Feature Extraction on Axially Symmetric Pottery for Hierarchical Classification

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ABSTRACT

Due to the mass of sherds and vessels that have been dug out by archaeologists over many years, the request for an automatic classification system has become obvious. This paper presents algorithmic key ingredients of such a system: segmentation, feature extraction and clustering. Therefore, the extensive analysis of a representative profile line is of high importance, because it helps not only to retrieve global measures and a segmentation of the body, but also to separate attachments like handles, lugs, feet or spouts for gaining an even more detailed description of the vessels. Finally, we present ways to use the extracted features for queries and hierarchical classification.

Keywords: Pottery classification, shape analysis, mesh segmentation, similarity metric.

1. INTRODUCTION
1.1 Motivation
One of the most time-consuming processes in archaeology is the documentation and classification of relics found at excavations. Low budgets and the lack of time often prevent a profound scientific evaluation and a complete conservation of the site. Beside that, the interpretation of findings has always been a cumbersome task. The inquiry for similar objects in large libraries as well as the assignment to cultural and epochal areas may be a matter of months or even years. Additionally, archaeologists have been reliant on hand-drawn sketches, which represent only one special subjective view on the relevant material.

To overcome these deficiencies we are currently working on an automated application-oriented documentation and classification system for archaeological vessels. Classifying especially vessels is expedient, because they form the far biggest part of the findings and they provide good insights into the life of their ancient manufacturers. The basic concept of our system has been published in [4].

By using a 3D laser scanner (Konica Minolta VI-910) we first create virtual copies of the troves. These 3D models may be used for the fast generation of standardized drawings, for the production of scaled replicas, for the publication in large world-wide databases and, of course, for automated classification issues. As our co-operation with archaeologists already shows, 3D laser scanning is fastening the documentation process by about factor 5 to 10, having the nice side effect of creating location-independent copies.

Since the classification of vessels is primary based on the comparison of visual properties, algorithms need to be developed that automatically and quickly extract those properties from the 3D model. Once the set of features has been transformed to a more abstract level, complex interactive queries can be processed within a short time. This enables the archaeologists to gain much more information about historical correlations than it would be possible without a computer-supported classification system.

1.2 Features of Archaeological Vessels
When speaking of features of pottery, it is reasonable to introduce a hierarchy, depending on their importance for classification. We call those features primary ones that determine the vessel's basic shape, so that main classes like amphorae, tureens, jugs, pots etc. can already be distinguished. Secondary features concern the design of particular segments like base, belly, shoulder, neck, rim, handles, feet etc. and determine the subclass or type in which the vessel is classified into. As well as primary features most of them can be obtained automatically. An even finer classification into subtypes and variants can be achieved, if tertiary information about spouts, surface material, ornaments or applications is available. Contrary to the prior attributes most of these can only be detected semi-automatically. However, in the field of ornaments some research on automated detection has already been done [15].

1.3 Scan Quality and Density

The size of our vessels varies from miniature bowls to storage vessels with a volume of more than 15 liters. For most of them the sampling density ranges from 200,000 up to 5,000,000 vertices, i.e. an average point distance of about 0.2 to 0.5 mm. So, for the processing of the scans only $O(n)$-algorithms, where n denotes the number of mesh vertices, are feasible. Furthermore, it has to be mentioned, that due to several reasons the majority of the scans is of inferior quality. The following six aspects are relevant:

- Influence of missing or at least partially missing inner walls (areas that could not be captured by the laser scanner, “sight shadows”),
- noisy raw data,
- irregular meshes (topological anomalies),
- incomplete objects (missing sherds),
- influence of ornaments and break lines,
- object alignment.

Due to these shortcomings for the segmentation (Sec. 2) as well as for the feature extraction at all, mesh-independent approaches are most promising.

1.4 Outline

In the following we present algorithms that are essential for the task of automated classification of archaeological vessels. At first, in Section 2, we describe a two-stage segmentation of the vessel. In the first step we employ its approximate rotational symmetry to separate attachments from the body. After that, the body itself can be decomposed into the commonly used segments base, belly, shoulder, neck and rim based on the shape of the profile curve. Section 3 is devoted to the topic of feature extraction. Here we describe the shape analysis of the body and the separated attachments as well as the determination of their geometric relations. We also discuss possibilities to measure the similarity between the extracted features. How these features and their similarities can be used for classification, is the topic of Section 4. Finally, in Section 5, we give examples for queries and an automatic generated clustering. These results demonstrate the power and flexibility of our approach. Although the classification system is still in a prototype state, the results already meet the requirements of archaeologists.

2. SEGMENTATION

2.1 Related Work

Segmentation algorithms for 3D objects have been investigated for many years. Skeleton-based approaches [16, 3] have been successfully applied for mesh decompositions. However, these approaches have serious problems with meshes that do not represent a closed surface.

A topological approach based on analytical Reeb graphs similar to [19] has been examined by ourselves. Unfortunately, it turned out that either the discrete Reeb graph is too coarse and inflexible to detect all types of asymmetric parts precisely or topological inconsistencies prevent the generation of a meaningful graph.

We also considered the related work of Mortara et al. [10] and Tierny et al. [17] where non-analytical Reeb graphs are generated by finding so-called feature points on the object's surface and performing a geodesic expansion afterwards. However, the time requirements of both algorithms are unacceptably high due to their superlinear complexity. Beside that, it cannot be assured that the resulting graphs are meaningful for our application. The “blowing bubbles” algorithm presented in [11] and [12] has an $O(n^2)$ complexity and hence has to be disregarded too.

Also 3D watershed segmentation based on curvatures as proposed in [14] fails due to rough surfaces and the fact that regions of high curvatures do not only occur at segment borders but also within the segments themselves.

A new promising approach by Katz et al. uses feature point and core extraction to segment meshes [9]. Although the algorithm's complexity is generally too high for our data, the approach could be of interest for the segmentation of non-rotatory vessels.

2.2 Separation of Attachments

Since the very most vessels have been designed as rotational bodies (whether on a throwing lathe or hand-crafted), it is reasonable to make use of this special property. Nevertheless, there may be attachments like feet or handles that are mounted below or above the axially symmetric vessel’s body. Two examples of such cases are shown in Fig. 2c and Fig. 2d. To simplify the description of our method we will first assume that the objects considered have no such attachments. How to proceed in the other cases well be explained in Sec. 2.2.4.

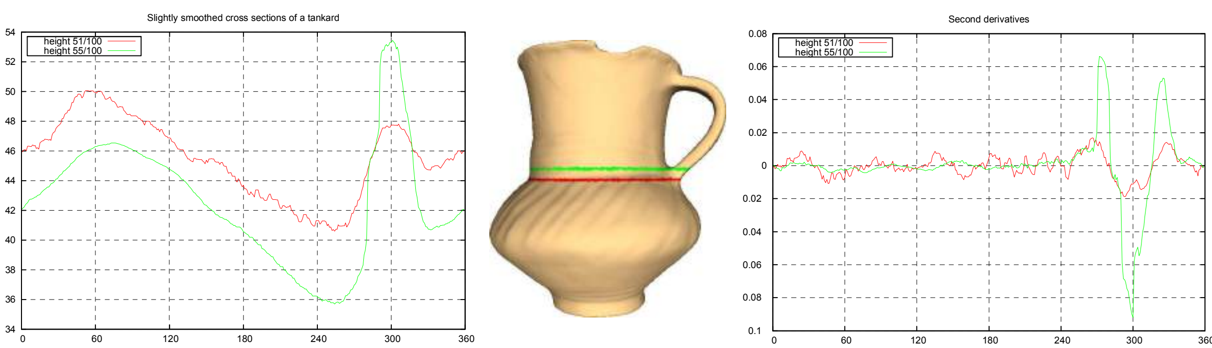
2.2.1 Computing Profiles and Distance Functions

The assumption above allows us to use the approximate rotational symmetry to isolate the attachments from the vessel's body. Operating only on discrete profile values and not on actual mesh points makes the approach independent from topological issues and the point cloud density. We will further assume that the axis of rotation has already been determined. Methods therefore have been presented for example in [5] and [8].

Usually the computation of profiles is performed by an intersection of the vessel with planes containing the axis of rotation. Doing this for a large number of profiles on the vessel is computationally expensive. Therefore we propose a different approach. We introduce a two-dimensional cylindrical grid around the axis of rotation with I grid points in vertical direction and J grid points on the circular intersections of the cylinder with planes perpendicular to the rotational axis. I is chosen with respect to the object's height in the range of 50 to 200. J is set to 360 so that profiles are taken at intervals of one degree. This resolution proved to be sufficient in our test cases.

The grid tessellates the bounding cylinder into cells so that each mesh vertex can be assigned to one of them depending on its cylindrical coordinates. For each cell we store the maximum distance towards the axis of rotation of all the vertices it contains. A horizontal subset of the grid covering all cells with the same height value is called a *slice*. For a fixed slice the map that associates intervals of angles with distances is called the *distance function* of that slice. This function might be partially undefined, if some cells are free of points, e.g. due to missing pieces of the vessel. In this case gaps of the distance function are closed via linear interpolation.

Fig. 1a shows the courses of two typical distance functions. Their sinusoidal oscillation originates from inaccurate object alignment or a slightly elliptic basic shape. It is present on virtually every vessel. Note that the red line at height 51/100 contains more noise than the green one due to ridges and valleys on the jug's belly being crossed. Furthermore, the red slice (Fig. 1b) intersects the vessel at a height where the handle has just begun. This already results in the small hill around 300° in the corresponding distance function. In Fig. 1c the second derivatives of the distance functions are depicted. Within the green function clearly observable peaks at the angles corresponding to the start and end points of the handle can be seen. However, as the red function already indicates, this cannot be a decisive criterion alone, since there might also be significant peaks when no attachments occur.



(a) (b) (c)

Fig. 1: Two distance functions (left) and their second derivatives (right) of a jug (middle).

2.2.2 Edge Detection

Since attachments cause notable deviations from the underlying sinusoidal oscillation of the distance function, the aim is now to isolate these from the rest of the curve. We therefore developed a simple heuristic method based on the following observation: In the absence of attachments tangents of the distance function cross the function again either never or immediately (in case of noise) or not until about a half period later. Attachments however will result in deviations being crossed by some tangents rather earlier (usually within the next 45 degrees assuming that the mounted segments have no larger extension). If now the resulting area enclosed by the tangent and the distance function exceeds a prescribed positive threshold, the low-frequent curve has apparently been interfered by one with a higher frequency – an "unexpected" hill has been detected. Finally, to locate the exact start and end points of the attachment, the local curvature, i.e. the second derivative of the distance function is consulted. The final border flags are set where the second derivative is maximal and greater than twice of the median value within a neighbourhood of ±5 degrees (cf. Fig. 1c). By running the mentioned procedure once clockwise and once counter-clockwise even the small hill in the red distance function in Fig. 1a can be detected.

2.2.3 Separation

After having determined start and end angles via edge detection, the attachments can easily be separated. Therefore all grid points between a start and end flag are marked as belonging to a segment. By the mesh-grid-correspondence this labeling is propagated to the actual mesh vertices. After all, a final post-processing step is necessary, because vertices on the body as well as parts of the inner wall would be counted as segment-related vertices too. This exclusion is performed similar to the hole-closing procedure (cf. Sec. 2.2.1) by linear interpolation of the distance values of the start and end angles.

In some cases pseudo-segments occur. This is a result of the strict choice of parameters and it happens when either the vessel is too distorted, badly aligned or the local curvature fluctuation is too high. To treat this, a minimum vertical extension for attachments of at least 5 slices is demanded.

The whole segmentation procedure is of $O(n)$ complexity, because only once for each vertex its corresponding grid cell and a distance value are computed and afterwards all operations are proceeded on the discrete profiles. With maximum 200 slices in each of the 360 profiles the number of profile values is usually much fewer than the number of mesh vertices.

2.2.4 Treatment of Attachments Above and Below the Body

As already stated, there might sometimes be attachments like feet, bails or rim-standing handles which are mounted near the base or the rim of the vessel. Since outside the body there is usually no axial symmetry, the so-defined segments have to be treated extra. Hence, the vertical start and end points, or more exactly the base and orifice points (cf. [2]) of the profiles have to be computed. After that, one can simply declare parts of the vessels below the bottom and above the top of the body as attachments by default. However, when dealing with bail cans (Fig. 2c) for example, it is somewhat difficult to estimate the location of the rim, because two separated profile parts (the body itself and the bail's top) emerge. To treat this special case we only consider the biggest connected part within the profile line.

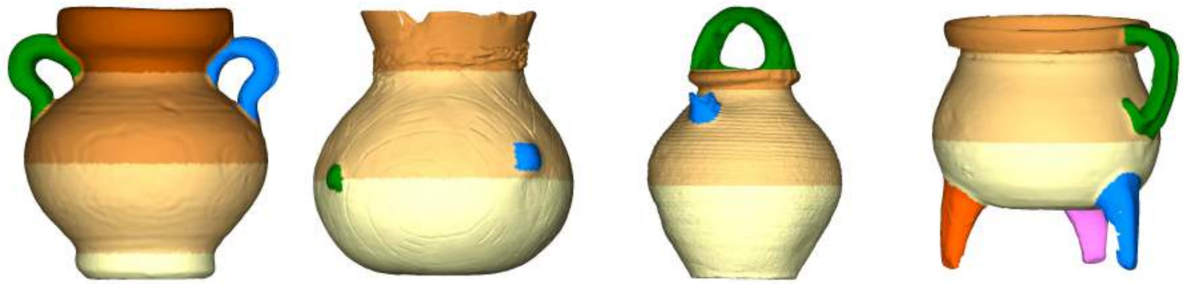
Alg. 1: Detecting attachments by means of edges within the distance function.

compute all profiles
estimate minimal and maximal height of the body
close holes virtually by linear interpolation
compute second derivatives of the distance function
for all *angles* (clockwise direction) **do**
    for all *slices* **do**
        if rising edge detected **then**
            set “segment starts” flag
for all *angles* (counter-clockwise direction) **do**
    for all *slices* **do**
        if falling edge detected **then**
            set “segment ends” flag
construct segments by means of start and end flags and the vertical extension of the body
delete pseudo-segments and exclude body-related vertices from asymmetric segments

2.3 Segmentation of the Body

Separating attachments from the body is only the first step within a complex shape analysis. To gain further information we also divide the vessel’s body into the standard segments defined by archaeologists. For this we extract characteristic points on the profile curve similar to [2].

To find a representative profile for analysis is not trivial, because especially in earlier eras where no potter’s wheel was used or burning temperatures where not adequate, the vessels have a more or less distorted basic shape. Also handles and other attachments prevent the use of a simple average profile. To overcome this problem we developed a two-stage process to define the profile curve: the computation of a median and an optimal profile. The first one is generated by sorting the distance values for each slice in ascending order and the final median profile is then the set of all median values. Note that this profile is only notional and independent from attachments. Afterwards we choose the profile that is most similar to the median profile as the optimal profile by finding the minimum of the Euclidean distance of all corresponding profile points. The computation of the optimal profile is necessary, because on the median profile significant features like corner points are possibly leveled out.



(a) (b) (c) (d)

Fig. 2: Segmentation results for vessels of different eras.

3. FEATURE EXTRACTION

3.1 Global Measures

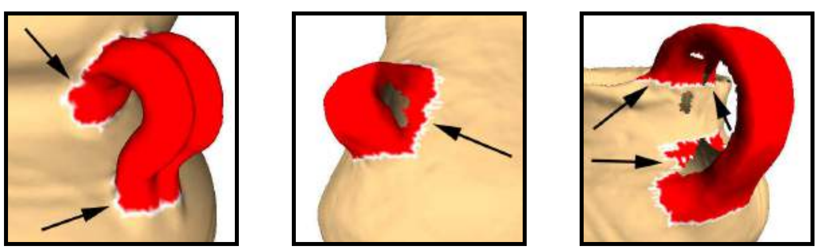
The most important primary features of vessels are global measures. Since the laser scanner returns absolute real world data and the vessels are supposed to be correctly aligned, the total height, the height of body segments, some special diameters (bottom, belly, rim) and the volume are trivial to extract. Furthermore, also the ratios of some of these values (often called "indices") are important. Finally, with the segmentation of the body one can create a profile signature by encoding the combination and shape of body primitives or the sequence of characteristic profile points. In our opinion this abstraction is more reliable and convenient than the complete comparison of the profile curves as done in [7].

Also some secondary attributes can easily be computed, e.g. the bulge of the base ("Omphalos"), the curvature at the belly and the design of shoulder, neck and rim. Even a few tertiary attributes like ornaments [15], roughness and uniformity [13] can already be taken into account.

3.2 Interpretation of Attachments

For a powerful classification system it is desirable that the severed segments could be tagged with some additional semantic information. However, doing this fully automatically is hardly possible. Firstly, as Fig. 3 shows, a topological interpretation is not yet robust enough, because the number of intersection curves with the vessel's body is not a reliable indicator due to holes on the inner walls or the special shape of the segments. Secondly, it is not easy to conclude from a segment's outer shape to its functionality. Therefore, several shape matching algorithms have to be examined in the future.

But as well as in the previous section, attachments can be tagged with geometric attributes. Properties which are easy to extract are for example the size (absolute and relative) and the position upon the vessel.



(a) (b) (c)

Fig. 3: Correct (a) and incorrect (b, c) computation of intersection curves.

3.3 Estimating the Similarity of Single Features

The feature extraction immediately raises the question how features can be compared at all. While for complex attributes special matching algorithms have to be developed, yet the comparison of scalar values, i.e. finding a metric for them is not obvious. Thus, as stated in [6] and elsewhere, continuous values should be transferred into nominal values if possible. This step does not only ease the correlation with linguistic terms but also the establishment of similarity matrices for different specifications of features. To have automatic comparison tools for continuous as well as for discrete data anyhow, we make four proposals, each having its pros and cons and each returning a value out of $[0,1]_{\mathbf{R}}$.

3.3.1 Relational approach

$$sim(a,b)=\begin{cases}\min\left\{\frac{a}{b},\frac{b}{a}\right\} & \mathrm{sgn}(a)=\mathrm{sgn}(b)\\ 0 & \text{else}\end{cases} \tag{1}$$

This approach is suitable for continuous values of equal sign. It has the disadvantage that a certain minimum similarity occurs and an interpretation of the resulting value is difficult, because both facts depend on the range of the value interval. So, a convenient normalization is required in advance.

3.3.2 Tolerating approach

$$sim(a,b)=\max\left\{0,1-\frac{|a-b|}{\delta}\right\} \tag{2}$$

The tolerating function is another method for continuous data. δ be the range of a tolerance interval in which two values still return a similarity amount. It has problems with non-uniform distributed values.

3.3.3 Boolean approach

$$sim(a,b)=\begin{cases}1 & a=b\\ 0 & a\neq b\end{cases} \tag{3}$$

The Boolean approach only returns a similarity (100%) if two values are exactly equal, otherwise zero. Thus, it is only suited for nominal data whose extraction is very robust.

3.3.4 Discrete approach

$$sim(a,b)=\begin{cases}1 & a\in I, b\in I\\ 0 & \text{else}\end{cases} \tag{4}$$

In the last approach the value range is discretized and two values are considered equal if they belong to the same interval *I*. This only makes sense if these intervals can be associated with a certain meaning.

3.3.5 Comparing the Shape of Optimal Profiles

Of course not all attributes can be represented by numeric or nominal values. What still is missing is a similarity metric for more complex ones. Among all features the profile line covers most information for the design of the final shape. Although some information about it is already immanent in the global measures and their ratios, a more precise comparison is demanded. Therefore, in principle two approaches are possible. The first tries to measure the distance of two functions that continuously define the profile line. Something similar has been done by GILBOA et al. in [7] where such functions have been introduced by means of rim points. Although their ideas, especially the correlation matrix seem quite promising, the approach does not return good results for complete profiles. That's why we use the already mentioned decomposition of the body into primitives which works on a higher abstraction level.

Because there is no "correct" or "incorrect" primitive matching algorithm, we only present a sample here: At first the similarity between two primitives has to be introduced. We chose to consider only the ratio of the top and bottom diameter and the relative position within the vessel but not the absolute height to achieve scale invariance at this stage. With $ratio_1$ and $ratio_2$ being the ratios of bottom and top diameter and pos_1 and pos_2 being the relative positions of the centre of the two primitives p_1 and p_2 in vertical direction the similarity between them is

$$sim(p_1,p_2)=\begin{cases}0.5\cdot\min\left\{\frac{ratio_1}{ratio_2},\frac{ratio_2}{ratio_1}\right\}+0.5\cdot\left(1-\frac{|pos_1-pos_2|}{0.25}\right) & \text{if } |pos_1-pos_2|<0.25\\ 0 & \text{else}\end{cases}\quad (pos_1,pos_2\in[0,1])\,. \tag{5}$$

This means, the similarity between primitives depends half on their shape and half on their positions, which however is zero if their distance exceeds 1/4 of the total body's height. Note that so a fluent transition between the primitive types funnel, cylinder and cone (cf. [4]) is realized and primitives of equal type but in different regions of the vessel are disregarded. The formula is easy to extend if more features like local curvature for example are to be considered too.

By using the above similarity function for primitives we now can proceed to the overall similarity. First of all we find the pair of primitives (p, q) with p out of vessel P and q out of vessel Q that returns the highest matching result and put it into the set M. Now, p and q are being marked and while there are still unmarked primitives in both of the vessels the next best matching pair is to be found and put into M. If the procedure has stopped, the final similarity is computed as

$$sim(P,Q) = \frac{\sum_{(p,q)\in M} sim(p,q)}{|M|} . \tag{6}$$

4. ALGEBRAIC APPROACHES TOWARDS CLASSIFICATION

4.1 Theoretical Overview

Classification in archaeology has always been a difficult task. There have been several trials to establish a unique and normalized classification process, but none of them prevailed. On the one hand this is also due to a missing standardized vocabulary as well as international language barriers and on the other hand due to many different systematic approaches and points of interest. EGGERT [6] as well as ADAMS and ADAMS [1] distinguish between historic-chronological, functionality-oriented and morphological-descriptive classification schemes. There are comprehensible arguments for all of them, but we think that the latter is best suited for us, because it is most objective and chronological as well as functional information is always only the *result* of a shape-based analysis. For further theoretical background we defer you to the corresponding literature (e.g. [1, 6, 18]).

4.2 Creating Groups of Similar Vessels

4.2.1 Computing the Overall Similarity

Before the classification process starts, it has to be clarified how the final similarity between two vessels is computed. With the above approaches for numeric and nominal features and some more complex matching algorithms, we obtain the similarity between single features. The principal idea is now to weight these and to sum them up in a convex combination. Note that possibly every feature has its own *sim*-function. Using the weights λ_i, for two objects A with features a_i and B with features b_i the similarity is computed as

$$SIM(A,B) = \sum_i \lambda_i \cdot sim(a_i, b_i) \quad \left(\sum_i \lambda_i = 1, \lambda_i \geq 0 \right) . \tag{7}$$

4.2.2 Prototype-Based Classification

Even among geometry-based approaches there are many ways to classify vessels. One of them is to create prototypes for each main and subclass. Then the vessel is classified into the cluster where the distance towards the respective prototype is minimal. If the minimal distance exceeds a certain threshold value, possibly a new prototype has been found. This proceeding requires an a priori knowledge, i.e. an archaeological expert has to establish a coarse typology himself previously. However, the manual creation of such prototypes takes the risk of an again (possibly unconscious) subjective and non-uniform classification.

4.2.3 Hierarchical Clustering

Another way to create clusters is the generation of so-called similarity or correlation matrices where all vessels are pairwisely matched and groups of elements with high similarity values are to be found. Contrary to the prior approach this needs no a priori knowledge.

Because the number of features can become quite high, a one-step approach with the above convex combination is hardly manageable. Not only that the cluster borders become unsharp, also a reliable subclassification becomes almost impossible. That's why we introduce a multi-step, decision-tree-like approach which besides is supported by the immanent hierarchy of the vessel features (cf. Sec. 1.2). Thereby for each classification step a relevant feature subset is chosen. So, a series of advantages emerges:

- The classification process becomes more selective and convenient. By reducing the number of parameters for the convex combination the result can be controlled much better.
- The subclassification becomes independent and flexible.
- Cluster borders become much sharper.
- By the hierarchical design a runtime improvement for queries occurs.

The only disadvantage of the multi-step approach is the necessity of a robust primary classification, because a once falsely classified object cannot be transferred into another cluster by the subsequent steps.

5. RESULTS

Although it is not yet clear in which order and with which weight the several attributes have to be considered, we already achieved good classification results by using an intuitive monothetic process. Our test set covers 104 complete or at least completely reconstructed vessels from the Bronze Age cemetery of Kötitz in Eastern Saxony.

During the first test series we tried to find out, if a one-step retrieval based on Eqn. (7) leads to reasonable results. We therefore used four features: The combination of body primitives (cf. Sec. 3.3.5) with $\lambda_1 = 0.5$, the ratio of height and maximum diameter (main index) with $\lambda_2 = 0.2$, the ratio of rim and maximum diameter (rim index) with $\lambda_3 = 0.2$ and finally the absolute height with $\lambda_4 = 0.1$. The last three features have been compared by the relational approach (Eqn. (1)). Of course, the choice of relevant features, weights and similarity metrics is only intuitive and not supported by archaeological cognitions. But anyhow, the results in Fig. 4 clearly indicate what power lies behind a feature-based retrieval system. By combining it with the previous mentioned multi-step approach even a reliable subclassification could be achieved. If the result does not fit the expectations the query parameters can be quickly changed and a new order is displayed. So the gaining of archaeological information is achieved enormously faster than with the traditional way.

Fig. 5, which was virtually obtained within less than a second, too, shows the automatic arrangement of 30 vessels with exactly one attachment. In the first step the ratio of maximum diameter and body height (the so-called "main index" *MI*) was split into 4 intervals: $MI > 2.0$ ("flat", A), $2.0 \geq MI > 1.33$ ("wide", B), $1.33 \geq MI > 1.0$ ("even", C) and $MI \leq 1.0$ ("tall", D). In the second step the combination of body primitives split the material into further subgroups (cf. Sec. 3.3.5). Admittedly, this proceeding is very coarse and it may not work for all types of vessels, but it already indicates that a feature-based approach can quickly lead to an intuitive classification. Note that with a more balanced combination of attributes and a polythetic approach for example even a missing handle might be compensated.

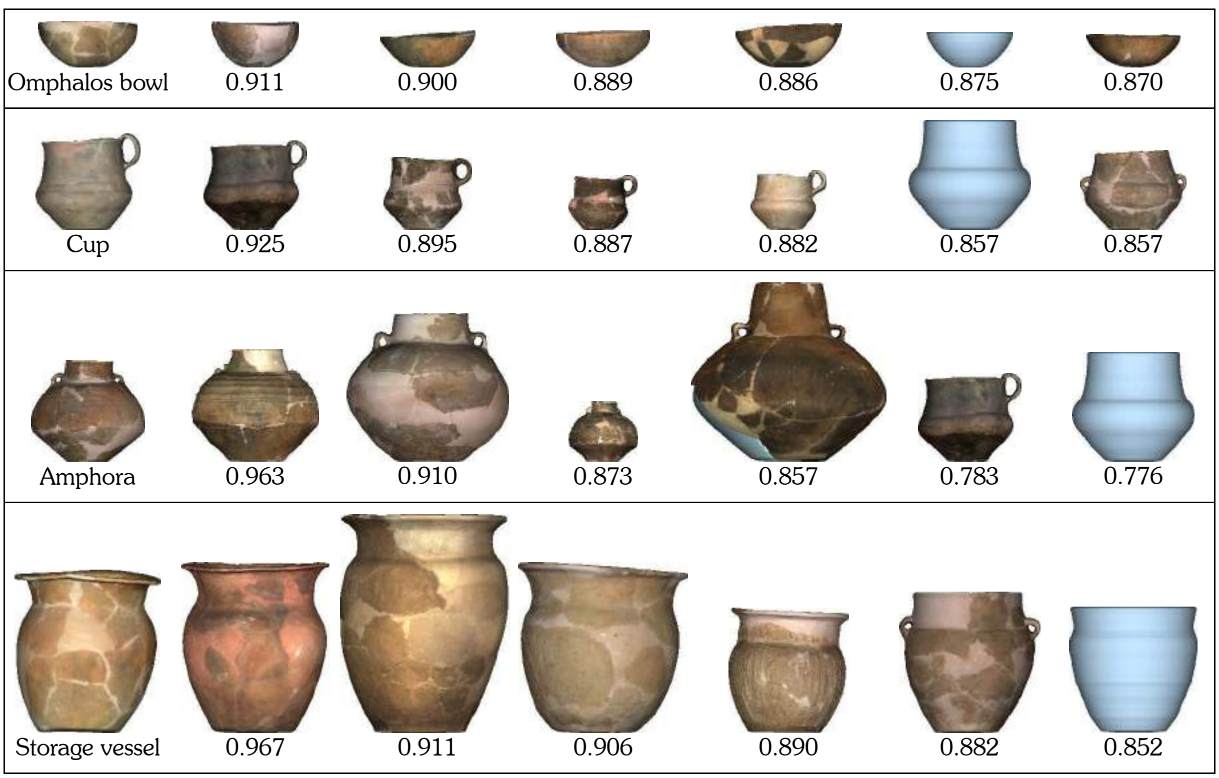


Fig. 4: Results for queries with corresponding similarity amounts (all vessels scaled by 1:10).

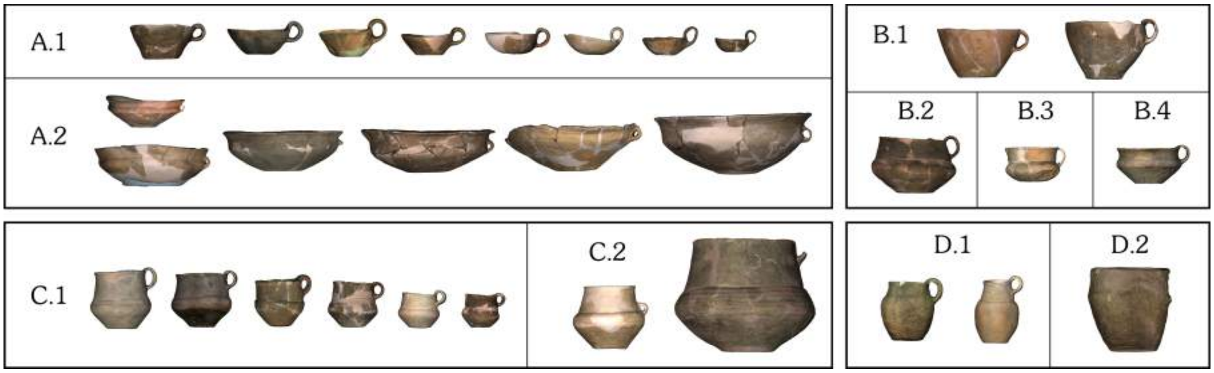


Fig. 5: Clustering of vessels with one attachment by considering (1) the ratio of height and maximum diameter and (2) the combination of body primitives.

6. CONCLUSION

As it could been seen, a reliable segmentation of vessels into primitives and attachments is a very important precondition for a mighty classification system. Independent from the final classification scheme, the existence or absence of handles etc. is often a decisive criterion for the function and use of the respective vessel. We therefore introduced a fast, robust and above all precise segmentation algorithm which also works for prehistoric, manually created pottery.

Following a feature-based approach we also presented metrics to measure the similarity between single features and a more abstract algorithm to compare the combination of body primitives. Although the chosen classification scheme was kind of arbitrary, it already shows the mightiness of a hierarchical approach. Depending on the archaeologist's special point of interest many different queries and results can be obtained within a few seconds.

In the future we are going to examine the power of decision tree algorithms like C4.5/C5.0 and LMT to retrieve information about the correlation and decisiveness of attributes, about the weighting of parameters and to get hints for still missing features. We also plan classification tests with neuronal networks.

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