using a one-vs-all strategy and data from a façade of the Chapel Royal of Stirling Castle (see Section 4.3), which presents various geometric and/or colour deteriorations.



Figure 19: Defective areas labelled by surveyors.

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Figure 20: South façade of the Chapel Royal in Stirling Castle.

## **CASE STUDY**

#### 4.3 CHAPEL ROYAL IN STIRLING CASTLE

The ML-based defect detection approach summarised in the previous section was tested on the main façade of the Chapel Royal at Stirling Castle (Figure 20). The castle typifies ashlar masonry construction and experiences many of the defects most commonly encountered in natural stone by surveyors, such as erosion and discolouration due to salts or moisture. The chapel is a Category A listed building and a scheduled ancient monument.

Several laser scans were taken at approximately 10m from the wall (Figure 21a), and a set of photographs taken to produce a 3D point cloud of the scene through structure-from-motion photogrammetric techniques. Both point clouds, obtained from TLS and PG, were registered in the same coordinate system. Subsequently, colour information in the TLS cloud was automatically replaced with RGB data from the photogrammetric cloud (Figure 21b), because colour from digital single-lens-reflex cameras is of higher quality than that captured by the TLS device. Finally, the ashlar stone segmentation algorithm presented in Section 3.2, was applied to detect all units of the main wall plain (Figure 21c).

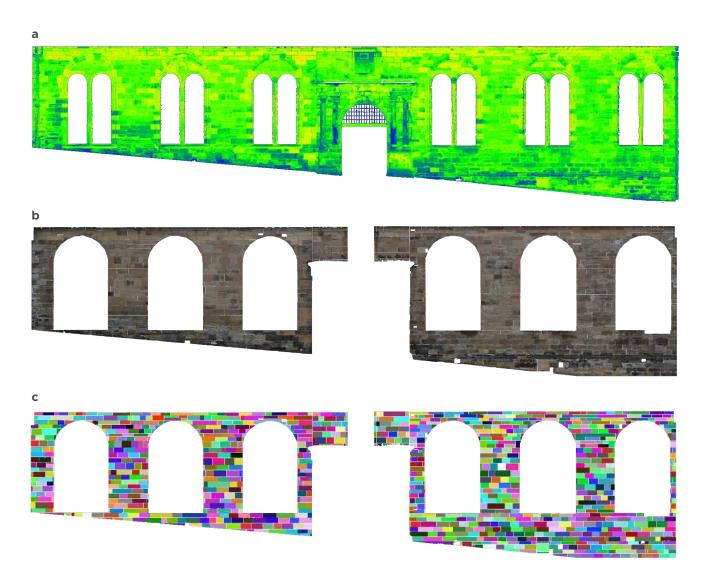
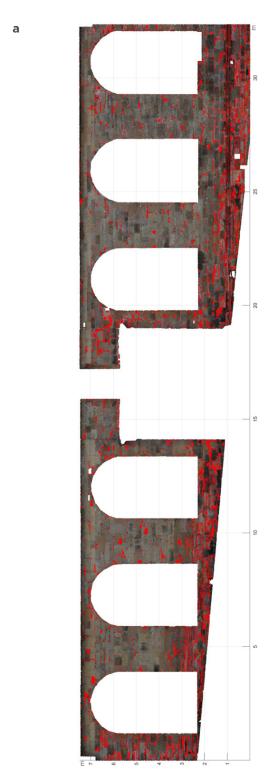


Figure 21: a) Point cloud obtained from terrestrial laser scanning; b) Point cloud coloured with photogrammetry RGB values; c) Segmented ashlar point cloud.

The developed ML model was then applied with detection outputs shown in Figure 22. As can be appreciated in Figure 22a, the bottom part of the façade is potentially more affected by geometric defect manifestations. Overall, the model detected 3,383 geometric defect manifestations covering 763 ashlar units.

In Figure 22b, darker regions in ashlar units are plotted in red, whereas lighter areas are highlighted in pink. Although ashlar units from the top part of the façade seem to be less affected by chromatic alterations, there is not a region on the wall particularly altered by this kind of defect. Overall, the model detected 3,621 areas affected by chromatic discolouration covering 672 ashlar units.



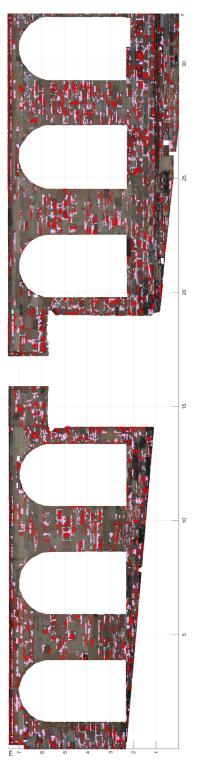


Figure 22: a) Potential defective areas associated to geometry-related decay; b) areas with high variation of colour.

# 5 MASONRY SURVEYING AND MAINTENANCE: **FUTURE PRACTICE**

The work reported above provides initial results demonstrating the combined potential of remote sensing technologies and powerful modern data processing methods, including machine learning. Much work remains to improve the robustness of those methods and validate them fully for use in practice. Nonetheless, their potential is recognised and it is important to reflect that these represent a small selection of the areas in which digitalisation is going to transform masonry surveying and maintenance. In the following, we discuss two other areas of current active research which will further reinforce the value of digital technologies for masonry surveying and maintenance applications.

The work presented in this report focuses on the application of TLS and PG, but there are other remote sensing technologies that could and can be used to further support masonry surveying and maintenance. Solla et al integrate PG, TLS, ground-penetrating radar (GPR) and infrared thermography to survey the masonry of the Monastery of Batalha in Leiria, Portugal, and detect pathology and analyse them in a more detailed and holistic way (Solla et al, 2020). Sciuto et al show how hyper/multispectral imaging can be used to support material characterisations in masonry structures (e.g. clusters of minerals in sandstone) (Scutio et al, 2019). It is noteworthy that their results suggest the data could also be used for masonry segmentation. Beside these ground-based or airborne remote sensing solutions, satellite-based remote sensing may also be of value to the surveying and monitoring of masonry and their surroundings. For example, both De Canio et al (2013) and Cavalagli et al (2019) explore the use of Interferometric Synthetic Aperture Radar (InSAR) to monitor the deformation of historic buildings and assess the correlation between the satellite data and structural monitoring data acquired in situ. The case studies of both works are historic masonry structures in Italy: the cathedral of Orvieto (De Canio et al, 2013) and the Consoli Palace and Town Walls of Gubbio (Cavalagli et al, 2019).

Whilst only briefly covered in this report, it is becoming increasingly beneficial to integrate the previously outlined techniques with information management technologies such as BIMs and increasingly progressive Linked Data (Sicilia et al, 2013). Indeed, remote sensing data (TLS and PG data in particular) can be used to generate BIMs of heritage buildings through a process commonly referred to as 'Scan-to-BIM' (L. Yang et al, 2020) or in the heritage context as 'Scan-to-HBIM' (X. Tang et al, 2020). While this remains a challenging task, some prominent examples include the work conducted by HES with the Edinburgh Castle project (Glasgow Caledonian University, 2017; Scottish Futures Trust, 2017). Currently, these models simply contain the structural components and fenestration of the building with limited additional information, e.g. about surveying and maintenance. The proposed data acquisition and processing techniques would enable further enrichment of these models with architectural detail (individual stones) and defects detected in consecutive survey scans. Using existing or new domain-specific ontologies, e.g. see the defect ontology proposed in Park et al (2013), and linking them semantically to BIM through IfcOWL (Pauwels and Tarkaj, 2016), semantically coherent linked data models would be generated where information is recorded in a unified, coherent way. This would enable surveyors to far more easily compare the outcomes of surveys conducted at intervals of multiple years. Besides, beyond local applications, the information could also be aggregated at regional and national level to enhance our understanding of stone decay and enable greater objectivity, data driven strategic decision making to occur regarding the financing and organisation of masonry maintenance.

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# 6 CONCLUSIONS

Current practice for masonry façade survey has been shown to be repetitive, costly and time consuming, requiring much meticulous and often tedious manual work that has been shown to be potentially subjective in reporting. Typically, this requires the generation of measured dimensional survey drawings (i.e. elevations), conducting visual surveys from ground level, and recording the information manually on those diagrams. Reports are then generated that, as a support, lack semantic connectivity and therefore are not effective for information retrieval. Compounding these issues are significant inherently practical challenges associated with visual surveys, such as an inability to gain safe access for inspection to occur, which limit the completeness of information collected. In addition, of fundamental importance is cost of access provision (e.g. scaffolding solutions) that significantly increase the cost of survey. The use of progressive digital reality capture technologies offer great potential for attaining survey data that is accurate, more complete, and is safer than classical visual survey methods.

HES, the University of Edinburgh and Heriot-Watt University have engaged in a continuous research effort to investigate how the use of digital documentation technologies, like TLS and photogrammetry, can help formalise and expedite some of the work above. The team investigated the development of new algorithms for the segmentation of masonry walls in individual units, showing good performance on real case studies. An exploration into whether machine learning techniques (the growth of which is currently exponential) could successfully detect common defects in such data was subsequently undertaken.

Both of these primary areas of fundamental research have shown encouraging results. Indeed, the automated masonry stone segmentation has been particularly successful and development and rollout of a free plugin tool in CloudCompare has been associated with considerable interest from industry practitioners and wider stakeholders. This plugin application is maintained by the academic partners and currently only supports the algorithm for segmentation of rubble masonry. It is however envisaged that this will be extended to include the ashlar segmentation algorithms in the future.

Whilst great advances have been noted, much further work is required before such technologies can be deployed widely in masonry surveying practice. The performance of stone segmentation can be further improved by investigating new and potential combinations of various data processing techniques. Machine learning based defect detection will require significant additional work, not the least to create ground truth datasets that are large and diverse enough to ensure the developed models can be trained effectively. Whilst therefore some way off in large-scale industry use, the potential benefits are significant for what are considered costly and time consuming activities. Finally, the integration with BIMs (more specifically Asset Information Models), and more generally with ontologies and linked data solutions, needs to be investigated so that a broader range of benefits can be realised.

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