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Short Paper

Towards an automatic 3D patterns classification: the GRAVITATE use case

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Abstract
When cataloging archaeological fragments, decorative patterns are an indicator of the stylistic canon an object belongs to. In this paper we address a quantitative classification of the decorative pattern elements that characterize the models in the GRAVITATE use case, discussing the performance of a recent algorithm for pattern recognition over triangle meshes.

CCS Concepts
•***Computing methodologies*** $\rightarrow$ ***Shape modeling; Shape analysis;***

1. Introduction

In archeology the study of style is one of the most important approaches in the study of the material culture of an ancient society. An important part of a stylistic analysis is the classification of decorative elements. Decorative elements and their appearance are an indicator of time, area of production and cultural influences. The way they are realized can also be a sign of different workshops and manufacturer techniques. Traditionally, their study consists in a visual inspection, drawings and a textual description of the decoration. Such an approach is time consuming and most importantly subjective because related to perception and interpretation of the individual studying the material. To correctly identify and classify a decoration a quantitative analysis is desirable. A numerical description of decorative elements introduces more objectivity to the classification process. Furthermore, it enables an automation of the identification process of similar elements thus saving time and making the analysis more efficient.

The automatic classification and recognition of archaeological potsherds [DTC*17, GSW*16] or decorative patterns [GRA18] are part of several research initiatives. Among these, the European GRAVITATE project aims to support scientists to Re-Assemble fragmented and broken heritage artifacts, identify and Re-Unify parts that were separated across collections and to recognize and Re-Associate cultural heritage artifacts that have common features, allowing new knowledge and understanding of past societies to be inferred. The project is building its research on real case-studies. The starting point was a collection of broken votive terracotta statues from Salamis, in Cyprus.The collection counts more than 250 fragments and most of them represent male standing, bearded figures, in different sizes. They are attributed to the Neo-Cypriote style, dating from the second half of the VII century BC to the early VI century BC [MTW91, Kar93]. The database was enriched with a second case-study: a selection of pottery vessels fragments from Naukratis, a Greek trading port on the Nile Delta, in Egypt. Thousand of finds dated from the VII century BC to the VII century AD, were uncovered at the site [lin]. Among them, around 70 pieces, between fragments and complete vessels, became part of the GRAVITATE dataset. Both datasets show a wide range of decorative elements (e.g. floral and geometric patterns, figurative elements, etc.) that are also representative of many other contemporary collectionsbut also present a variation in the technique. Indeed, the decorative elements can be applied, incised, stamped and/or painted on the artifact. Hence, the objects within these collections represent suitable and challenging material for this study.

2. The GRAVITATE use case

The votive fragments of terracotta statues from Salamis were acquired by laser scans, while the vessels fragments from Naukratis are obtained with photogrammetry. All the 3D models are part of the GRAVITATE use case [GRA18]. Each model is represented as a triangle mesh, equipped with colorimetric information on the vertices. The 3D models are stored in the STARC repository [STA]. The 3D models achieve a very high precision over the small details (which is a key factor for the analysis of the decorative elements) and have millions of vertices. Therefore, besides a geometry processing to remove small mesh artifacts (like self intersections, non-manifold vertices, etc.) the models underwent to different simplified versions of the meshes were extracted (with 1M, 100K and 50K vertices) to simplify the computational complexity of the geometry processing algorithms [MPS17].

The dataset is characterized by peculiar decorative elements, i.e. features or patterns, that are relevant for their classification. A tax-

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Figure 1: *The frequent/relevant patterns and features in the GRAVITATE dataset. We adopt the italics and bold styles to highlight the pattern classes considered in the GP dataset and the CP dataset, respectively.*

onomy of the decorative elements in the dataset was done with the support of the archaeologists involved in the project. The resulting classification is summarized in Figure 1; 32 classes of characteristic elements have been identified. Figure 1 contains a representative picture for each class, together with the respective label. We grouped the elements in two categories (see Figure 1):

- *Geometric* - These elements represent small variations on the surface geometry such as *repeated and small* incisions, chiseling, bumps, or by stippling the model surface with a small object.
- *Colorimetric* - These elements present small painted decorations on the surface. Colors are stored in the models as RGB values.

Among the GRAVITATE style elements, here we focus on patterns, i.e. elements on the surface that are repeated to become a decorative or a functional part. Examples of geometric patterns are the so-called *Spirals*, *Smooth Fringe*, *Band (Ridge)*, while examples of colorimetric patterns are the *Chequer*, *Six Petals* or *Guilloche* (labels are adopted according to Figure 1). Note that, in our understanding, a single or a couple of decorative elements (i.e. a button, a rosette, etc.) do not represent a pattern.

3. Pattern classification

To address the quantitative analysis of the pattern elements, we adopt the *Edge Local Binary Pattern* (edgeLBP) descriptor defined in [MTB18a, MTB18b]. The edgeLBO overcomes the benchmarks in the literature [Be17, MTTW*18] and only recently another method has shown comparable performances [Gia18] for the comparison of geometric patterns.

3.1. Pattern description with the edgeLBP

The *edgeLBP* extends the Local Binary Pattern [OPH96] to surface meshes. For each vertex v of a triangle mesh T, a ring of radius R is defined as the intersection of the mesh edges with a sphere of radius R centered in v. For each ring, the piecewise linear curve C that represents the intersection of the mesh with the sphere is detected. Due to the unpredictable structure of the triangulation (the vertex distribution, the mesh connectivity, etc., are not a-priori known and uniform along T), each curve C is oversampled or sub-sampled with P points. Each ring is then represented by P samples, which are points in $\mathbb{R}^3$. Concentric rings (N_r) for each vertex are used in or-

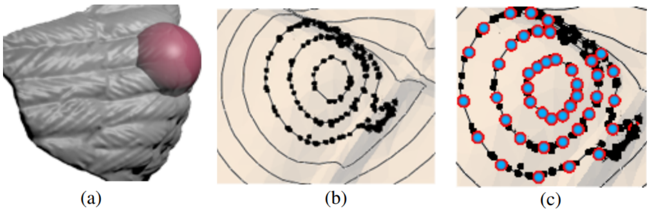

Figure 2: *(a): An example of mesh-sphere intersection. (b): The black dots highlight the intersection points between the spheres and the edges of the mesh. (c): The blue-red dots represent the uniformly-spaced samples over the curves.*

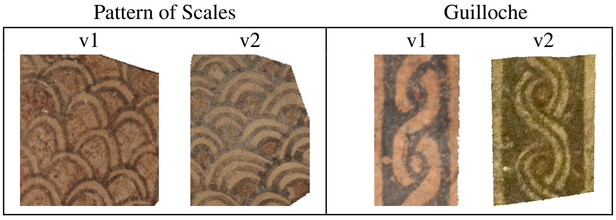

Figure 3: *The scale and guilloche classes contains decorations that are semantically the same but differ from the geometric point of view (for instance the number of curved lines, for this reason we subdivided them in two different classes.*

der to achieve a multi-ring description. The radius R of the largest sphere, the number of rings N_r and the number of samples P are the parameters of the method. This process is synthesized in Figure 2.

The pattern evolution is coded according to a local property represented as a scalar function $h : V \rightarrow \mathbb{R}$, where V is set of vertices of T. In case of images, h is the gray-scale value; in our experiments we adopt the *shape index* [KvD92] for the analysis of the geometric patterns and the *L-channel* of the CieLAB color space embedding [HP11]. For each model, its descriptor is the normalized histogram of the LBP values for all the vertices of the model. The distances among the descriptors is the Bhattacharyya distance [DD09].

The settings of the algorithm depend on the dataset considered. The value of the radius R determines the granularity of the descriptor: the smaller R, the more the edgeLBP will focus on small surface details, and vice-versa. For the parameter settings considered in this work, see Section 3.2.

3.2. Experimental settings and classification performances

From the GRAVITATE use case, we select the most frequent patterns and created two datasets, one for the geometric patterns (GP dataset) and the other for the colorimetric ones (CP dataset).

- the *GP dataset* derives from the four classes labeled in red in Figure 1. From the models with these patterns, we extracted 60 sample patches, grouped in 6 classes of 10 patches.
- The *CP dataset* is derived from the eight classes labeled with a blue font in Figure 1. In particular, two of the classes (Pattern of Scales and Guilloche) present a large intra-class variation that from the geometric point of view suggests to split them into two sub-classes (see Figure 3). We then consider four classes instead of two (Scale v1, Scale v2, Guilloche v1 and Guilloche v2). From models with colorimetric patterns, we extracted a dataset of 49 patches grouped into 10 classes, where each class contains from 4 to 7 elements.

The classification performance obtained by the edgeLBP is evaluated with respect to the *Nearest Neighbor*, *Fist Tier* and *Second Tier* per class of pattern (for details on these evaluation measures we refer to [SMKF04]). Moreover, we report the *Confusion Matrix* over the pattern classification obtained with the NN classifier.

Discussions Multiple settings are used in our tests, with encouraging results. In Figure 4 we detail the performances for the best edgeLBP runs. The outcome of the experiments show a very good classification performance (we reach an overall 95% classification rate with the NN classifier) for the geometric patterns. The only confusion comes between 3 Line patterns that are classified as Hatched Fringe, however, this is not surprising because in both cases we are dealing with linear incisions of comparable size. Things are more complex for the colorimetric patterns. For instance we see that specific patterns like the Guilloche ones are well classified while more complex decorations like the Six petals, the Lotus and Bud and the Scales (v1) are often confused. We think that this effect depends on two effects: the non uniform decoration (there are thin and fat lines together) and the fact at the moment we are able to consider only one channel at a time (the L-channel corresponds to the luminosity thus forgetting the other colorimetric information). To fix this limitation, we are currently working on the extension of the edgeLBP to multidimensional properties.

4. Conclusions

Current experiments are performed on patches fully characterized by a single pattern at a time and the similarity distance is defined on the whole patch. To fully address the pattern recognition problem over surface meshes, we need some further steps, like the automatic recognition and localization of multiple patterns over the same object. Recently, a benchmark was delivered for the automatic recognition of relief patterns [BMTB*18] over a set of models from the GRAVITATE use case but, unfortunately, none of the methods tested on that contest gave satisfactory results. However, the number of participants highlighted that this is a lively and challenging problem that deserves further exploration. Out next plans to address the pattern recognition problem include the combination of the shape description step with segmentation techniques, the adoption of multi-scale representation to distinguish what is noise and what is relevant, the aggregation of parts made of vertices with similar local descriptions.

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edgeLBP settings: $n_{rad} = 7$, $N = 15$, $R = 0.6$cm					
Class considered	NN	FT	ST	e	nDCG
Feathered Pattern	1.000	0.722	0.911	0.434	0.934
Pattern of Circles	1.000	0.922	0.978	0.439	0.989
Spirals	1.000	0.644	0.756	0.385	0.911
Line Pattern	0.700	0.300	0.367	0.263	0.661
Smooth Fringe	1.000	0.467	0.500	0.229	0.804
Hatched Fringe	1.000	0.400	0.589	0.371	0.773
Overall	0.950	0.576	0.683	0.354	0.845

edgeLBP settings: $n_{rad} = 5$, $P = 15$, $R = 0.5$cm					
Class Label	NN	FT	ST	e	nDCG
Guilloche v1	1.000	1.000	1.000	0.171	1.000
Six Petals	0.500	0.500	0.767	0.270	0.720
Chequer	0.857	0.571	0.738	0.271	0.811
Striped band	0.800	0.200	0.400	0.222	0.544
P.o.C. (Painted)	1.000	1.000	1.000	0.171	1.000
Lotus and Bud	0.500	0.333	0.583	0.171	0.666
Scales v1	0.429	0.310	0.619	0.316	0.579
Scales v2	1.000	1.000	1.000	0.171	1.000
Guilloche v2	1.000	1.000	1.000	0.171	1.000
Pattern of Curves	0.500	0.250	0.250	0.086	0.424
Overall	0.735	0.582	0.723	0.217	0.758

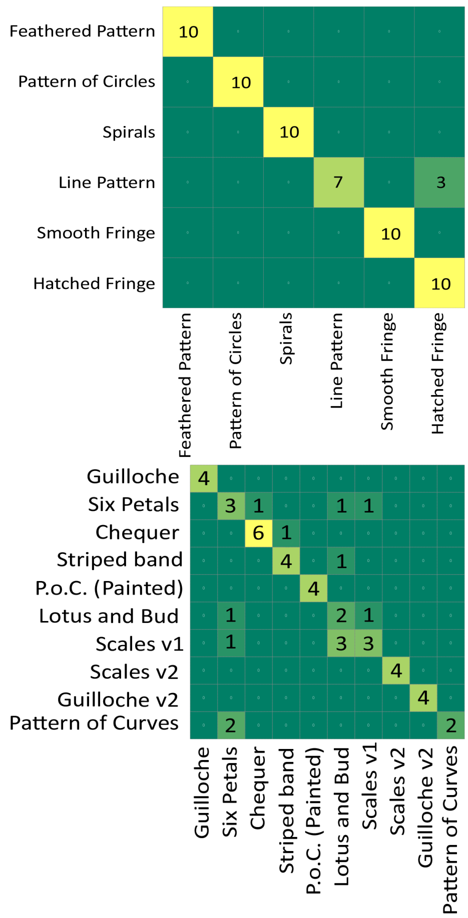

Figure 4: *Classification performances of the edgeLBP over the patterns selected.*