SCHEMATA: 3D Classification and Categorization of Ancient Terracotta Figurines

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Abstract: The goal of the starting case-study is not only to develop procedures for automatically generating corpora using 3D pattern recognition, but also to reflect on the associated schematizations and how they can be applied in computer science and visual sciences. For this purpose, methods of object mining in 3D data are to be developed. We chose an object group which is defined by its complexity in shape and the similarity between the objects: In 4th and 3rd century BC ancient Greece small terracotta figurines used to be an art form that was quite common. Based on 200 of those terracottas, a classification system will be elaborated with digital methods, which is able to meet the complexity of the artefacts. In close cooperation between computer science and archaeology, this experimental process leads to a fundamental examination of the concept of pattern recognition as a humanities category. The discussion of the various concepts and methods will be carried out in two complementary dissertations.

1 INTRODUCTION

Three-dimensional objects with complex forms are inadequately classified both in applied computer science and disciplines dealing with material artifacts. Archaeologists are confronted with the problem that although resemblance in shape can be recognized and established, it is much harder to support it with reasons and to describe adequately in language what may be visible for the eye. Furthermore, archaeologists have yet to make sufficient use of automated 3D shape recognition in seeking to differentiate the mutual, formal dependency of similar figures.

Archaeologists and Art Historians categorize their objects by creating typologies, thus being able to make statements about the similarity of objects, about their purpose, production or style. A computer has no problem recognizing identically shaped objects, but has yet to learn our human perception and understanding of similarity. The approach to this is to develop shape recognition procedures that link the degree of simplification and abstraction not only to human recognition and dissemination patterns as a means of incrementally evaluating and classifying unknown objects, but also to categorizations developed in archaeology and art history. 3D pattern recognition of the main components must therefore go hand in hand with archaeological subcategorization and suitable forms of machine learning

This paper will show work in progress on developing those procedures for automatically generating corpora and will reflect on the associated schematizations and how they can be applied in computer science and archaeology. The goal of the project is to create and evaluate a multi-step classification process. Eventually, there might be an object mining that will automatically compare various grades of similarity and determine to which category and sub-category (or type) the respective artifact belongs.

2 RATIONALE AND OBJECTIVE

Classification procedures and pattern recognition methods are as relevant to visual and object oriented disciplines as they are to computer science. Both seek to determine how closely two objects resemble each other and both use this information for a classification, even though their objectives differ. Whereas the goal in computer science is to automate the classification of unknown objects by means of pattern matching, typologies created in archaeology serve as a categorisation criterion for sociocultural

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questions regarding the dating, production, or functioning of artefacts. But both approaches combine a formal description of the objects with analytically interpretive approaches.

2.1 Main Objective

Big Data and Cultural Analytics methods require an appropriate structuring of data, which has not yet been sufficiently explored for three-dimensional objects. The methods of 3D pattern recognition are usually based on cognitive psychology concepts for object recognition by David Marr and Irving Biederman. The shape of an object described geometrically is divided into geometric primitives and analysed statistically by parts and part segmentation. Machine learning algorithms help to automate this process. However, for the classification of artefacts these methods can provide only rough approximations. The highly differentiated methods of biometric face recognition, for example, do not work with ancient portraits, because their visible appearance is rather determined by certain hair designs as by individual face shapes (Schofield et al., 2012; Lu et al., 2013). These insights lead to the fact that based on archaeological standards, a computational feature extraction actually can only be conducted manually by qualitative shape comparison. Nevertheless, this process cannot be used automatically yet. In addition, in areas where the sum of individual characteristics is too large, too complex or too heterogeneous to easily create an appropriate typology, archaeological methods failed. Therefore, methods of computational shape recognition might be helpful to define suitable archaeological categories.

In Archaeology and Art History, typologies are created to make historical and cultural statements. These qualitative analyses are based on a scientific framework of classification criteria that are not necessarily congruent with the concepts of cognitive psychology, since human perception is not anthropologically constant, but relies on certain viewing habits and varies significantly depending on period or culture. In cases where a large number of artefacts has quite a similar shape but differs significantly in certain details, as in serially produced terracotta figurines that were reworked subsequently, the concept of typology has reached its limits (Bell, 1993; Burn, 2012). In terms of perception and value of the figurines, there are too many different criteria that might bear a meaning. Only a statistical approach concerning the main features in combination with archaeological sources and the intrinsic aesthetic values (such as colour, execution, or style) may solve the problem.

On the one hand, the algorithms to be developed must take into account that pictorial works own a certain complexity of information. They have to represent the variety of image immanent features in a better way than a verbal description can provide and try to follow a genuinely image-oriented logic of detection and development when capturing visual

Figure 1: Different grades of similarity in ancient terracotta figurines (after Jeammet, 2003 no. 118–120. © Museum for Fine Arts Boston).

phenomena. On the other hand, it is the task of Archaeologists to determine the impressions and viewing habits of the ancient viewer and classify them in terms of cultural history. By contextually analyzing the respective conditions of reception, one tries to reconstruct how the ancient beholder may have absorbed and processed the visual impressions. The results of archaeological research must therefore be equally incorporated into the digital recording of the pictorial works.

Consequently, the project aims to combine qualitative and quantitative classification methods to revise the typology of artefacts. Here, the methods of computer science (object recognition, shape comparison and shape analysis) and archaeology (typology, “Kopienkritik” and contextual analysis) should benefit from each other, so as to overcome the aforementioned shortcomings. The conceptual development-oriented reflection of the approach, which combines the use of pattern recognition with a consistent methodological reflection, goes hand in hand with media reflective studies. The dissertations that will be developed in the course of this project aim to conduct preliminary work for the development of large technical or mental image corpora. However, both studies also investigate the capabilities of computer-aided analysis, the limits of this approach for addressing internal structures, the possibility of developing novel analytical methods, and the implications that this approach will have in general for future archaeological research.

2.2 3D Shape Analysis of Terracotta Figurines as a Case Study

Ancient terracottas are particularly well suited for questions of precise classification. The term “terracottas” refers to figurines made of fired clay that are not hand sculpted, but rather produced serially from moulds (Burn, 2012; Erlich, 2015). With regard to production, distribution, and usage, the items in question are therefore ancient handcrafted products that rank below marble and bronze figures in terms of quality and uniqueness. But they do have the advantage of having survived in large quantities and in a wide variety of shapes.

Ancient terracottas resemble each other to differing degrees. These degrees of resemblance can be precisely defined by archaeologists and evaluated progressively by means of classification procedures at different levels of precision (Muller, 1997): There are figures that were produced from the same mould and therefore exhibit an exact correspondence; alternatively, there are those that were produced in new moulds using an already fired figurine (Fig. 1a/b/c). These terracottas differ only in size from the source object. Also, there are figures taken from the same mould that nonetheless differ in appearance due to additions or changes by hand (Fig. 1b/c), as a result of which they no longer belong to the same type. The next category of terracottas bear strong resemblances to each other in terms of posture and how the costume is draped, yet they stem from different moulds (Fig. 1a/d). And finally, there are terracottas in which the same figure schema occurs in various free configurations (Fig. 1e). Admittedly, it is possible to verify at the craftsmanship level that two terracottas were produced in the same workshop. But if this is not the case, there are not yet sufficient suitable criteria for determining degrees of similarity.

New possibilities for artistic formal analysis and classification can be realised by combining geometric analysis and information known to archaeologists, because the traditional archaeological method of typology is based only on 2D photographs and subjective judgment which is not as convincing as a quantitative analysis with 3D models.

3 STATUS OF INTERNATIONAL RESEARCH AND DISCUSSION

3.1 Applied Computer Science / Computational Archaeology

In their manual, Juan A. Barceló and Igor Bogdanovic provide a detailed outline of the current state of research and an in-depth analysis of how archaeology and computer science might influence each other (Barceló / Bogdanovic, 2015). They, too, draw attention to the fact that economic mass digitisation of 3D artefacts still constitutes an unsolved problem. Though the semantic enrichment of 3D data itself remains challenging, methods for using the geometry of the 3D shape for data mining is a lively area of research (e.g. De Luca et al., 2014; Aggarwal, 2015; Fouhey / Gupta / Zissermann, 2017). Various methods for recognising 3D objects have been around for years: CAD models, data-driven geometric primitives, surface type classification using the Gaussian image (Amann, 1990. Taylor / Kleeman, 2006) and digital image comparison (Hueting et al., 2015). They mainly involve automatically extracting primitives from range data and referring to known patterns in order to classify unknown objects. The shape analysis is usually performed statistically (Dryden / Mardia, 1998). Statistical values describing geometric properties of similar shapes are evaluated with the principal component analysis (PCA) (Jolliffe, 2002) to analyse the shape variability. In addition, partial shape matching methods are widely used (Funkhouser / Shilane, 2006; Bronstein et al., 2009). Furthermore, outline comparison of one or more slices of the 3D model (Tal, 2014), as well as using image-based 3D reconstruction approaches and formalised primitives in order to generate a library of elements through the simple declaration of a sequence of architectural moldings (De Luca et al., 2014), are utilized. In general, it is much easier to retrieve the shape of a concentric solid (Hörr, 2011) than that of a complex structure; the available methods and technologies so far do not offer a final solution for the latter. Actual research topics in content-based 3D object retrieval address different methods. There is retrieval and classification on textured 3D models as well as 3D shape retrieval based on distance scanning. Methods of shape retrieval on non-rigid and large scale 3D watertight meshes are used as well. They are complemented with 3D object retrieval with multimodal views [see titles in the Eurographics workshops on 3D object retrieval 2014 and 2015]. These different algorithm-based approaches classify 3D models only in terms of basic instances (such as woman, dog, cup etc).

Thus far, these methods have rarely been used for the automated capture of artefacts, though experiments with curve detection and relief detection are already approved with archaeological artefacts (Tal, 2014). There are several reasons for this. Firstly, there are not enough 3D models of sculptures to test the feasibility of this procedure on a significant scale. Secondly, works of art (unlike structural elements or plants, for example) pose significant challenges for all types of computer-aided classification due to their complexity and variability. It is much more difficult to assign a specific instance to a more general class in this context, because works of art can differ significantly from each other in terms of shape, size, and colour. Therefore, a simple computational shape comparison for “best fit” was used by archaeologists to analyse the similarity of two artefacts (e. g. Beenhouwer, 2008). “Best fit” processes are established in engineering and similar industries and there are numerous software solutions. These tests are qualitative rather than quantitative and were already used for tolerance-based Pass/Fail shape comparison of ancient sculpture (e.g. www.digital sculpture.org/laocoon/index.html; Lu et al., 2013; Frischer, 2014; Rieke-Zapp / Trinkl / Homer, 2017). The problem with „best fit“ is that only two models are ever compared to each other, so that a generally valid extraction of 3D information to compare the objects does not take place. It is possible to compare each object with one aother, but only with morphologically strongly resembling models a meaningful result can be obtained.

As a result, it is not enough to dismantle the models into simple geometric forms. A much more promising approach is to develop shape recognition procedures that link the degree of simplification and abstraction not only to human recognition and dissemination patterns as a means of incrementally evaluating and classifying unknown objects, but also to categorizations developed in archaeology and art history. 3D pattern recognition of the main components (shape, size, and colour) must therefore go hand in hand with archaeological sub categorisation and suitable forms of machine learning (Bishop, 2006).

3.2 Computational Science

For many years, shape comparison has been an active research topic at various institutions. Not lastly, because the shape of a concentric solid is easier to compare than a complex structure. There is no definitive solution for these very structures. For this reason, various basic methods for content-based shape recognition and shape comparison already exist in the 2D and 3D area.

However, the often-used partial decomposition into the basic geometric forms is not suitable for a final determination of the similarity of complex works of art, which represent a great challenge due to their high variability, since much information is lost and the result becomes too inaccurate. Usually, similarity is based on a list of numeric attributes (interest attributes) to be determined. If more than one feature is specified for matching input features, similarity is based on averages for each of the interest attributes. Still, this approach treats all interest attributes the same and does not match the perception of the terracotta figurines. Therefore, one must try to determine a weighting of interest attributes that is close to both the ancient and modern perception of the figurines. Here, only archaeological research can help to distinguish certain types and motives. In addition, it is more difficult to assign a specific instance to a general class in this object area, since the differences in

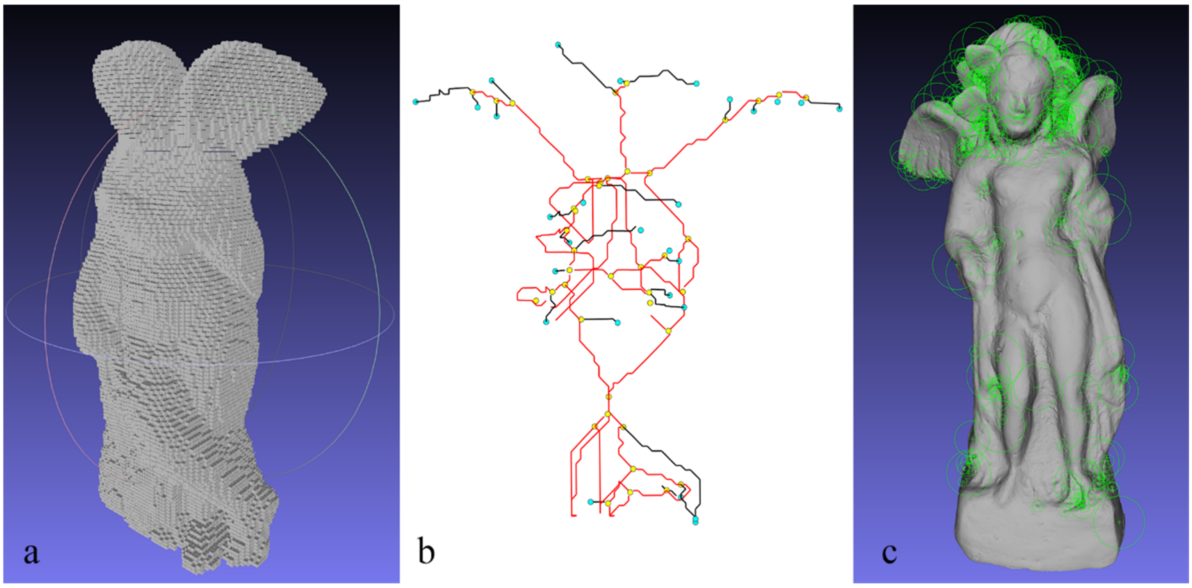

Figure 2: a - Voxelised model, b - extracted Skeleton Graph, c - Feature Point Extraction of an ancient terracotta figurine (Göttingen TK23).

shape, size and colour can be considerable. In order to obtain a more precise result for works of art, pattern recognition methods mustlink the degree of simplification and abstraction to human recognition parameters and in this way redefine a similarity of the objects. Methods that are based on simple geometric shapes must not take up the main part of the recognition process, but rather represent a possible assistance.

The aim of the project is to develop a possibility for the automated processing of 2D and 3D data that goes beyond the usual similarity parameters of linguistic usage by overcoming everyday paradigms on the subject of similarity. For this purpose, it is urgently necessary to shed light on the technical side of shape comparison and analysis and to evaluate and combine different methods. As a result, variants of similarity shall be found that would not be detectable without the help of the computer, but which have to be compared with conventional interpretations based on the parameters of archaeological perception in order to obtain a useful result. It is important to consider the differentiation between both sides and to create a link between the two approaches to the object. Surely, there is the informatics aspect in which the aim is to capture and process the complexity of this data in its entirety in order to deliver new results. Nevertheless, these results can only be used by the humanities if they can be combined with established definitions of archaeological findings or are able to challenge them. This is why the side of informatics has to be in constant check with the side of humanities.

3.3 Planned Implementation

The data to be used will be recorded in the first year of the project. For this, a number of museums will be visited to scan nearly 200 Objects. There will be high-resolution 3D scans of ancient terracottas which will be created with the structured light scanner in our 3D Lab. The figurines to be scanned are chosen on the basis of archaeological terms of similarity.

The first step in the process for recognising patterns in 3D data should be to carry out a series of tests with tolerance-based Pass/Fail shape comparison ("Best Fit"; Figure 3) of the figurines before moving to shape analysis. During this procedure, the results will be contrasted with archaeological theory concerning the concepts of similarity, seriality, typology and copy. This will keep the archaeologists and computer scientists in constant communication and will help to reset expectations and to define initial criteria of similarity.

The second step in the process for recognising patterns in 3D data, by means of the description and segmentation of surface areas ("feature patch"), is to evaluate the existing matching procedures (statistical analysis, CAD comparison, structural pattern recognition) with a view not only to conducting (semi-)automated processing of large quantities of

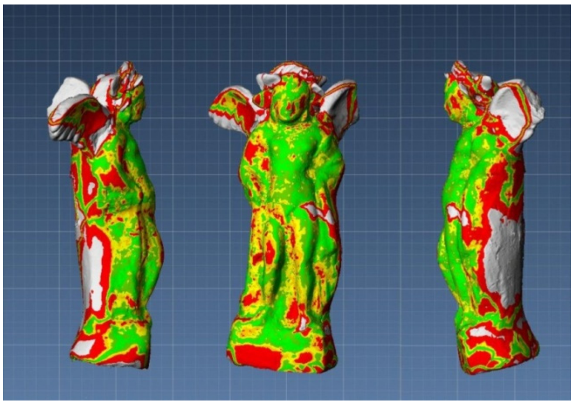

Figure 3: "Best Fit" comparison between the two Erotes Göttingen TK22 and TK23.

data, but also in terms of quality and correctness. The goal should be to determine the degree of similarity, so that the type of resemblance can be determined from it. To accomplish this, the results of learning algorithms will have to be constantly compared to archaeologist's expectations as a means of identifying and eliminating system errors in classification (Hörr et al., 2014).

The next step is to search the 3D models or segments for common patterns on the basis of the defined model group. The objective here is to transcend the tolerance-based shape comparison with identified methods of shape recognition creating a process for model-based shape analysis. For these, algorithms will be tested and validated which have not been used for this kind of data yet, but seem useful for a similarity comparison. A rough allocation to the species and an exact similarity comparison within the species must be carried out in parallel. Those parts will converge during the project and go hand in hand at the end.

The approach might therefore make it possible to carry out a "best fit" shape comparison with selected comparative pieces first and then use this comparison to fine tune the pattern recognition function progressively from "pose schema" and "figure type" to "mould identity" (and vice versa). For the goal is to develop a case study to achieve a finely tuned categorisation and classification method that goes beyond verbal, descriptive approaches.

The methods used in this step of development are various shape recognition techniques of shape analysis in the 2/3D range, not only to link the degree of simplification and abstraction with human patterns of recognition and dissemination for the gradual evaluation and classification of objects, but to use the categorisations developed in archaeology and art history as well. In this regard, extracting feature regions that distinguish subcategories from each other and subspace clustering deem to be useful. For this, *Feature Detection and Extraction* (Figure 2 c), *Image Labeler*, volume-based investigations and Voxelisation/Skeletonisation (Figure 2 a/b) among others are used.

After the evaluation of the methods, they are combined and assigned to a ranking list according to their stability which is accompanied by an internal evaluation system when extracting data from an object.

Thus, although the totality of data that can be extracted is to be collected, its interpretation is to be restricted according to parameters that have been optimised by investigation in order to avoid a threshold value for defining similarity that is too high or too low.

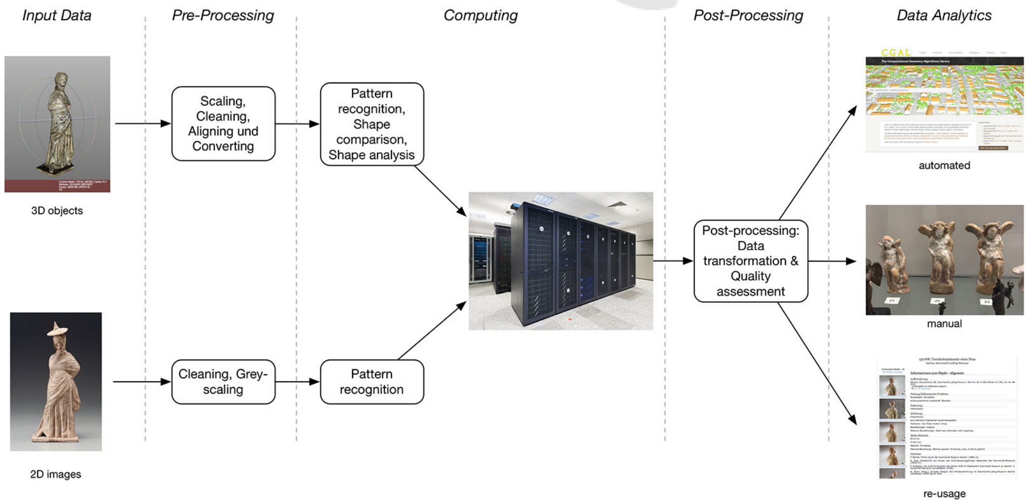

Figure 4: Model of the data pipeline.

Since the material in the image and object area is very complex, a partial objective is to test and compare the different procedures not only for their productivity, but also for their stability and effectiveness.

A data pipeline will be experimentally developed for this purpose. This is an established method in data analysis that is also suitable for processing big data. A series of processing elements is connected in a chain, whereby each step generates the output for the next step from an input (see Fig. 4 for a general concept). It implements the different parts of data processing pipelines that are needed to create consumable data products: Pre-Processing, Computing and Post-Processing. With this, it should be possible to automatically extract data for the determination and categorisation of similarity in art historical objects and to create a repository from it. This repository contains 2D and 3D objects that have been combined with data that was extracted using shape analysis. This data can be used for finding new categorisations or to be linked with existing humanities categorisations as additional digital investigations.

4 CONCLUSION

Archaeology as a scientific discipline sees its task above all in extracting patterns from the sum of surviving remains of past societies which allows conclusions to be drawn about the conditions at that time. For this reason, it has always used forms of pattern recognition to describe artefacts and images, although it has continually referred to it more as structural analysis, typology or seriation. The question arises whether the methods of archaeological “Formanalyse” are congruent with the corresponding methods of digital pattern recognition. Therefore, the methods will be compared during an intensive discussion on archaeological concepts for describing similarity and machine learning techniques for classification. The discussion has two objectives: The first is to provide archaeology with nonverbal forms of description that make it possible to classify not only typological dependence relations, but also other degrees of similarity. This may enable scholars to obtain a more explicit view of the ancient perception of terracottas concerning types, variants and motives. The second is to significantly improve the object mining process, so that a large percentage of data on objects in a collection can be automatically stored in databases in the future. On the one hand, this will revitalise the somewhat deadlocked debate on types and schemas through the adaptation of established shape recognition methods from the fields of mathematics and computer science. On the other hand, concepts of comparative visual analysis, developed in visual disciplines, will be applied in the area of shape recognition. This project will therefore investigate theoretical aspects of practical importance, such as a modified definition of the similarity concept. What does it mean for two shapes to be similar? How do you describe and define the uncertainty of the concept? What further conclusions can be drawn from this for scientific work in archaeology and computer science?

The capture, analysis and publication of historically relevant objects as 3D models offers art historical and archaeological disciplines numerous advantages: In addition to global availability, simple and non-intrusive handling, and unlimited reproducibility, the main advantage is that the viewpoint is highly adjustable (for example via rotation, zooming or juxtaposition of objects) as compared to established documentation methods (such as orthophotography or plaster casts), thereby making the objects far more accessible to researchers. This approach also allows researchers to recreate historical conditions (in the sense of an object biography), assign fragments and reconstruct positioning. As a result, traditional academic viewpoints and analytical methods will not only be expanded, but even called into question. The large-scale virtualisation of objects in collections will in general have major ramifications for visual identification processes in historical and visual disciplines. Also, comparative visualisation of similarity makes the results of formal analysis measurable and hence objectifiable, therefore the visual identification methods used by researchers in visual disciplines must adapt to new forms of visualisation which will lead to standardization processes based on new methodologies. Beginning with the methodology comparisons proposed in the project, it will be investigated and described how archaeological research will be transformed using 3D models.

REFERENCES

Aggarwal, C. C. 2015. *Data Mining: The Textbook.* Heidelberg: Springer.

Amann, H. P. 1990. *3D object recognition based on surface representations*. Neuchâtel.

Barceló, J. A. / I. Bogdanovic (eds.). 2015. *Mathematics and Archaeology*. CRC Press, Taylor & Francis Group.

Beenhouwer, J. de. 2008. *Datamanagement for moulded ceramics and digital image comparison. A case study of Roman terra cotta figurines.* In: *Layers of Perception. Proceedings of the 35th International Conference on Computer Applications and Quantitative Methods in Archaeology (CAA)*, Berlin, Germany, April 2-6, 2007. Bonn: 160–163.

Bell III, M. 1993. *Tanagras and the idea of type*, Bulletin of the Harvard Museum 1: 39–53.

Bishop, C. M. 2006. *Pattern Recognition and Machine Learning*. Berlin: Springer.

Bronstein, A. M. / M. M. Bronstein / A. M. Bruckstein / R. Kimmel. 2009. *Partial similarity of objects, or how to compare a centaur to a horse.* Int. J. Comput. Vision 84 no. 2: 163–183.

Burn, L. 2012. Terracottas. In: T. J. Smith / D. Plantzos (eds.). *A companion to Greek art.* Chichester: Wiley-Blackwell: 221–234.

De Luca, L. / D. Lo Buglio. 2014. *Geometry vs Semantics: Open Issues on 3D Reconstruction of Architectural Elements* In: Ioannides M. / E. Quak (eds.). 2014. *3D Research Challenges in Cultural Heritage. A Roadmap in Digital Heritage Preservation.* Heidelberg / New York: Springer: 36–49.

Dryden, I. L. / K. V. Mardia. 1998. *Statistical Shape Analysis*. New York: John Wiley & Sons.

Erlich, A. 2015. Terracottas. In: E. A. Friedland / M. G. Sobocinski with E. K. Gazda (eds.), *The Oxford handbook of Roman sculpture.* Oxford: Oxford University Press: 155–172.

Fouhey, D. F. / A. Gupta / A. Zisserman. 2017. *Understanding higher-order shape via 3D shape attributes.* IEEE Transactions on Pattern Analysis and Machine Intelligence 7 issue 1.

Frischer, B. 2014. *3D data capture, restoration and online publication of sculpture.* In: F. Remondino / S. Campana (eds.). *3D Recording and Modelling in Archaeology and Cultural Heritage.* Oxford: Archaeopress: 137–144.

Funkhouser, T. / P. Shilane. 2006. *Partial matching of 3d shapes with priority-driven search.* In: *Proceedings of the fourth Eurographics symposium on Geometry processing,* ser. SGP '06: 131–142.

Hörr, C. / E. Lindinger / G. Brunnett. *2014. Machine learning based typology development in archaeology.* Journal on Computing and Cultural Heritage (JOCCH) 7.1: 2.1–2.23.

Hörr, C. 2011. *Algorithmen zur automatisierten Dokumentation und Klassifikation archäologischer Gefäße* (Chemnitz 2011).

Hueting, M., M. Ovsjanikov and N. J. Mitra. 2015. *CrossLink: joint understanding of image and 3D model collections through shape and camera pose variations.* ACM Transactions on Graphics (TOG), 34 (6), 233.

Jeammet, V. (ed.). 2003. Tanagra. *Mythe et archéologie.* Exhibition catalogue Musée du Louvre 15 september 2003 – 5 january 2004. Paris: Editions de la Réunion des musées nationaux.

Jolliffe, I. 2002. *Principal Component Analysis, 2nd ed.* Heidelberg: Springer.

Lu, M., Y. Zhang / B. Zheng et al. 2013. *Portrait sculptures of Augustus: Categorization via local shape comparison.* In: *2013 Digital Heritage International Congress.*

Muller, A. 1997. *Description et analyse des productions moulées. Proposition de lexique multilingue, suggestions de méthode.* In: *Le moulage en terre cuite dans l'antiquité. Création et production dérivée, fabrication et diffusion.* Actes du XVIIIe Colloque du Centre de recherches archéologiques, Lille III, 7 - 8 décembre 1995. Villeneuve d'Ascq: Presses universitaires du Septentrion: 437–463.

Rieke-Zapp, D / Trinkl, E. / Homer, L. 2017. *Face to face – Considering the moulding of Attic head vases reconsidering Beazley's groups by quantitative analysis.* Journal of Archaeological Science: Reports [https://www.sciencedirect.com/science/article/pii/S2352409X17305345]

Rumscheid, F. 2006. *Die figürlichen Terrakotten von Priene.* Wiesbaden: Reichert.

Schofield, D. / K. Lorenz / St. Davy-Jow / M. Anderson. 2012. *Roman Portraiture and Biometric Identification.* In: *Electronic Visualisation and the Arts (EVA)* London: 163–171 (http://ewic. bcs. org/content/ConWebDoc/46119).

Tal, A. 2014. *3D Shape Analysis for Archaeology*. In: Ioannides M. / E. Quak (eds.). *3D Research Challenges in Cultural Heritage. A Roadmap in Digital Heritage Preservation.* Heidelberg / New York: Springer: 50–63.

Taylor, G. / L. Kleeman, 2006. *Visual Perception and Robotic Manipulation: 3D Object Recognition, Tracking and Hand-Eye Coordination.* Heidelberg: Springer.