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Advances in digital pottery analysis

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Abstract: Rapid progress in digitisation and computer techniques have enabled noteworthy new pottery analysis applications in recent decades. We focus on analytical techniques directed specifically at archaeological pottery research in this survey and review the specific benefits these have brought in the field. We consider techniques based on heterogeneous sources such as drawings, photographs, 3D scans and CT volume data. The various approaches and methods are structured according to the main steps in pottery processing in archaeology: documentation, classification and retrieval. Within these categories we review the most relevant papers and identify their advantages and limitations. We evaluate both freely and commercially available analysis tools and databases. Finally, we discuss open problems and future challenges in the field of pottery analysis.

Keywords: archaeological pottery research, computing humanities, data management and retrieval, image manipulation, science history

ACM CCS: Applied computing → Arts and humanities → Fine arts, Computing methodologies, General and reference → Document types → Surveys and overviews

1 Introduction

Pottery analysis in archaeology addresses many topics ranging from the resources of the potter's clay, the forming of pottery, the vessel shapes and painting styles – including their development over time – to its use, trade, discard and reuse [1]. Pottery is a source of insights into people and cultures of our past, providing information about their religion, economy, society, and daily life. Studying pottery is a painstaking occupation. On the one hand pottery is preserved in huge masses on almost all find spots around the world, and to make matters worse, mostly broken in small and worn-off fragments (sherds). On the other hand, each sherd holds a set of intrinsic properties which first have to be unveiled by a meticulous investigation. During this process, the sherds are catalogued and classified based on an adequate documentation and a methodological concept to identify meaningful structures and finally to establish a historical context [2]. Computational application have been available to support this pottery processing for quite some time, especially for building databases and statistical analysis.

In this survey we are focusing on computational applications which specifically benefit pottery analysis in its three main categories, displaying the archaeological pottery processing: documentation, classification and retrieval (Fig. 1). We are aware that by limiting our survey to pottery analysis, we are excluding essential research on cultural heritage objects made from other materials such as stone (e. g. marble), glass or even ceramics, if they are not pottery in the proper sense (e. g. cuneiform tablets). But in contrast to almost all other archaeological finds, pottery has one common geometrical property: the vessel shape corresponds approximately to a rotational body due to the manufacturing method on a potter's wheel. A property which is still inherent in small broken parts (sherds) and was recognised relatively early in computer science as essential for many computational applications. The common property of rotational symmetry, as it is also assumed in archaeological research for prehistoric pottery which was thrown either on simple rotating devices or by some other rotating movement during the forming process, is of course, an idealised concept of these hand-crafted objects. Handles or other attachments can be added to the vessel but the basic body of assumed rotational symmetry is nevertheless still preserved.

The intention of this survey is to structure previous studies (papers) and to review the most relevant publications in these three main categories of digital pottery analysis. The last survey comprising the entire area of computer applications in archaeological pottery was written by *Martínez-Carrillo 2011* [3]. A review of computer applications related to classification and reconstruction are given

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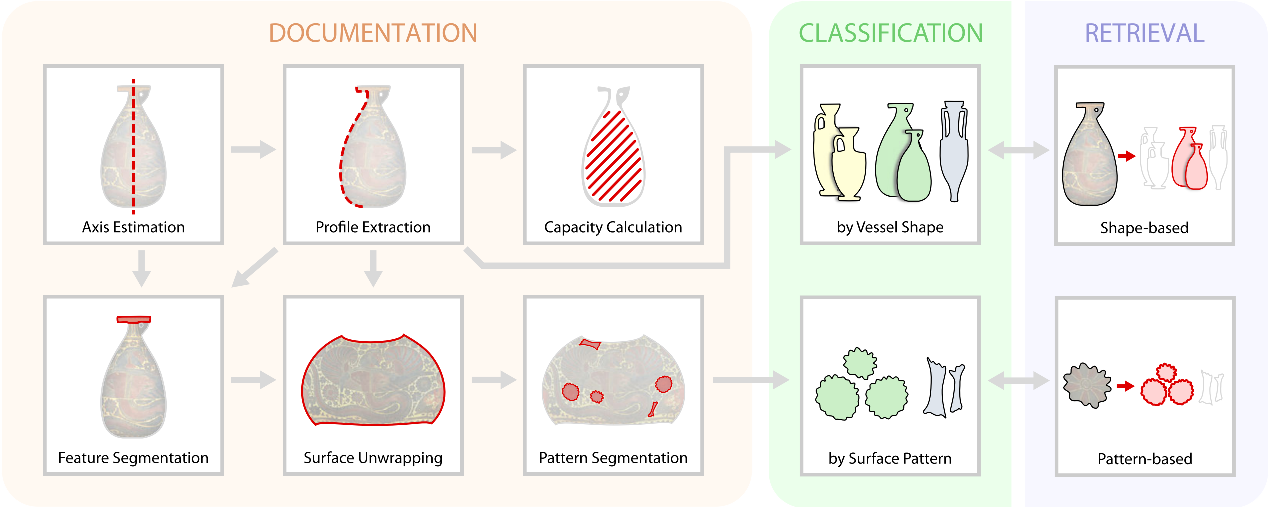


Figure 1: Overview of the typical workflows and major tasks of digital pottery processing covered in this survey. First processing steps based on input 3D data typically cover the extraction of geometric measures and descriptors such as the main axis of rotation, curvature profile and features. An unwrapping of the surface can be additionally the basis for the segmentation of patterns in image space. Both the vessel shapes and their surface patterns represent the main features used for classification and retrieval of the vessels.

by *Rasheed and Nordin 2015* [4], who are primarily focusing on the aspect of fragment matching. The seminal paper *Pintus et al. 2016* [5] presents a general review of geometric analysis in the entire sector of cultural heritage. Although recent surveys exist for the field of pottery analysis, undertaken by *Eslami et al. 2020* [6] and *Di Angelo et al. 2021* [7], these all treated the topic with a focus on sherd reconstruction (fragment matching). Here we focus primarily on the use and utilisation within the practise of archaeology pottery analysis using a taxonomy from the archaeological workflow of pottery processing [8].

This paper is organised as follows: Section 2 outlines the scope of the survey, how we delimited the area, collected the papers and how we structured the data. Section 3 recalls the early works in this field where the foundation of digital pottery analysis has been laid out. Section 4 gives a review about those papers which are most relevant in the specific categories of digital pottery analysis, thereby identifying advantages and limitations. Section 5 discusses available tools and databases for pottery analysis. Section 6 provides some open problems and future challenges which is followed by concluding remarks based on the archaeological practicing perspective of pottery research.

2 Scope

We are looking particularly at automated or at least semi-automated methods, which are based either on images or on 3D data. By focusing on this computerised analysis, we do not consider equally important works in this field, such as the research in improved data acquisition, rendering, filtering or enhancement techniques or the usage of statistical analysis based solely on manually measured intrinsic properties or on other metadata. Additionally, we exclude all applications for fragment matching, which belong rather to the field of conservation and restoration or cultural heritage preservation, and on smaller very specific categories, like manufacturing techniques or pottery fabrics.

The survey ranges from 1997 to the end of 2021. This period is systematically investigated. Earlier work before 1997 is discussed in a separate section (Sec. 3). We have taken the year 1997 as our upper limit for the following reason: To the best of our knowledge the automatic estimation of the rotation axis was proposed for the first time in 1997 [20, 21], which was a fundamental step that formed the basis for many algorithms in the years to follow.

For the collection and selection of relevant publications, we have systematically checked conference proceedings from the field from 1997 onwards, e. g. the Conference on Computer Applications and Quantitative Methods in Archaeology (CAA), the International Symposium on Virtual Reality, Archaeology and Cultural Heritage (VAST), and the Eurographics Workshop on Graphics and Cultural Heritage (EG-GCH). The same process has been followed for journals and this led to the inspection of journals including the following Journal of Computer Applications in Archaeology (JCAA), Journal of Archaeological Science

(JASc), Journal of Archaeological Science Reports (JASc Rep.), Journal of Cultural Heritage (JCH), and the Journal on Computing and Cultural Heritage (JOCCH). Additional references were found by recursively following citations in selected papers. Although we tried our best to collect systematically any published paper to our scope, we are aware that a completeness could hardly be achieved.

Our survey on computational applications in pottery research is structured according to the main steps of pottery processing which are established in archaeology for years: recording (single object), ordering (many to many) and searching for similarities (one to many). This taxonomy is derived from common archaeological practice [2]. In the course of a first overview of the selected papers single tasks could be identified. These tasks could be clearly attributed to one of these three steps in pottery analysis which we translate to terms which are more common in computer sciences:

- Documentation / by recording
- Classification / by ordering
- Retrieval / by searching for similarities

Figure 1 presents an overview of our structure according to a typical workflow in pottery analysis showing the major tasks in relation to their categories.

3 Early works

Computing in archaeology started on a regular basis in the 1970s, the first CAA was held in 1973. At the University of Keele (UK), Wilcock's PLUTARCH (Program Library Useful to Archaeologists) system is a milestone in the field of computing archaeology which considers already remote devices. Wilcock underlined that by practicing computed archaeology "visual presentation is extremely important, and all facilities are designed with the end-product in mind: a hard-copy diagram in publishable form" [9]. Today, we are going for digital figures too and we have other storing devices at our disposal than punched cards, magnetic tapes etc., but we should stick to the whole philosophy. Wilcock also addressed the interlinkage of the "facilities for information retrieval, statistics and graphics" [9].

In a manner comparable to that of archaeological field work without any technical equipment, the early works of computed archaeology emphasised the documentation of pottery and at first especially the profile line. In the PLUTARCH project Wilcock and Shennan transformed the profile line of a vessel in machine readable codes, by using two methods, slicing or the more complete mosaic method, to proceed with statistical operations [10].

Pioneering in this field was the SAMOS (Statistical Analysis of Mathematical Object Structure) project and the work done by the Germans Clemens and Cornelius Steckner in the late 1980s [11, 12]. A digitised drawing is computed into a virtual whole shape, from which all measurements are taken automatically, also including the calculated empty weight and capacity of pottery objects. Comparable to Wilcock and Shennan they aimed at an automatic classification.

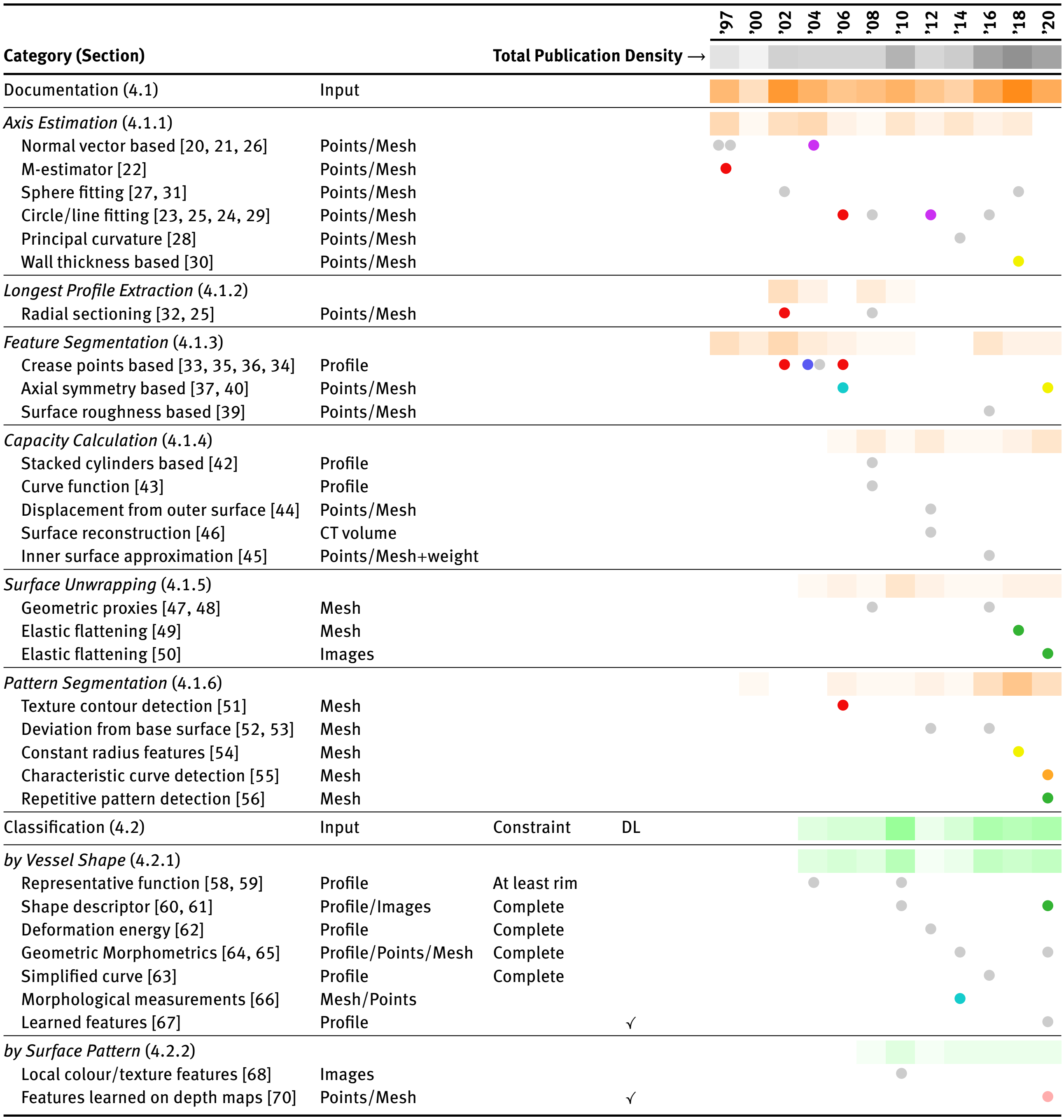
The main goal of the GOAD (Graphically Oriented Archaeological Database) project, a collaboration between university and business, was a graphical database which was more than a simple storage capacity and should provide answers to archaeological questions [13]. Hence, it addressed explicitly two issues, the automatic extraction of explicit shape information from raster images of line drawings and techniques for representing shape for effective shape retrieval and classification. The second of these built on the first. The strong emphasis on the shape made the use of a graphical user interface necessary providing a zoom option and measuring tools. The minimal computing power in the early days was a drastic limitation on performance. Nevertheless, the use of the pattern matching algorithm known as generalised Hough transform (GHT) to compare the improved drawings was a big step forward, even when only incomplete shape information is available. The calculation and the ranking of the similarity value is a basic requirement for computational classification.

At the University of Southampton, Durham and Lewis from the computer sciences, and Shennan from archaeology, proposed another system in the mid-1990s: SMART (System for Matching ARTefacts) [14].

Like GOAD it uses the GHT, which was tested for classification in comparison to normalised central (NC) moments used with k-nearest neighbours. It results that the latter is slightly less successful concerning the classification results as well as the computing time. They also applied a neural net for the same task at a very early stage, although with even less success.

The development of stereo and structured light as acquisition methods of 3D surfaces of archaeological finds, presented by *Sablatnig and Menard 1992* [15], has paved a way to numerous applications. At first, based on the rotational symmetric of pottery objects, *Halíř and Menard 1996* [16] proposed a method for an estimation of the diameter, by which the sherd is manually oriented in the measurement area illuminated by a laser plane and the diameter is acquired knowing the orientation parameters of the sherd,

Table 1: Overview of the corpus of work examined in this survey. We structure the selected work into categories, tasks and method class. Coloured dots on the right illustrate the first-author affiliation and the publication of the selected work (in 2-year bins). Colour bars at category headers illustrate the total amount of publications in our supplemental list addressing the respective category per time bin.



Category (Section)		Total Publication Density →		'97	'00	'02	'04	'06	'08	'10	'12	'14	'16	'18	'20
Documentation (4.1)	Input														
Axis Estimation (4.1.1)															
Normal vector based [20, 21, 26]	Points/Mesh			●●			●								
M-estimator [22]	Points/Mesh			●											
Sphere fitting [27, 31]	Points/Mesh					●								●	
Circle/line fitting [23, 25, 24, 29]	Points/Mesh							●	●		●		●		
Principal curvature [28]	Points/Mesh											●			
Wall thickness based [30]	Points/Mesh													●	
Longest Profile Extraction (4.1.2)															
Radial sectioning [32, 25]	Points/Mesh					●			●						
Feature Segmentation (4.1.3)															
Crease points based [33, 35, 36, 34]	Profile					●	●●	●							
Axial symmetry based [37, 40]	Points/Mesh							●							●
Surface roughness based [39]	Points/Mesh												●		
Capacity Calculation (4.1.4)															
Stacked cylinders based [42]	Profile								●						
Curve function [43]	Profile								●						
Displacement from outer surface [44]	Points/Mesh										●				
Surface reconstruction [46]	CT volume										●				
Inner surface approximation [45]	Points/Mesh+weight												●		
Surface Unwrapping (4.1.5)															
Geometric proxies [47, 48]	Mesh								●				●		
Elastic flattening [49]	Mesh													●	
Elastic flattening [50]	Images														●
Pattern Segmentation (4.1.6)															
Texture contour detection [51]	Mesh							●							
Deviation from base surface [52, 53]	Mesh										●		●		
Constant radius features [54]	Mesh													●	
Characteristic curve detection [55]	Mesh														●
Repetitive pattern detection [56]	Mesh														●
Classification (4.2)	Input	Constraint	DL												
by Vessel Shape (4.2.1)															
Representative function [58, 59]	Profile	At least rim					●			●					
Shape descriptor [60, 61]	Profile/Images	Complete								●					●
Deformation energy [62]	Profile	Complete									●				
Geometric Morphometrics [64, 65]	Profile/Points/Mesh	Complete										●			●
Simplified curve [63]	Profile	Complete											●		
Morphological measurements [66]	Mesh/Points											●			
Learned features [67]	Profile		√												●
by Surface Pattern (4.2.2)															
Local colour/texture features [68]	Images									●					
Features learned on depth maps [70]	Points/Mesh		√												●

camera and laser. *Halíř and Flusser 1997* [17] extended this approach. They now used the rule that intersections of a plane perpendicular to the axis with the surface of a sherd are constantly circular arcs in each position along the axis. The correctness of a manually oriented sherd is evaluated by multiple intersecting the object in parallel planes and projecting all intersections into a plane. In case of correct orientation these intersections form a bundle of concentric circular arcs; if not, the orientation of the sherd is again manually improved and the intersections updated. This was repeated until a correct orientation was achieved. Finally, this iterative approach paved the way to an automatic orientation of pottery fragments.

Table 1 (continued)

Category (Section)		**Total Publication Density →**		'97	'00	'02	'04	'06	'08	'10	'12	'14	'16	'18	'20
Retrieval (4.3)	Input	Preservation	DL												
Shape-based (4.3.1)															
Profile drawing [62, 73, 74]	Profile	Complete									●●				●
Profile drawing [75]	Profile	Sherd										●			
Photographs [76]	Images	Complete							●						
Photographs [77]	Images	Complete	√												●
Photographs [78]	Images	Sherd	√										●		
3D model [37, 79, 80, 81]	Points/Mesh	Complete						●		●●			●		
Benchmark [82]	Points/Mesh	Complete	√												●
3D model [34, 83, 84, 85, 86]	Points/Mesh	Sherd						●				●	●	●	●
Pattern-based (4.3.2)															
Texture [69, 94]	Images									●	●				
Texture [97]	Images		√												●
Texture [87, 88, 89, 56]	Points/Mesh													●●	●●
Relief [95]	Images		√										●		
Relief [93, 53, 87, 89]	Points/Mesh									●			●	●	●
Relief [96]	Points/Mesh		√											●	
Benchmark [91, 92, 90]	Points/Mesh		√										●	●	●

● Vienna, PRIP; ● Genova, IMATI – CNR; ● L'Aquila, DIIIE; ● Graz, CGV; ● Xanthi, ATHENA; ● Chemnitz, Computer Science; ● Xanthi, Dept. Electrical and Computer Engineering; ● Rehovot, Weizmann Institute of Science; ● Providence, Division of Engineering; ● Pisa, MAPPA Lab; ● Haifa, Technion; ● Columbia, CEC; ● Orleans, PRISME; ● Other; Histogram maxima: ■■■ 18 ■ 43

The automated procedure versus manual drawings was evaluated by *Poblome et al. 1997* [18] in course of pottery recording campaigns at Sagalassos / Ağlasun in Turkey. They showed that the automated procedure measured the sherds more accurately and consistently, allowing a better definition of types and variants. They concluded that the recording procedure is very appropriate for statistical typological research.

4 Main categories in digital pottery analysis

4.1 Documentation

Any pottery analysis starts with a throughout documentation of a given object, both descriptive and graphical [8]. This includes the object as a whole as well as significant attributes of the object itself like relief or painted patterns. The choice of the most suitable method is generally defined in reference to the respective research question to be tackled. For comparability of objects relative to each other, however, a consistent and normalised documentation is an indispensable prerequisite. Compared to the usually applied procedures in archaeology by means of manual drawings or photography, computer-aided methods can provide a more objective documentation, in particular since they are traceable and reproducible.

4.1.1 Estimation of the rotation axis

Archaeological pottery finds are typically documented using profile drawings that show a cross-section of the sherd or the complete vessel representing not only the external but also the internal contour. Such profile based shape representations as planar curves is an important criterion for identifying the type and hence the age, function and origin of the pottery. Manual drawings are subjective and error-prone. The correct orientation of a sherd, i. e. the estimation of the axis, and the measurement of its diameter, depend strongly on personal skills and professional experience. In most cases the sherds have small dimensions which further reduce the manual measurement accuracy. Prompted by low-cost 3D scanning methods several efforts have been undertaken to develop automatic computer-based methods to estimate the axis of rotation for broken pottery objects, which is the basis for a correct sherd orientation and size estimation. Previous solutions for this task can be roughly classified into two categories, which are exploiting a specific property of radially symmetric objects. The first category exploits the assumption that normal vectors at any surface point (internal or external or both) pass approximately through the axis of rotation (normal intersection method or Pottmann et al.'s method [19]). The second category makes use of another constraint: parallel planes orthogonal to the rotation axis and intersecting a fragment form circles whose centres lie on this axis (circle-and-line fitting method) [30].

The first papers on automatic axis estimation date back to the year 1997. They used the per-vertex normal information stored in meshes to estimate the rotation axis of the object. For the position of the rotation axis *Ben Yacoub and Menhard 1997* [20] proposed an approach based on the Hough transform, whereas *Halíř 1997* [21] used a numerical optimisation. *Halíř 1999* [22] extended this approach by using a M-estimator method and an iterative refinement on the circle-and-line fitting method, thus creating a hybrid approach. Inspired by the manual method of archaeologists, *Mara 2006* [23] introduced an approach that uses circle templates for the estimation of the axis (*circle-and-line fitting method*), without the evaluation of the differential geometrical properties. *Son et al. 2013* [24] extended this approach by incorporating RANSAC for circle fitting and final axis estimation. *Karasik and Smilansky 2008* [25] proposed a semi-automatic procedure, first establishing a pre-orientation by three user-selected points and then applying the iterative circle-and-line fitting method following Mara's approach [23]. For the final tuning they introduced another iterative procedure based on the convergence of the projected vertical profiles (*rim-tangent method*).

Willis et al. 2003 [26] chose the normal intersection method to estimate an axis/profile curve pair for a sherd by finding the axially symmetric algebraic surface that best fits the surface and associated normals. Another method presented by *Cao and Mumford 2002* [27] is based on the principle that maximal spheres with tangents to the surface have centres on the symmetric axis. The centres of these spheres are determined by the curvature radius of the surface that is tangent to each of the point/normal pairs. The axis and the profile curve is estimated by a weighted iterative least-squares framework.

A method considering multi-scale and principal curvatures constraints was proposed by *Han and Hahn 2014* [28]. Another method for finding the axis was taken by *Sipiran 2017* [29] who clustered the centres of a set of circles inscribed to the given 3D surface points to determine the dominant axis. *Di Angelo and Di Stefano 2018* [30] proposed the so-called *thickness versor intersection method*, which is based on the principle that the minimum path of a point on the external wall to the internal wall of a pottery object is on a straight line passing through the axis. Noticeable is the evaluation of the trueness of the proposed method on archaeological sherds using the radial runout of the sherd's surface corresponding to the estimated axis, which shows promising results. The most recent method by *Hong et al. 2019* [31] extended the Cao and Mumford's method. A two-stage axis estimator *PotSAC* was introduced, which is based on a variant of the RANSAC algorithm followed by a robust nonlinear least-squares refinement. The high accuracy of this approach as stated by the authors was measured by applying bootstrapping. The technique was demonstrated on a broken pot from the 15th century which was successfully reassembled based on the estimated axis.

4.1.2 Extraction of the longest profile

Having an estimated axis, the next step is to generate a vessel profile, which goes beyond a simple sectioning of the 3D model by a plane through the rotational axis. In pottery studies a profile drawing includes the maximum of preserved information of the profile. Sherds are mostly transversely broken, so that a radial section is insufficient and multiple vertical sections are needed. A solution was proposed by *Kampel and Sablatnig 2003* [32] by projecting the longest profile from several radial sections. *Karasik and Smilansky 2008* [25] finally introduced the concept of the "mean profile", which uses the entire information and excludes local non-representative deformations. This is obtained by minimising the mean width of the projected profiles on the plane containing the axis.

4.1.3 Segmentation of morphological features

In pottery studies, the vessel shape is divided into single elements or "primitives" following an anatomical structure, such as mouth (rim), neck, shoulder, body or foot (base). Such elements can also be identified in broken parts. Terms like rim, base or wall piece characterise also the specific type of preservation conditions of a broken pottery object. In addition to the primitives, other features can be detected, such as the internal or external and the fractured surfaces or "facets". These semantic morphological features (primitives and facets) provide valuable information for subsequent classification and retrieval procedures, but also for fragment matching. However, an automatic recognition of these features from 3D geometric data is not trivial.

The first attempt towards automatically segmenting a profile into its primitives was started by *Mara et al. 2002* [33] using points with local changes in the curvature of the external profile line. The basic idea is to store its shape characteristics in a description of the profile to raise the level of abstraction of 3D data, which facilitates further evaluation as stated by *Kampel and Sablatnig 2007* [34]. Almost at the same time in the early 2000s a similar approach was undertaken by a project at the Arizona State University aiming to investigate vessel uniformity and proportionality as indicators of the development of craft specialisation and complex social organisation in prehistoric times [35]. Based on planar vessel profile curves, *Saragusti et al. 2005* [36] demonstrated the application of closed-curve representations for the quantitative analyses of various shape properties like symmetry and deformation. *Hörr et al. 2007* [37] presented a two-step procedure within this shape analysis approach with the aim of establishing hierarchical classification based on extracted intrinsic features of 3D scanned vessels: first, a segmentation of attached elements like handles and of the body in its primitives, and second, feature extraction by global measures. A complete list of extracted discrete features was given by *Hörr 2011* [38]. This system is strongly designed to the requirements of pottery archaeologists.

The identification of a sherd facet that is fractured and one that is intact can be solved either using the axial symmetry of the vessel or purely on the geometrical properties of roughness of the fracture facets. *ElNaghy and Dorst 2017* [39] took the latter approach. They estimated the local surface properties by applying weighted eigenanalysis of local neighbourhoods. In the course of the GRAVITATE project, which focuses on terracotta fragments having normally larger fracture surfaces than pottery objects the authors demonstrated a complete pipeline for faceting archaeological fragments, also including some pottery fragments. In contrast, *Di Angelo et al. 2020* [40] made use of the property that a pottery fragment is bounded by an axially symmetric surface, which is only true for the internal or external wall, the rest belongs either to fractured surfaces (also chips) or to attached elements (e. g. handles). Additionally, their segmentation includes the recognition of the primitives. This proposed symmetry-based method fails for worn-off surfaces (negative) and encrustations (positive) due to chemical and mechanical processes.

4.1.4 Calculation of vessel capacity

The detection of standardisation for vessel sizes with specific capacities improves our understanding of the ancient production management, the distribution and consumption of pottery and the underlying economic organisation.

The vessel capacity is traditionally estimated by direct measurements. A method requiring either unbroken or fully restored vessels. In this case the vessel is filled with liquid, sand or rice, which are then measured using a graded beaker. But this procedure has risks for the conservation of the object on the one hand, while on the other it can often lead to inaccurate measurements.

For this reason, several computer-assisted methods have been developed to calculate vessel capacity, which can be roughly classified in three groups. The first group consists of methods which are based on a division of the capacity space from the vessel's base to its rim in geometric figures using a 2D vessel profile. These are either stacked cylinders or stacked truncated cones which are in turn measured and each dimension of each figure is calculated and then added together. This mathematical procedure, which has a long-standing history in pottery research [41], requires no direct access to the vessel and the application also works on partly broken objects if a complete profile is preserved or can be restored. The correct result depends on an accurate scaled and recorded profile drawing. A freely accessible online application, developed by Engels, Ereck and Warzé from the CReA-Patrimoine of Bruxelles in the late 2000s and published by *Engels et al. 2009* [42], contains additionally an algorithm for detecting the revolution axes within the uploaded profile drawings, separating and identifying the inside profile automatically. By this means the capacity is mathematically determined, whereas the filling level can be interactively modified.

The second group of methods also use 2D contour lines of the vessel profile. Thereby, as it was proposed by *Karasik and Smilansky 2006* [43], that the capacity is reconstructed and estimated using a curve function by revolving the interior profile contour around the axis.

Calculations based on 3D models of pottery objects belong to the last group. Due to the handmade crafted vessels having only approximately followed a rotational body, 3D scans provide an accurate recording of the surfaces in spatial terms and thus achieve the best possible result. Whereas for open vessels, like cups, bowls etc., the determination of the capacity was achieved by simple volume calculation of a phantom capacity body, the closed vessels, i. e. vessels with a narrow mouth, like amphorae, lekythoi, aryballoi, etc., need other approaches to address the problem that the internal surfaces cannot be determined by 3D scan technologies. *Mara and Portl 2013* [44] proposed a method for this by which the internal surfaces are estimated based on a rough estimation of the wall thickness. The external surface was virtually displaced in a negative direction into the interior of the vessel in accordance with the estimated thickness. Another method using the weight of the pottery additionally for estimating the ceramic volume was developed by *Spelitz 2017* [45]. This approach first determines an expected ceramic volume based on the weight and the ceramic material density of the pottery object in question. Then, in course of an iterative process the outer shape was shifted inwards aiming to minimise the difference between the expected and the achieved ceramic volume. Finally, the capacity was estimated based on the computationally generated internal surfaces. This method has some drawbacks however, because the weight of a pottery item can be influenced by several factors (material added in the course of restoration work, fracture of the vessel, humidity, etc.) and almost no reference data is available for ceramic material density in archaeological pottery research.

Finally, there is computed tomography (CT), which is the only recording method in the cultural heritage field to visualise interior (hidden) structures. The application on Greek pottery was described by *Karl et al. 2013* [46]. Based on CT volume data and surface reconstruction using a threshold value, this technique accurately captures the internal surfaces of closed (and completely preserved) vessels with all their irregularities. While radiation influences on scientific dating methods such as thermoluminescence are negligible on correct implementation [46], the main weaknesses of CT are high costs and the immobility of its devices; the objects have to be transported to a CT-Lab.

4.1.5 Unwrapping of paintings

In studies of painted pottery a task of great significance is the unwrapping, or unrolling, of the painted surfaces which in most cases cover the whole vessel. These unwrappings show the depictions without photographic distortions or sectioning by separate photos, enabling archaeologists to analyse and interpret the image as a whole in terms of style, dating and iconography. Rollouts are typically created manually using tracing paper, which is time-consuming, error-prone, and frequently not even permissible due to the induced wear caused by the required contact with the fragile surfaces. During the past decade in particular, computer-assisted methods have greatly enriched this archaeological task thanks to the improvements of high-quality texture acquisition methods.

Bechtold et al. 2010 [47] presented a method to create distortion-minimised rollouts from 3D-scanned triangle meshes by approximating the actual vessel shape with conical frustums and cylinders that each cover a vertical section of the vessel along the rotational axis. Each of these sections thus forms a body of revolution around the vessel's rotational axis. The resulting surface sections are developable, i. e., they can be flattened (mapped to a 2D plane) without introducing distortions in the process. The authors further showed that for certain vessel shapes, individual sections can use special projections. For example, Corinthian aryballoi feature an almost spherical body, thus a cartographic map projection yields less distortions when mapped to the plane, than the flattening of several approximating conical frusta [48]. One drawback is that due to using several sections for the rollouts, the flattened image is no longer a connected surface. Hence, the user has to find a trade-off between using more sections to achieve less distortions at the cost of more disconnected rolled-out bands on the one hand, and using less sections, yielding an almost connected 2D rollout, though potentially introducing more unwanted distortions on the other hand.

A different approach was taken by *Preiner et al. 2018* [49] who described a technique to flatten vessels given as 3D meshes, with the result that distortions are globally minimised, even in the presence of highly curved shape profiles. In contrast to the *proxy geometry* method [47], the resulting unrollings form one connected 2D surface. This is achieved by simulating a physically-based relaxation process of a damped mass-spring system defined on an initial simple (for example cylindrical) rollout, where the spring tensions correspond to the difference between the true edge lengths given by the scanned 3D model, and the edge lengths in the rollout. By allowing these spring tensions to relax over the course of several simulation iterations, the resulting flattened 2D representation of the vessel surface gradually reduces distortions introduced by the initial mapping of the 3D surface to the plane.

Houska et al. 2021 [50] observed that most vessels are documented in the form of small sets of photographs from different view directions only, so that none of the techniques that operate on 3D meshes are applicable for generating high-quality rollouts (Fig. 2). The authors showed how these photographs can serve the same purpose as 3D meshes for this specific application. By assuming rotational symmetry of the artefacts, the silhouette visible in the photographs encodes the geometric shape of the object with sufficient accuracy for the initial cylindrical image-based rollouts to be calculated for each image, while storing estimated surface distances for each pixel. The rollouts are then stitched to create a connected depiction of the entire painted surface. In a final step, the *elastic flattening* technique [49] is applied to the stitched image, where the spring tensions are derived from the estimated surface distance stored in each pixel, instead of requiring these distances to be read from a 3D input mesh.

(a) Corpus Vasorum Antiquorum (CVA) Photographs

(b) Complete Elastic Unrolling of Surface Motifs

Figure 2: Unwrapping of paintings. Generating high-quality rollouts based on a set of photographs captured from canonical views by computing a complete elastic unrolling of their painted surface area that minimises projective distortions. Courtesy of *Houska et al. 2021* [50], © 2021 The Authors. Eurographics Proceedings © 2021 The Eurographics Association. Reproduced by kind permission of the Eurographics Association.

4.1.6 Segmentation of surface patterns

Pottery is traditionally divided into coarse and fine pottery in archaeological research. Fine pottery includes mostly tableware or other representative pottery objects. The more expensive pottery tended to use a decoration, which can be broadly categorised as painted or relief decorated. Apart from the elaborate paintings as we can see in the black- or red-figured pottery of ancient Greece for example, the decoration consists mostly of geometric or other simple ornaments applied circumferentially on the vessel surface and, usually in a repetitive manner. These ornaments, painted, stamped, moulded or applied, have been executed since prehistoric times and are crucial in pottery studies, providing essential information e. g. for dating or locations of origin. For decades they were meticulously recorded by manual drawings or photography, catalogued and classified, filling several publications, e. g. for the painted ornaments of Greek pottery, the decoration of Hellenistic relief bowls, the moulded as well as stamped decoration of Roman terra sigillata and many more.

A pioneering attempt to assist this procedure of archaeologists by computational applications was approached by *Mara et al. 2007* [51]. They proposed a detection of the contours of painted patterns for subsequent segmentation. This edge detection using a convolution technique was applied on 3D surfaces, in this case on painted Nasca pottery of Peru.

Due to the insufficient quality of the texture acquisition by scanning technologies at this time, computational research in this task of pattern segmentation turned increasingly to the analysis of geometric data, e. g. of relief decoration.

Relief analysis and extraction were applied on relief pottery by *Gilboa et al. 2013* [52] which separated the feature from the (unknown) base surface by a base normal estimation and a height function calculation following threshold segmentation and filtering. In the ARCADIA project (Automatic Recognition of Ceramics Achieved by Digital Image Analysis) another method for recording the engraved friezes of stamped pottery was described by *Debroutelle et al. 2017* [53]. This uses a depth map of a projected 3D point cloud and creates a binary image of the pattern by employing a local variance operator for enhancement and a density-based spatial clustering for the segmentation. *Di Angelo et al. 2018* [54] identified a new geometric pattern on pottery surfaces which can be automatically recognised. These are linear patterns caused by either sweeping or engraving the surface using a tool with a rounded end or by finger pressure. This manufacturing process leaves traces with an almost constant radius. Due to irregularities of hand-made pottery the proper segmentation was performed using an algorithm based on the fuzzy concept of dissimilarity and by a fitting method. The demonstration of this methodology on the recognition of an embossed decoration of an ancient vessel is promising, opening various further applications in pottery research (e. g. for pottery with incised decoration).

A new method for recognising relief but also painted decoration was proposed by *Romanengo et al. 2020* [55]. This is based on the analysis of characteristic curves on textured 3D surfaces. They developed a two-stage method, which first identify the characteristic surface points on the surface, each corresponding to a potential characteristic curve (from a dictionary of curve families) and then uses a HT-based curve recognition algorithm for each cluster for finding the best match. This approach of approximating detected curves to known curves is remarkable. Based on this approach a further development could be the replacement of these synthetic curves with ancient ornaments already catalogued in pottery research.

Another method is to look at painted ornamental bands with repetitive patterns running horizontally around the vessel and thus following the same rotation symmetry as the vessel itself. Repetition and rotation symmetry provides two properties for supporting a computer-assisted detection and segmentation of such pattern characteristics. This was demonstrated by *Lengauer et al. 2020* [56] using a semi-automatic extraction tool based on a combination of user-defined queries and self-similarity detection.

4.2 Classification

The classification of artefacts has played an important role in archaeological research as a means of organising find material [57]. An organisation method of this kind is a first approach that makes it possible to deal with the sheer quantity of material remains recovered on excavations. In archaeology, a class is commonly understood as a generic term referring to a group of objects having the same or similar properties, which can be distinguished from other objects. A simple classification can be seen for example, in the division between coarse and fine pottery, a distinction that was first made in pottery processing. The forming of a typology is also based on similarity properties, but in contrast to a classification, this is done with the purpose of finally defining a "type" which can be taken as a representative for a specific group of similar objects. A "prototype-based classification" with pre-defined types as it is called by *Hörr et al. 2007* [37] is in our sense an attribution to an existing typology.

4.2.1 Classification by vessel shape

The classification of pottery according to the vessel shape contour or to numeric/nominal shape features (diameter, height, etc.) is a common manual task in archaeology. Computational applications for a classification based on profile drawings – which are omnipresent in pottery studies - has already been in use since the mid-1970s, e. g. in the PLUTARCH system and later within the SAMOS and GOAD project (Sec. 3).

The first attempt to apply mathematical curvature functions for describing the vessel shape was presented by *Gilboa et al. 2004* [58]. Their aim was to develop a computerised typology and classification for pottery. They used digitised profile drawings for this purpose. The degree of similarity between objects is quantified by measuring the distance between the curvature functions. Finally, a cluster analysis is applied for the grouping. The method was later extended by *Karasik and Smilansky 2011* [59], who added two further curvature functions for radius and tangent. The three representative functions are then finally averaged. In addition to cluster analysis, discriminant analysis is also introduced to reveal a hierarchical classification of pottery objects. The method was tested on a benchmark assemblage consisting of 358 fragments from the early Iron Age at Tel Dor resulting in c. 95 % correctly identified pieces. One drawback of this method, however, is that the curvature functions need a preserved rim of the vessel for normalisation (the rim maximum was used as reference point), which means this method cannot be applied for base or wall pieces.

The feature descriptor Shape context was used by *Van der Maaten et al. 2010* [60] for shape comparison. The pairwise (dis)similarities are visualised using a technique known as t-distributed stochastic neighbour embedding (t-SNE). This method was applied on 996 pottery profiles showing a meaningful distribution. Within the Linked Views Visual Exploration System (LVVES) proposed by *Lengauer et al. 2020* [61] a Shape contour descriptor was selected for establishing similarity relations, in this case based on the external contour of the vessel derived only from images (Fig. 3). *Martínez Carrillo et al. 2012* [62] pro-

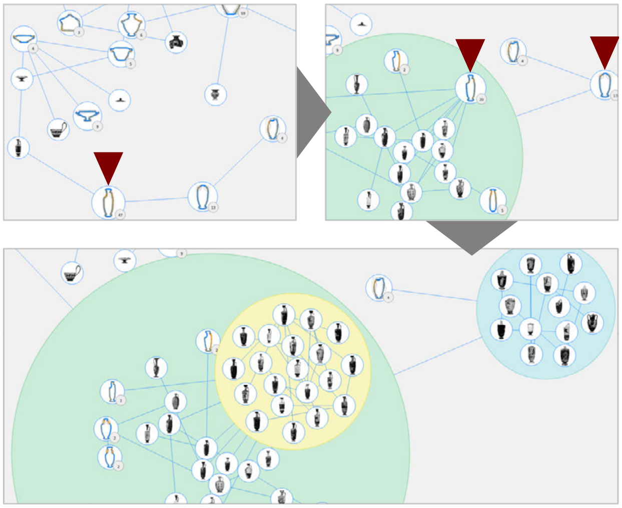


Figure 3: Classification by vessel shape. Clustering of similar vessel shapes based on photographs using a Shape contour descriptor. The balloon views show different levels of recursion depth. Courtesy of *Lengauer et al. 2020* [61], © 2020 The Authors. Eurographics Proceedings © 2020 The Eurographics Association. Reproduced by kind permission of the Eurographics Association.

posed a unique method. They designed a comparison technique on non-rigid deformation analysis. Similarity is expressed in deformation energy against a prototype. Another method was presented by *Lucena et al. 2017* [63] who used simplified curves and a five-segment polyline from the rim to the base. All these methods are restricted on completely preserved vessels.

Since the mid-2010s Landmark-based geometric morphometrics have been introduced into the field of pottery analysis. Due to the curvature of vessel shapes a morphometric outline approach is effective for assessing morphological variations. For the computation of shape variables *Wilczek et al. 2014* [64] used an elliptic Fourier analysis (EFA) for closed outlines (silhouette) and a discrete cosine transform (DCT) for open outlines (profiles). The method was proven on 154 vessels with completely preserved profiles from the Bibracte Gallic *oppidum* and attributed to 8 main shapes. After performing an unsupervised model-based clustering, the results show relatively good matching with the existing attribution performed by archaeologists. A recent practical application of geometric morphometrics and EFA was applied by *Wang and Marwick 2020* [65] on pottery from northeastern Taiwan, especially for comparing pottery shape standardisation and to detect European influence in local pottery production. Additionally, geometric morphometrics allow an average shape calculation, i. e. a representation of a type (and not of an individual), but this shape analysis, however, requires vessels with completely preserved or restored profiles.

Hörr et al. 2014 [66] proposed a three-step classification adapting a knowledge discovery process (KDP) model. During the first unsupervised phase numerous meaningful morphological features are detected which require a comprehensive inspection of the find material and archaeological expertise (Sec. 4.1.3). The second semi-supervised phase consists of the weight of the overall similarity function, the definition of prototypes based on the now available reasonable similarity metric and in a removal of highly correlated and irrelevant features. The supervised third phase employs a machine learning algorithm which is trained with the already labelled data and continuously improved during this phase. The entire classification process is strongly focused on the forming of a typology. A big advantage of this approach is the ability it has for handling missing data, i. e. broken parts etc. The method was successfully tested on 3D data of almost 600 vessels from the large cemetery of Kötitz in Eastern Saxony.

Machine learning (ML) techniques as such as Deep learning (DL) are becoming widespread in many different areas of contemporary life (and research). DL is a powerful tool for exploring large datasets and discovering new patterns. Groundbreaking in pottery classification is the research undertaken by the Department of Computer Sciences of the University of Jaén in Spain, which can look back to a long tradition in computer-assisted pottery analysis [3]. In a recently published work by *Navarro et al. 2021* [67] DL architectures without prior knowledge or engineered features were described which are able to classify profile drawings automatically. The authors proposed a residual neural network for automatic feature extraction and classification which has been trained with binary images of Iberian pottery. After training the network the resulting algorithm achieves a mean accuracy of 0.98 over a test set.

4.2.2 Classification by surface pattern

Classifying and forming typologies of painted or relief ornaments are common in pottery studies.

Automatic classification processes based on painted patterns are surprisingly rare, although there several attempts have been made in this direction since the turn of the millennium. Exceptional for this task is a work in Pennsylvania where several ten-thousands of thin-shell porcelain fragments with mostly multicoloured linear decoration from the late 18th/early 19th century were found during excavations. For the classification of these numerous sherds with highly visible textures *Smith et al. 2010* [68] proposed a method based on colour and texture characteristics. The texture similarity is estimated by producing a new image feature descriptor based on total variation geometry (TVG). This sherd descriptor vector achieves satisfactory results in the textured sherd classification.

Applications for classifying unordered material and forming a typology are indissolubly interlinked with retrieval tasks of searching for closest matches based on the vessel shape and/or surface decoration. The stronger the ML strategies that are involved, the more the boundaries between classification and retrieval disappear. A research group of the Laboratoire PRISME of the university of Orléans in France started quite early with a classification approach to order different design classes impressed on pottery sherds by a carved wooden wheel (from the medieval ages), with an imagery process derived from 3D scans. When they started using conventional descriptors based on Gabor filters and a bag of visual words in 2015, the results were modest. This changed radically on the inclusion of modern ML methods and by training Convolutional Neural Networks (CNN), with the result that classification accuracies of around 95 % are now achieved according to *Chetouani et al. 2020* [70].

4.3 Retrieval

Retrieval tasks are crucial to success in pottery analysis, when searching for similar artefacts in the vast quantities of published or otherwise available data generated by archaeologists over many years [71]. The task of retrieval deals with the access to information items, characterised by a *user information need* [72]. To identify the set, if items satisfying this information need, it first of all requires to be translated into what is known as a *query*, a well-defined digital description of the input for a search engine. In most cases this query is restricted to textual inputs which are relatively easy to process. However, over the past few decades *content-based* retrieval methods, in which the query is comprised of other data types, e. g. images, have received increased attention. With regard to archaeology, such approaches are a great support if the aim is to find similar objects to a given artifact which cannot be sufficiently well described with keywords. We differentiate roughly between retrieval based on shape (Sec. 4.3.1) and retrieval based on pattern (Sec. 4.3.2).

4.3.1 Shape-based retrieval

Two different aspects of a query exist in general. First, the modality which describes the data type of the input, e. g. profile drawings, images or 3D models. Second, how complete the input is. Some approaches require a whole vessel as a query since they leverage properties of the solid of revolution, while others are tailored to the retrieval from fragments, as they make use of characteristics of the fracture lines.

The first approaches targeted at the retrieval were based on the profile curves illustrated in scientific literature. *Martínez Carrillo et al. 2012* [62] presented the CATA project, an online pottery classification system. They employed a non-rigid deformation analysis for the comparison of vessels, which captures the deformation energy required to deform one profile curve into another. *Hristov et al. 2013* [73] worked along similar lines and determined similarities based on the vessel profiles extracted from archaeological drawings. The approach differentiates between inner and outer vessel profiles and defines their similarity measure with a combined correlation coefficient of both profiles. *Wilczek et al. 2021* [74] identified four alternative profile features which can be used for the comparison of the discretely sampled profile contour: (i) the root-mean-square distances between the registered points of source and target; (ii) a spectral representation of the contours; (iii) the point-wise distances from the rotation axis, together with the angle between the point tangent and the rotation axis as well as the rate of change of this angle; and (iv) the approximation of the contour with a few polyline segments.

While these approaches are only applicable if the profile curve is given for a whole solid of revolution, *Piccoli et al. 2015* [75] looked explicitly into the case of a query being comprised merely of a single fragment. They employed local features – numeric descriptions of significant areas – in contrast to the previously mentioned global approaches.

In the CLAROS (Classical Art Research Online Services) project initiated by the University of Oxford, presented by *Kurtz et al. 2009* [76], it was planned to build up a large international research database for Greek pottery, similar to the well-known Beazley Archive. The proposed system also supports searching in their large corpus with an image as a query. Their retrieval is based on a comparison of the parametrised profile curves, which they extract from the images by a foreground separation and discarding any non-object information, a symmetry axis detection and lastly the sampling of the object contour. *Núñez Jareño et al. 2021* [77] tackled the problem of pottery classification from images with a DL approach. Even though DL represents the state-of-the-art in image classification it can frequently not be applied, as it requires a vast amount of labelled training data. The authors circumvented this limitation by generating the necessary data synthetically. To do this, they generated several thousand images, based on the profile curves published in *P. Webster, Roman Samian Pottery in Britain, Practical handbooks 13, Council for British Archaeology, London, 1996* with a *shape-from-profile* technique and also 3D rendering tools.

Banterle et al. 2017 [78] followed a similar path in the ArchAIDE project as they also made use of similarly generated synthetic vessels for training a neural network. However, in contrast to the former project, their approach does not address the retrieval of complete or near-complete vessels but merely sherds. Consequently, the synthetically generated 3D models are subjected to a sophisticated fracturing step in order to mimic the appearance of real-world fragments, before they are fed into the network.

The biggest group of methods, especially in recent years, operate on 3D inputs. A first concept for describing 3D vessel shapes was given by *Hörr et al. 2007* [37] who combined a set of global measurements like the object's volume and the profile signatures of individual body primitives with a geometric attribution of vessel attachments like handles. Later on Koutsoudis et al. showed the capabilities of 3D pottery retrieval based on a parametrisation of the shape in *Koutsoudis et al. 2010* [79] as well

(a) 3D Input (b) Alignment (c) Sketch (d) Inpainting (e) Retrieval Results

Figure 4: Shape-based retrieval. Searching for similar vessels by enabling domain experts to add missing geometry of incomplete objects and applying an automatic texture inpainting. A conventional image-based retrieval returns similar objects in a ranked list. Courtesy of *Lengauer et al. 2019* [85], © 2019 The Authors. Eurographics Proceedings © 2019 The Eurographics Association. Reproduced by kind permission of the Eurographics Association.

as a set of depth maps, obtained from the 3D shape, in *Koutsoudis et al. 2011* [80]. *Sfikas et al. 2016* [81] applied the PANORAMA descriptor, a well-established feature descriptor from the field of 3D object retrieval, on pottery objects. The idea behind this approach was to compute a panoramic depth map of the solid of revolution, from which local image features are extracted for the comparison.

A very recent entry in the 3D Shape Retrieval Challenge (SHREC) – an annually held challenge for evaluating the effectiveness of 3D-shape retrieval algorithms – by *Sipiran et al.* [82], has indicated that the identification of 3D pottery shapes is still an unsolved research objective. Within this challenge contestants were asked to conduct a retrieval on a given set of pottery artefacts from pre-Columbian cultures in Peru, exhibiting multifaceted shapes and varied artistic styles. To this end, a training dataset with about 1,000 objects from the same corpus was provided. The submitted approaches were predominantly learning-based, which show a clear predominance over engineered methods, in the basis of sufficient training data.

Apart from these approaches which are tailored for 3D models of (near-)complete objects, concepts have also been developed for 3D models of fragments as input. One of the earlier works here was that of *Kampel and Sablatnig 2007* [34]. In their approach they leveraged the assumption that pottery sherds are parts of a solid of revolution. The sherd model is registered by determining it's rotation axis. In a second step its profile curve is obtained by intersecting the sherd with a plane aligned to the rotation axis, before a heuristic-based partial matching with known profile curves is conducted. A more recent publication by *Roman-Rangel et al. 2015* [83] followed a different approach by categorising Teotihuacan and Aztec potsherds based on state-of-the-art local 3D surface descriptors. *Savelonas et al. 2016* [84] also used local shape descriptors which are combined with a Fisher encoding. One of the more recent approaches was given by *Lengauer et al. 2019* [85], extended in the year 2020 [86]. Their approach tackles the omnipresent incompleteness of archaeological pottery objects by enabling an experienced user to add a suggested completed outline (a *sketch*) to the sherd model before a conventional image-based retrieval is conducted (Fig. 4).

4.3.2 Pattern-based retrieval

In the past few years, the topic of surface pattern detection and classification has intensively been researched in the GRAVITATE project [87] led by the IT Innovation Centre at the University of Southampton. For example, *Moscoso Thompson and Biasotti 2018* [88] presented the edge-based LBP descriptor, an adoption to the local binary pattern (LBP) description for the three dimensional case which allows classification of pattern type for a point location on the surface mesh by looking at the colour variances in the neighbourhood of the point. The approach was later improved by *Moscoso Thompson et al. 2020* [89] in order to work on point cloud inputs and for geometric patterns.

Itskovich and Tal 2011 [93] presented a method to find the best match of a relief mesh in another mesh at a relatively early research period. This calculates similarity measures based on both salient per-vertex features, as well as between components that result from segmentation. The authors demonstrated that their algorithm is successful in finding similar reliefs even if there is no exact match for the query.

Within the field of Greek painted pottery, *Crowley and Zisserman 2013* [94] proposed a method to annotate automatically figural depictions such as gods, humans, animals, etc. on painted surfaces and using a suitable textual description by employing a weakly supervised learning approach. For this, they processed the huge Beazley Vase Archive at Oxford University, where each vase is not only photographed from at least one direction, but the depicted scene on the vase surface is also briefly described in a text. By forming clusters of matching images and their descriptions, they were also able to achieve an automatic textual annotation of depicted scenes.

Zhou et al. 2016, 2019 [95, 96] focused on the ancient Native American paddle-stamping tradition, in which carved wooden paddles were used to impress characteristic designs on pottery. They employed DL techniques to link excavated sherd artifacts to the wooden paddle stamps that gave rise to the specific relief pattern on the sherd. In the course of their research, they switched the input modality from RGB depictions of sherds [95] to 3D-scanned point clouds of sherds [96], since geometry-based pattern extraction turned out to be more robust for the type of artifacts at hand. *Debroutelle et al. 2017* [53] presented a similar technique as *Zhou et al. 2019* [96], but instead of relying on a CNN they followed an engineered approach.

The published corpora of painted patterns in archaeology are important sources for research on retrieval methods. Already in the 2010s a group from Catania [69] proposed a retrieval approach for decorative patterns on Minoan pottery (the Kamares ware). The system was designed as shape matching to a reference image database of characteristic ornaments for this pottery ware. Another approach for pattern detection by *Lengauer et al. 2020* [56] addressed the repetitiveness of painted ornaments in bands or friezes running horizontally around the vessel according to the assumed rotational symmetry.

Pawlowicz and Downum 2021 [97] described a method to assign a type (from a small set of reference types that each exhibit discriminative painted geometric shapes) to photographs of decorated pottery sherds with the help of a deep neural network. Furthermore, the system supports querying of a database by comparing feature vectors that the network calculates for a given input using cosine similarity based on the idea that similar images should yield similar feature vectors, and that comparing those feature vectors is more robust than comparing two images directly. The authors even addressed the “black-box” aspect that is often associated with neural networks, by showing heatmap overlays on the input images that highlight those areas that contribute most to the final network decision. When classifying sherds, their method yields comparable assignments as those done manually by four experts in the respective field of pottery research (Tusayan White Ware pottery from the American Southwest).

To further the development of new surface pattern retrieval methods *Lengauer et al. 2021* [90] presented an appropriate benchmark dataset comprised of a subset of the pre-Columbian pottery dataset [82] with detailed surface annotations. The recognition of surface patterns was also the topic of several SHREC tracks, such as the 2017 track on “Retrieval of surfaces with similar relief patterns” by *Biasotti et al. 2017* [91] or the 2018 track on “Recognition of geometric patterns over 3D models” also by *Biasotti et al. 2018* [92].

5 Available tools and databases

Several of the methods described in the previous section have been integrated in open accessible tools or databases. They can be roughly divided into documentation tools (processing a single pottery object) and databases for storing, classifying and retrieving pottery data.

The *GigaMesh Software framework* (https://gigamesh.eu) is an open source software framework especially adapted to the needs of archaeologists. Assisted by different grids the manual orientation of pottery fragments is facilitated and improved to a remarkable extent. Once orientated, the axis can be set and one or more profile line(s) of the pottery object can be exported as svg-files. Meshes can be easily unrolled using rotational symmetric geometric proxies like cylinder, cone or sphere.

A complete workflow from the orientation of a sherd to the final archaeological drawing ready for publishing is realised by the application *Computer-Assisted Drawing of Archaeological Pottery* (DACORD) [98]. It offers several functions, as optimisation of the rotation axis position after a pre-orientation based on three points, different styles of drawings (linear, photographic, shading) or a visualisation of pottery regularity. DACORD is available via the public Git-repository (https://github.com/jwilczek-dotcom) or as supplementary material in [98]. Written in the R language and using various libraries, external applications and software environments (R project, RStudio and MeshLab), the installation of DACORD (and also RACORD, see below) is not easy. Two other software systems *TroveSketch* and *Vessel Reconstructor* were developed in cooperation between the Archaeological Heritage Service of Saxony and the Chemnitz University of Technology [99] (http://www.3dinsight.de). They create multi-colour or stylised images of pottery objects ready for publication, generate profiles, create unrollings of the surfaces (but not spherical) and reconstruct vessels based on one or more sherds.

Various public pottery databases exist for retrieving pottery data. A well-known database is the *Beazley Archive Pottery Database* (BAPD) (https://www.beazley.ox.ac.uk/carc/pottery). It is the largest database of ancient Greek painted pottery in the world comprised of records for almost 130,000 objects and some 250,000 photographs or drawings. Specific pottery databases storing 3D data are rare. One exception is the *Online database for research on the development of vessel shapes and capacities* (ODeeg) (https://odeeg.acdh.oeaw.ac.at) holding 237 objects in total. Linked to the research on painted pottery from ancient Greek territories and Cyprus, it focuses on capacities, metadata, measurements, 3D data acquisition/processing and to long-term archiving. Comparable to BAPD, it is strongly connected to the international *Corpus Vasorum Antiquorum* (CVA) project.

More important in our scope are databases which assist the manual classification and retrieval that is normally carried out by pottery specialists. One of the earliest was *The Pottery Informatics Query Database* (PIQD) [100] which incorporated methods for classification by vessel shape based on the encoding of the profile lines (from drawings or 3D data) as mathematical representations [58, 59]. Designed as open-source online tool, the objects could be enriched with archaeological metadata. A spatial analysis of objects was delivered over a Google Earth-based user interface. In 2015, PIQD joined the CRANE Project (https://crane.utoronto.ca) of the University of Toronto. There several improvements were implemented as a profile matching and visual features extraction approach [75]. The recently developed *Computer-Assisted Shape Classification of Archaeological Pottery Fragments* (RACORD) [74] is also based on 2D profile drawings. It enables a supervised retrieval, i. e. the user has full control over the criteria used for the best-matching. This best-match retrieval procedure calculates a minimum distance (“similarity”) which can be used for unsupervised classification or also for the quantification of similarity and shape variability. Again, RACORD is written in the R language, available via the public Git-repository (https://github.com/jwilczek-dotcom).

The *ProDesLab Pottery Management System* [101] is a structured database able to store and process 3D models of pottery. The focus of this concept is to extract automatically relevant dimensional attributes and features (axially and non-axially symmetric) to support a “semantic decomposition” of the pottery objects. The database facilitates queries of the large amount of information extracted.

ArchAIDE (http://www.archaide.eu) [102], a project funded by the EU, seeks to redefine the established process chain in archaeology pottery research. It is a recognition system based on a deep learning approach which starts from a simple photo of a sherd taken by a mobile device. It takes into account the shape, i. e. the profile, and the decoration of the sherd. Up to date the reference database is populated with Roman Terra Sigillata (TS) and medieval and postmedieval Majolica. It remains to be seen whether this system can really assist archaeological work; e. g. for correct identification of TS pottery one needs an assessment of the fabric, i. e. the ceramic material.

6 Open problems and future challenges

We have reviewed the most important papers (Sec. 4) for each of the three main categories in digital pottery analysis, documentation, classification and retrieval, which form the standard “pottery processing” chain in archaeology (Sec. 1). This selection is based on a total of 243 papers related to our scope (Sec. 2), which we have collected during this work (see supplementary material). Whereas Table 1 gives an overview of those contributions which we have discussed in our paper, Figure 5 shows a centrifugal distribution of all papers in relation to the tasks and affiliations of the first authors.

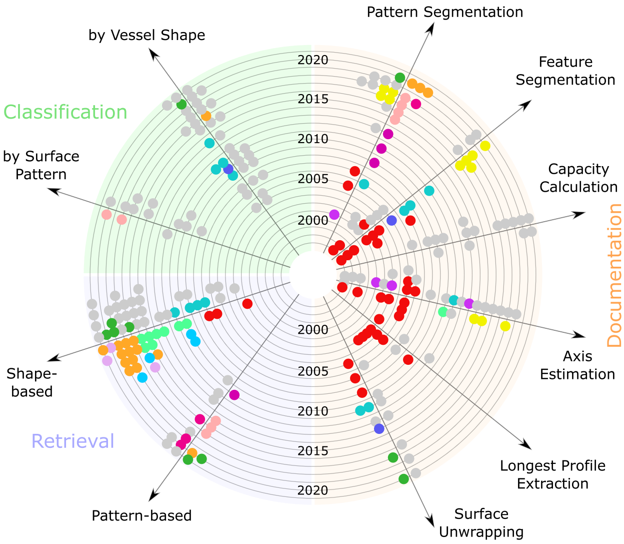


Figure 5: Density of work published by time (radius), category (axes) and first-author affiliation (colour codes as in Table 1).

If we move from the centre of Figure 5 outwards several clusters can be identified. For instance, the development of methods for the estimation of the rotation axis, the longest profile extraction and the segmentation of morphological features produced many contributions from the beginning until 2007, mainly from the Vienna University of Technology Pattern Recognition and Image Processing Group (PRIP). The topic of axial symmetry continued to gain attention, but on a weaker level until recent times, with this mostly aiming to improve established methods. Another cluster has occurred very recently in the segmentation of painted or relief decorated patterns task. This group turned up as a result of two new aspects that emerged at this time. Firstly, from new developments in 3D data acquisition technologies (e. g. Structure-from-motion) which are now able to provide colour information (textures) in a resolution that is adequate for archaeological needs. Secondly, from contributions to the SHape REtrieval Contest SHREC '19 track on feature curve extraction.

Two further clusters can be recognised along the time axis of the classification by vessel shapes (one around 2010, the other from 2016 until today). The former is related to a cooperation between archaeological institutes at Haifa and Jerusalem and the Weizmann Institute of Science at Rehovot aiming to develop mathematical and computational tools for pottery analysis. The latter is a development resulting from the advent of Machine Learning in archaeology from which, moreover, the retrieval tasks of pottery analysis have benefited very greatly. In the category of retrieval, works on pattern-based retrieval emerged late, which was the result of the improved documentation methods. A last striking cluster occurred in the shape-based retrieval task in 2018/19 which represents again contributions initiated by the SHREC contest tracks, this time to the SHREC '18 track on the evaluation of the performance of retrieval algorithms. Additionally, this cluster was populated by outcomes of the ArchAIDE project running at the same time.

The distribution chart reveals also sparsely populated areas, as along the axes of surface unwrapping and classification by surface patterns. It is noticeable that computational applications in this important field of pottery analysis (e. g. for vase painting studies) are almost completely lacking.

Based on the reviewed papers from over a quarter of computational research, we derive a set of lessons learned to be considered in developing and implementing methods in archaeological pottery research. Remarkable is that methods based on 2D vessel profiles – as in the early works before 1997 – have shown the most significant progress, nowadays reinforced by applying machine learning methods. Nevertheless, we must state that digital pottery analysis has only found its way into the everyday practice of pottery archaeologists in rare cases. A main obstacle is that many of the proposed methods are developed without close cooperation to practical pottery archaeologists. The open problems that have prevented a broader usage can be summarised according to key criteria for future challenges:

Scalability: Pottery has come down to us in huge masses. Sherds in the hundreds per excavation day are not unusual. The scalability on large-scale data of pottery finds of the proposed methods is significant. Structured databases providing tools for feature recognition and attribute extraction are to preferred here, enabling additionally a storage of the object's metadata (e. g. the pottery fabric, but also find site, trench, stratigraphic layer, etc).

Applicability: Pottery is mostly broken in small fragments and their surfaces are usually eroded or worn-off. The performance of computational applications based on images or 3D data is mostly affected either by the preservation condition of the object, the quality of the input data, or both. Archaeological researchers working on large find assemblages have to perform their analysis on all finds with the same care independent of their preservation condition. This stresses the importance of the applied methods needing to be designed in a sufficiently robust manner to handle this aspect of "real-world" objects.

Adaptability: Scanning of pottery objects to acquire 3D models is time-consuming. If only the vessel profile is of importance (e. g. for analysis of the shape development), then a *Laser Aided Profiler* is an efficient alternative. In this context we must have in mind the fact that archaeological pottery research is mainly based on photos and drawings (mostly vessel profiles) which have been published in numerous books, articles and papers since the 19th century. Therefore, addressing and exploiting these various modalities of archaeological data for a consistent analysis will be a key factor in future challenges.

Visibility: The potential of digital pottery analysis is almost unknown by the archaeological community. Only in the last few years has it been possible to recognise an increase of publications in journals close to archaeology, such as the Journal of Cultural Heritage or the Journal of Archaeological Science (including the reports series). Publishing in journals of the proper archaeological domain has an essential added value, fostering awareness and acceptance by pottery archaeologists.

7 Conclusion

Computer-based methods for digital pottery analysis can definitely help archaeologists to analyse data and to understand past life. Within this survey of 25 years of digital pottery analysis research, we have shown the rapid developments of different methods for supporting certain tasks in this specific field of archaeology.

In the classic digital processing workflow we are focusing on the three major categories of pottery analysis, the documentation, the classification and the retrieval of pottery objects. Methods addressing these analysis tasks mostly operate either on 3D geometric shapes (meshes, point clouds, CT volume data) or on 2D image data (profile drawings, photographs, relief maps, surface unwrappings). While earlier approaches were mainly based on classic 3D data such as (textured) meshes, recent advances in deep learning methods build more frequently on simple image-based representations.

The vast quantity of illustrative drawings and photographs created and captured over more than a century in particular, include a significant share of the archaeological domain knowledge. New learning-based methods raise the potential to exploit this vast quantity of image-based data to enrich different archaeological analysis tasks as well as to open new research on a much wider basis of data. However, making this data accessible and usable for these methods often requires suitable data structuring and annotation, which at the moment is still an expensive and time-consuming task. A particularly important direction for digital pottery analysis in the near future therefore appears to be the investigation and development of improved methods for the computer-aided preparation and annotation of large pottery data quantities. The most recent works covered in this survey have already paved the way to the pursuit of this goal.

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