Gabor Filter-Based Texture Features to Archaeological Ceramic Materials Characterization

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Abstract. This paper presents a self-learning system for automatic texture characterization and classification on ceramic pastes or fabrics and surfaces. The system uses Gabor filter as pre-processing methods with feature extraction possibilities. On these features it applies a linear discriminant analysis (LDA) and k-nearest neighbor classifiers (k-NN) with its best parameters. Experimental results of the recognition ceramic materials, deals on the field and in the laboratory, for different ceramic pastes and surfaces show a good accuracy and applicability of the process on this type of data.

Keywords: Egyptian ceramic materials, ceramic fabrics and surface, texture characterization, feature extraction, classification algorithms.

1 Introduction

The history of archaeological Egyptian ceramics is an evolving discipline with new grid interpretations and pottery analysis, that archaeologists explore jointly taking two fundamental elements of ceramics study.

- The first element is the cultural aspect of the pottery vessel (archaeological context, chronology, shape, coating, decor, manufacturing techniques, function, etc.)
- The second element is the technical aspect of ceramic materials (characterization of the fabric: group designation for all the properties of the clay. The paste of the potter is a term for the plastic material from which the pots were made with the non plastic inclusions of mineral or organic origin [1])

The technical aspect constitutes a significant part of the pottery discovered at archaeological sites. It is considered as an identity card [1, 2, 3]. Now, the importance of material characterization to ceramics study is well established [1, 4]. The progress realized in this field during the last thirty years places the archaeological finds in several levels of analysis (production, consumption and distribution). For distribution levels, ceramic materials recognition is crucial because it shows the reconstruction of the traffic of archaeological objects in the inter-regional or international trading

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routes, to allow us to distinguish between chronological and ethnic groups and to give some information on cultural relationships [5].

Traditionally, archaeologists examine the ceramic sherds on the field and thereafter in the laboratory [1, 5]. Generally, they use a binocular microscope to describe the fabric using a fresh break cut parallel to the vessel rim, and also the inner and outer surfaces of the sherd. This step represents the basis for any ceramic production classification to create groups of different fabrics [5, 6]. It is based on visual criteria (nature, size, shape, repartition of mineral and/or organic inclusions contained in the paste made by the potter, shaping methods, texture, color, methods of surface treatments, the firing of pottery). When it is necessary, the last levels for recording the properties of a pottery fabric are two main laboratory methods: the petrographic analysis (using thin sections) to identify the inclusions and chemical analysis to measure the chemical constituents of ceramic [2, 5]. Generally, these techniques are complementary and have two main goals:

- Establish and validate the classifications obtained on visual criteria with the microscope
- Characterize the ceramic fabric of the ceramic sherd in order to define the productions and to seek - where possible - the geographic origin

In some cases, however, the field and laboratory methods can provide contradictory conclusions. They therefore remain complex to interpret and there are uncertainties because every characterization process is done manually, by different archaeologists and under varying environments [6, 7]. In this context, archaeologists need to use machine vision to archive their ceramic materials [8, 9]. In this paper, we propose a solution based on texture analysis. Firstly, the ceramic paste or fabric on fresh break sherd and surface textures are described by texture characterization methods and secondly, obtained feature vectors are used to compare textures using several classification algorithms to allow the classification of ceramic materials.

2 Related Work

Texture analysis is the process to characterize and to classify different textures from the given images. It is considered as a key problem in a large variety of pattern recognition application areas, such as object recognition [10], industrial inspection [11], wood species recognition [12], rock classification [13] and so on. This kind of process requires the identification of proper features that differentiate the textures in the image for classification and recognition. In the real world, the images are often not uniform (changes in orientation, scale or other visual appearance) [14] and the extracted features are assumed to be uniform within the regions containing the same textures [14]. Several methods have been proposed in literature. Surveys of existing and comparative texture analysis may be found in Refs. [14-17].

The most important part of the historical ceramic materials classification is to define invariant features characterizing ceramic paste and surface textures, and which make possible a distinction between different kinds of ceramic materials. This application is similar to rock texture analysis [13] but is more difficult. Unlike rock textures, ceramic paste and surface texture analysis is quite demanding. They are non-homogenous and not clear directional (when a vessel is shaped on a wheel, the inclusions like rod-shaped particules and straws follow the orientation and are parallel in the fresh break section to the rilling lines of the pot [1]). Also different granular size and other very small objects and straws can be integrated in some ceramic materials. [18-20] use texture analysis for quality control in ceramic tile production. Lindqvist and Akesson [21] present a literature review of image analysis applied to characterize rock structure and rock texture analysis. In Singh et al. [22], texture features for rock image classification are compared. The best performance was obtained by using co-occurrence matrices. Few research works on this few topic have been published. Smith et al. [23] use color and texture features based on well-known Scale Invariant Features Transform and we formulate a new feature based on total variation geometry for the reconstruction of archaeologically excavated ceramic fragments. Kampel and Sablatnig [7, 9] are developing an automated classification and reconstruction system for archaeological fragments based on shape and color information as a pre-classification process.

3 Archaeological Site

A set of macroscopic photographs made in IFAO laboratory by a device composed of :

- Reflex photo Kodak DCS-14 N camera.
- This camera is mounted on a Zeiss stemi 2000-C stereomicroscope.
- Schott KL 1500 LCD cold light source at a temperature of 3200 K.

They were obtained from ceramic materials classification of different fabrics representatives of Egyptian/local pottery production of three different sites. The samples cover a wide geographical area of Egypt (Marsa Matrouh, Abu Roach, different sites of Kharga oasis) and a large chronological period from the end of the Neolithic period (around 4800 BC) to the medieval period. The selected ceramic samples for this paper are derived from the Abu-Roach archaeological site which is located in Egypt in the Memphite area near the modern Cairo [24].

Abu-Roach, is an archaeological site[1] which is mainly known for Old Kingdom period (around 2500 BC) to be the pyramid complex of the king Djedefrê. The samples choose are the more representative from the classification of fabrics pottery link to the repertoire of pottery of this period found during the excavations. The vast majority of pottery vessels served domestic purposes (storage, preparation and consumption of food) and other types served ritual purposes (miniatures). But the site continues to be occupied after this period until the medieval period [3]. Few sherds from New Kingdom pottery (around 1300 BC), beginning of Ptolemaic pottery (around IVe century BC), and beginning of the Arabic period in the VIIe century AD have been also selected for this paper.

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[1] `http://www.ifao.egnet.net/archeologie/abou-roach/`

The ceramic paste used in the manufacture of these objects includes the Nile fabrics or alluvial paste, the marl fabrics or marl clays (calcareous), and mixed clays fabrics (combination of marl and alluvial clays), and the foreign fabrics (Palestinian fabrics, Nubian fabrics, etc.). For this paper only Egyptian pottery sherds are presented here and the majority of these pots are locally produced in the Memphite area. If the fabrics are important to characterize and identify the pottery production, the ceramic surface too. For the selected samples from Abu Roach presented in this paper we found two main treatments of the ceramic surfaces (slip or not slip, and not slip with diffuse surface). For the not slip pots, the surface could be diffuse and present variation of colors on the surface, all this depends on the firing process.

4 Ceramic Pastes and Surfaces Characterization

Archaeologists consider that visual inspection is an important part of ceramic materials examination. However, this step remains complex because the ceramic pastes used in different manufacturing processes are extremely diverse and have heterogeneous composition. Similarly, ceramic surfaces of objects are often non-uniform. Thus automated visual inspection based on the machine vision system to ceramic materials classification requires the use of features and should describe the desired properties of ceramic pastes and surfaces.

4.1 Ceramic Texture Characterization Based Gabor Filter

In order to make an automated classification between different ceramic materials, some features have to be extracted, from ceramic pastes and surface textures. In this paper we try to apply a Gabor filters-based texture features. It has been successfully and widely applied to image processing, computer vision and pattern recognition [25, 26]. Its use is motivated by various factors. The characteristics of the Gabor filter, especially the frequency and orientation representations, are similar to those of the human visual system [27]. The statistics of these micro-features in a given region are often used to characterize the underlying texture information. In addition to accurate time-frequency location, they also provide robustness against varying brightness and contrast of images. A circular 2D Gabor filter in the spatial domain has the following general form [28]

$$G(x, y, \theta, u, \sigma) = \frac{1}{2\pi\sigma^2} e^{\left\{-\frac{x^2+y^2}{2\sigma^2}\right\}} \times e^{\{2\pi i(ux\cos\theta + uy\sin\theta)\}}$$

where $i = \sqrt{-1}$; u is the frequency of the sinusoidal wave; θ controls the orientation of the function and σ is the standard deviation of the Gaussian envelope. A filter bank of Gabor filters with various scales and rotations is created. In this work we have considered scales of 0, 2, 4, 6, 8, 10 and orientations of 0°, 45°, 90° and 135°. For each obtained response image we extract first three moments as features.

4.2 Ceramic Texture Classification

In image classification, the objects which are characterized by a feature vectors should describe the visual appearance of the texture or other attributes as accurately as possible. Generally, the features extracted are overlapping in the feature space and this makes the classification challenging. In this work, the classification algorithms are a supervised approach and a non-parametric discriminant analysis. In order to classify new samples we need a training set representing each category of ceramic pastes and/or surfaces. After wards, the linear discriminant analysis [29, 30] and the k-nearest neighbour, classifier [31] are applied on training set to estimate the optimal models. Finally, the tests set are assigned using these models. The selection of these classifiers is due to their robustness with homogenous and non-homogenous feature distributions of the ceramic paste and surface textures.

Linear Discriminant Analysis (LDA)

The linear discriminant analysis [29, 30] finds a transform matrix W, such that

$$W = arg\max_{W} \frac{W^T S_B W}{W^T S_W W}$$

where S_B is the between-class scatter matrix and S_W is the within-class scatter matrix, defined as

$$S_B = \sum_{i=1}^{c} N_i (x_i - \mu)(x_i - \mu)^T$$

$$S_W = \sum_{i=1}^{c} \sum_{x_k \in X_i} (x_k - \mu_i)(x_k - \mu_i)^T$$

In these expressions, N_i is the number of training samples in class i, c is the number of distinct classes, μ_i is the mean vector of samples belonging to class i and X_i represents the set of samples belonging to class i.

k-Nearest Neighbour Classifier (k-NN)

The k-NN classifier is very simple to understand and easy to implement. It is based on a distance function such as the Euclidean, City block, Cosine distance, Pearson's correlation or so on. These functions are computed for pairs of samples in N-dimensional space (number of features). Each sample is classified according to the class memberships of its k nearest neighbours, as determined by the distance function. k-NN has the advantages of simple calculation and the ability to perform well on data sets that are not linearly separable, often giving better performance than more complex methods in many applications [31]. Given the training feature dataset $X = \{x_1, x_2, \ldots, x_n\}$, and a test feature vector x, we will find the distance function and the k nearest neighbors to the test feature vector, where each nearest neighbor has one vote for the class label c. The test label will base on the majority of the votes according cross validation accuracy (10-fold) to select the best parameters for k-nearest neighbor classifier.

5 Results

In this paper, we experiment with the texture analysis process to classify Egyptian ceramic materials. These materials are described by images representing fresh break section of the sherd, inner and outer surface view (figure 1).

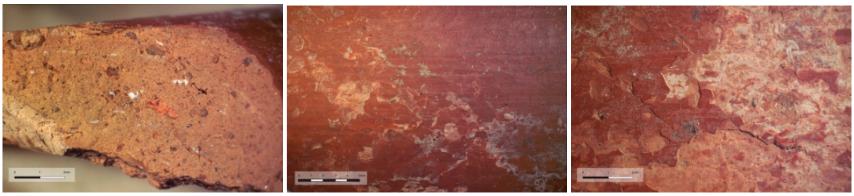

Fig. 1. Images representing fresh break section of the sherd, inner and outer surface (Abu-Roach site: sample n°1762)

In fact, the samples are manually classified by archeological experts based on the kind of ceramic fabrics and treatments of the surfaces. Table 1 shows the different categories and the sample's number in each category. Each sample is labeled by a value coded on three digits. All digits are ranging from 1 to 3). The First digits indicate the nature of samples (rupture, inner or outer view respectively 1, 2, 3). The second digits show the used characteristics (ceramic pastes or ceramic surface. The digit is 1 or 2 respectively. Finally, the third digits describe the nature of categories (1 for marl clay or Slip surface, 2 for alluvial clays or diffuse/not slip surface and 3 for mixed-clays or not-slip surface). Table 2 represents an example of three labeled samples. In this example, we can easily observe that the samples 1790 and 1771 have the same ceramic paste and their ceramic surface is different.

Table 1. Numbering of samples for different Abu-Roach ceramic categories

	Categories	Numbering of samples
Ceramic pastes fabrics	Marl (Ma)	1769, 1785, 1788, 1800, 1764, 1765, 1767, 1784 1791, 1795, 1798, 1777, 1796, 1797, 1761, 1762, 1772, 1779, 1780, 1781, 1782, 1783
	Alluvial (Al)	1763, 1790, 1774, 1775, 1776, 1778, 1787, 1789, 1771, 1792, 1794, 1768, 1793, 1766
	Mixed-clay (Mi)	1770, 1786, 1799, 1773
Ceramic surfaces	Slip (S)	1761, 1762, 1763, 1764, 1765, 1766, 1767, 1768, 1769, 1770, 1773, 1775, 1776, 1777, 1787, 1790, 1793, 1794, 1795, 1798, 1799, 1800
	Diffuse/not slip (D)	1796, 1797
	Not-Slip (NS)	1774, 1771, 1772, 1778, 1779, 1780, 1781, 1782, 1783, 1784, 1785, 1786,1788, 1789, 1791, 1792

Table 2. Samples labeled according ceramic pastes and surfaces

Samples	Ceramic paste	Ceramic surface
1790	1-1-2	1-2-1
1771	2-1-2	2-2-3
1796	3-1-1	3-2-2

Now, in each sample we have several images which represent both ceramic paste (fresh break section) and surfaces. Each image is labeled according to its belonging sample defined by archaeologist experts. Therefore, we have a database composed of 599 images with resolution 4500×3000 pixels. From each of these images, we have extracted four representative sub-images of size 512×512 pixels. Thus a new database is formed and it contains 2396 sub-images. The sub-images are distinguished by their origin, ceramic pastes or surfaces properties and other archaeological criteria. Fig. 2 shows an example of homogenous, non-homogenous and non-directionality textures.

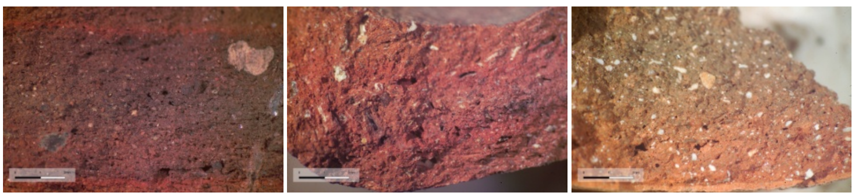

Fig. 2. Textures corresponding to the samples in table 2

Once ceramic pastes and surfaces databases are defined, the Gabor filter-base texture features are computed in each sub-image. The obtained feature vectors are divided in training and test set using K-cross-validation method (K = 10). In order to obtain significant and correct statistical values, this operation is repeated 100 times. To study the effects of the feature extraction method on ceramic materials recognition by applying LDA and k-NN classifiers, we computed a better model for the training set. The influence of changing parameters can be assessed through examining the classification accuracy. The implementation of this procedure was performed in a batch mode. The best models or parameters retained are then used to predict the association of each pixel to adequate class. Accuracy assessment of four classification figures was performed by computing overall and category by category user's and producer's (Figures 3) accuracy using the validation dataset [32]. In fact, for k-NN classifier, we choose $k \in \{1; 2; \cdots; 15\}$ and we have used four different distance measures: Euclidean, City block, Cosine distance and Pearson's correlation to study the effect on classification accuracy.

Figures 3 shows the performance of Gabor filter-based texture features to characterize ceramic pastes and surfaces separately. Regarding the overall classifications accuracies results (first tow bars), we can conclude that k-NN classifier have produced a best results and they show the quite similar overall accuracy

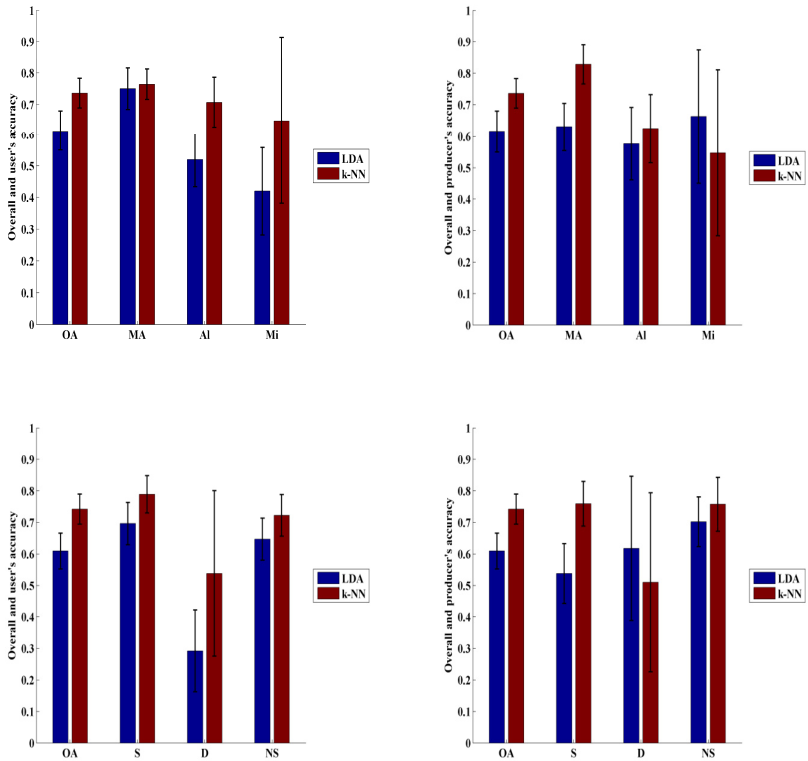

Fig. 3. Overall accuracy. By column: user's and producer's accuracy. By row: ceramic pastes and surfaces

between ceramic pastes and ceramic surfaces. Indeed, the best values obtained for LDA and k-NN are respectively (0.615±0.065 and 0.736±0.047) for ceramic pastes and (0.609±0.057 and 0.742±0.048) for ceramic surfaces. At Single category level, we observe a same results, k-NN classifier performed are better than LDA, specifically in user's accuracy. In producer's accuracy, the LDA return best results for mixed paste (Mi) and diffuse surface (D). For the classification of our complex data sets and when we choose good parameters, Gabor filter-based texture features and k-NN classifier appear to be the best classifier and texture features options because they can be used with any data. When we compare the accuracy classifications between ceramic pastes and ceramic surface separately, we observe that accuracy is differing from one category to another. For example, see results returned by LDA in figure 3. The LAD returns a lower value of user's accuracy (0.292±0.129) from diffuse ceramic surface (D). To improve final classification results and take advantage of each single category best classification through combination between ceramic pastes and surfaces results could be used to improve results. Therefore, the results have shown that machine vision based on image texture analysis for Egyptian ceramic materials classification can constitute a cost-effective approach for a characterization, assessment and archiving archaeological finds. Due to the good recognition and the existing complementarities between ceramic pastes and surfaces, using Gabor filter-based texture features and k-NN classifier should be confirmed by applying this process in other Egyptian archaeological sites.

6 Conclusion

In this paper, a texture analysis process based on Gabor filter-to texture feature extraction and classification algorithms (LDA, k-NN), to classify and analysis a non-homogenous Egyptian archaeological ceramic textures were proposed. In general, this is a difficult classification task due to strong homogeneities within samples in the same category. In fact, to classify the Abu-roach archaeological database, the ceramic materials are characterized separately by their ceramic paste and surface textures. The results are shown that texture analysis yields promising accuracy. It leads to an effective process for Egyptian ceramic materials recognition.

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