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Short Paper

Automated classification of crests on pottery sherds using pattern recognition on 2D images

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Abstract

Manual classification of artefacts is a labor intensive process. Based on 2D images and 3D scans of - for example - ceramic shards, we developed a pattern recognition algorithm which automatically extracts relief features for each newly recorded object and tries to automate the classification process. Based on characteristics found, previously unknown objects are automatically corelated to already classified objects of a collection exhibiting the greatest similarity. As a result, classes of artefacts form iteratively, which ultimately also corresponds to the overall goal which is the automated classification of entire collections. The greatest challenge in developing our software approach was the heterogeneity of reliefs, and in particular the fact that current machine learning approaches were out of question due to the very limited number of objects per class. This led to the implementation of an analytical approach that is capable of performing a classification based on very few artefacts.

CCS Concepts

• ***Computing methodologies*** → ***Image processing;*** • ***Applied computing*** → ***Archaeology;***

1. Introduction

We develop approaches [STD*20] for high-quality, efficient and fully automatic 3D digitization of objects of almost any shape and materiality with the aim of creating digitized copies of real objects that are as realistic as possible. We design, develop and implement autonomous 3D scanning systems based on our expertise in software development, 3D digitization and automation as well as hardware design.

The presented work was performed in a national funded project called "Medium:Keramik" and one of the aims was to identify and test suitable algorithms for feature extraction from 2D images and 3D models using the example of ceramic pottery sherds, in order to automate the assignment of an object to a class of objects.The reason behind this objective is the recurring, tedious task, especially in archaeology, of classifying hitherto unknown or unclassified artefacts by comparing them with illustrations and descriptions in numerous works of literature, i.e. assigning them to a class of comparable artefacts. The automated solution is intended to facilitate and support the questions and tasks of archeology in this regard as far as possible. In addition, the software tool developed should not remain limited to the example of pottery sherds, but should flexibly be applicable to the most diverse classes of objects.

2. Implementation

Our automated classification approach consists of two simple steps. In the first step, the user specifies 2D images or 3D models of known objects, representing objects of specific classes. In the second step, the user enters a 2D image or 3D model of a new object, and the software then automatically determines the class to which this object belongs. The functional principle is visualized in Figure 1 as an example.

The Rheinisches Landesmuseum Bonn, or LVR-LandesMuseum Bonn, is a museum in Bonn, Germany, run by the Rhineland Landscape Association. To evaluate our approach we digitized 53 ceramic pottery sherds exhibiting historic family crests made available to us for the duration of the project, both in the form of image data (Figure 1 and 2) and 3D models.

The sherds provided included many representatives of several classes of crests and led to two conclusions. Firstly, that one of the greatest challenges to a solution for automatic classification has to cope with the high levels of artistic freedom found among sherds of the same class, the heterogeneity of the patterns and their deviations from one another (see Figure 3), and secondly, that current very popular methods of machine learning are not an option, as they require several hundred or even thousands of examples to ensure a reliable and robust classification. Therefore, we developed an analytical solution that has the great advantage of providing a reliable classification of an unknown object into existing classes based on

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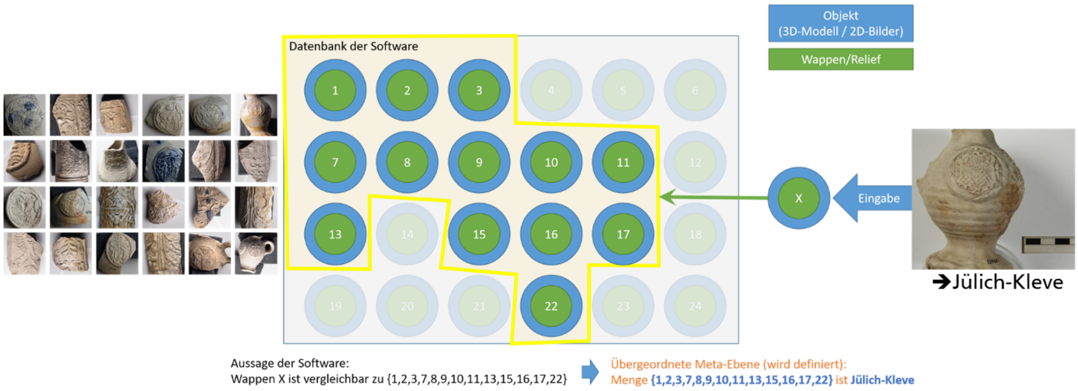

Figure 1: *Functional principle of the automatic classification based on analytical methods.*

Figure 2: *Images of a total of 53 sherds of pottery, both with a professional lighting setup and with a current smartphone as proof of the low requirements of the classification solution on the input data.*

just a few input images. Also the software requires no training as opposed to machine learning solutions.

Initially we pursued pattern recognition on both, 2D images and 3D models. However, the approach based on 3D models turned out to be much more complex. To identify similar features on 3D models we had already ported 2D HOG (Histogram of Oriented Gradients) approaches to 3D [TSS*16]. However, they would not give us the detailed resolution needed here without an appropriate 3D segmentation of the model, which was out of the scope of the current project, but can be part of a follow-up project. In addition, on one hand, we had to be able to identify the front view of the artefact, and on the other hand we had to separate the object's background from its relief overlay on which the classification would be based [ZTS09]. Since these steps were to run as automatically as possible without involving the user, we ruled out the 3D method due to its complexity, and focused on the 2D image-based classification of objects. Also, 2D images would be much easier for the user to generate. Even pictures taken with a smartphone would suffice.

Figure 4 shows how much instances of exactly the same historic family crest and therefore the same pattern can ultimately differ on pottery sherds, even if they would belong to the same class. Furthermore, different surface materials will also affect pattern recognition, as can be seen in the first (glazed surface) and second image (grayscale conversion of the first image). In the third image, for example, the lily cross exhibits significantly different proportions compared to the first and second images.

In order to achieve the necessary robustness against strong heterogeneity even based on simple smartphone images, i.e. to design the classification software as tolerantly as possible to large deviations of patterns and at the same time achieve a high level of accuracy when assigning similar patterns to the same class, we developed and implemented a multi-stage algorithm. The basic procedure for making two objects comparable via their images is to derive a kind of "fingerprint" within the relevant areas of the objects, which represents their essential characteristics and is also invariant to rotation and scaling of the object images, inspired by [Low99]. In other words, we search for a fingerprint that does not change if larger or smaller image sections are selected or the objects are captured from different perspectives.

Figure 3: *3D renderings of selected objects from the 53 pieces of pottery, which were digitized in the form of 3D models with the autonomous 3D scanner CultArm3D (see Figure **??**) from Fraunhofer IGD.*

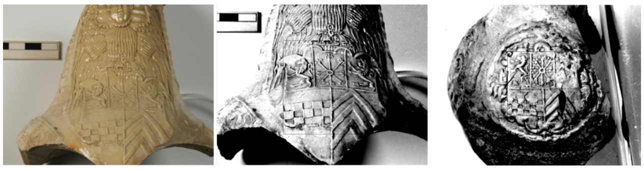

Figure 4: *Artistic freedom and heterogeneity of "same" patterns of the same class among each other.*

To start the recognition of a crest, the user only has to manually select a relevant area (green frame in Figure 5), within which specific features such as corner points, edges and gradients and their characteristics are then automatically extracted using various image processing algorithms and filters (second false-color image in Figure 5) and then compared to the collection of sherds. The tolerance for different manifestations of the same pattern on different objects is achieved in particular in the subsequent step through spatial abstraction, by dividing the relevant area into a grid so that the focus is on smaller substructures, such as the sub-areas of a coat of arms, inspired by [HR08]. This is important because coats of arms are often divided into substructures, which in turn often have very different motifs, which should lead to a different classification of the object as a whole. On the other hand, the extracted structures of the partial areas are in turn divided into sectors in order to represent their respective orientation. Both levels of abstraction are shown schematically in the third image and as an overlay with the extracted features in the fourth image - in Figure 5.

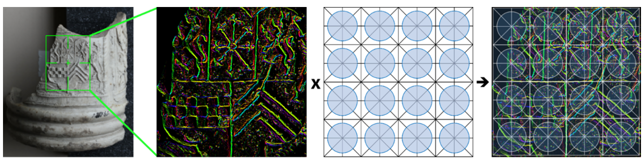

Figure 5: *Selection of the relevant area (green frame), extraction of the specific features, and spatial and angular abstraction.*

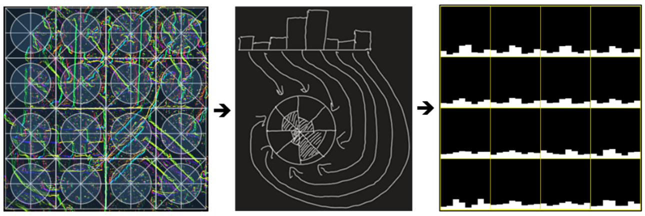

Figure 6: *Creation of a spatially distributed and orientation-based abstraction by analyzing the frequency distribution, the specific "fingerprint" of the object.*

The actual fingerprint of an object, based on the selected relevant area of its relief, results from a sector-by-sector analysis of the frequency distribution per sub-area. This is shown as a histogram in the second image in Figure 6. The application of this step to all sub-areas results in a matrix of frequency distributions as in the third image in Figure 6, which is ultimately used for the quick and abstract comparison of objects and their classification.

The current prototype software already performing the fully automatic classification of an object based on its image and a selection of its relevant areas, is shown as a screenshot in Figure 7.

Figure 7 (left) shows our Windows application. The user has the option of defining an initial image data set, which, as shown in Figure 1, serves as a basis for comparison for the classification of new objects. In the second step, any images can now be loaded for still unknown objects, which are then automatically assigned to one of the existing classes, represented by the initially loaded image data set.

Figure 7 (right) shows the result of the automatic assignment by the application for a sample image. The new input image of the still unknown object is displayed in the upper area, and the selected relevant section (ROI - Region of Interest) of this image (yellow heading) is displayed in the lower area (left). The images of the initial image data set serving as a reference, which were identified as most similar by comparing the previously known objects with the new object by fingerprint, are shown in the lower area in the center and on the right (turquoise heading). Figure 7 shows the two most similar objects found and classified, as well as their respective relevant areas exhibiting a "double-headed eagle", which matches the pattern found on the new image.

It may happen that the set of objects recognized as the most similar ("result set") contains one or more "false positives", for example due to unfavorable selection of the relevant area, or also due to excessive heterogeneity of reliefs among objects of the same class, or due to input data of insufficient quality. In previous tests, the majority of the result sets always contained representatives of the correct class, which corresponds to the class of the object to be determined. Therefore, a final step in the development of the software was to introduce a majority vote. The class most frequently represented in the result set is returned as the result of the assessment making the algorithm robust against deviations.

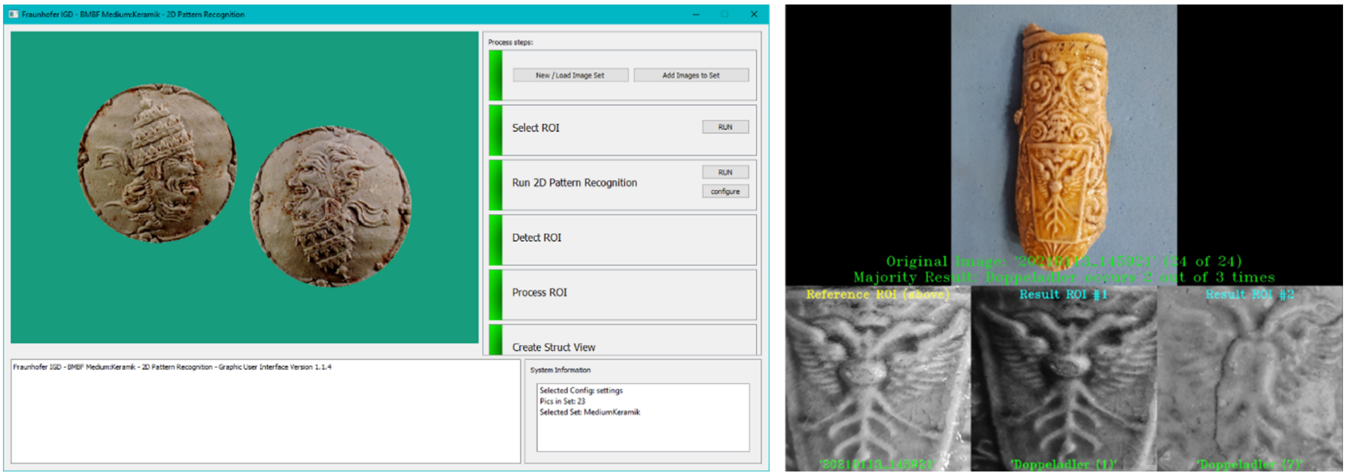

Figure 7: *Prototype software for pattern recognition and classification (left) and result view (right).*

The algorithm can be adapted to collections of the most diverse artefacts by adjusting the level of discretization when dividing an image area into a grid (Figure 5). Also the size of the result set on which the majority vote is to occur can be parameterized. Due to our algorithms O(n log n) on 2D images we expect this solution to scale well with masses of pottery shards available from the state offices for archeology.

3. Conclusion

In line with the overall objective of the European Commission's Digital Agenda for Europe [Com11a] [Com11b], our approach provides a contribution to ease the process of classification of artefacts for curators. In summary, the Medium:Keramik project resulted in a large data set consisting of 2D images as well as 3D models of 53 ceramic sherds, used to further develop the classification software and for other research questions beyond the project period. On the other hand, the goal of taking a first step towards the automatic classification of objects based on 2D images was actually achieved and without the use of machine learning methods - the resulting algorithm already works robustly on small amounts of data, which even a standard smartphone is sufficient to collect without much effort. The classification software is easy to install and easy to use without prior knowledge, offering a graphical user interface. A tutorial has also been written to guide the user through the necessary steps from installation to running a built-in example, and finally to successfully assign an unknown shard to its correct class.

4. Acknowledgements

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