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SELECTING THE IMPORTANT FEATURES TO CLASSIFY THE ARCHAEOLOGICAL FRAGMENTS BY USING STATISTICAL TOOLS

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Abstract

Feature selection, the process of representing an object in the least dimensions, is one of the most important and difficult steps in pattern recognition. Therefore, meticulous selection of important features for classification is required. In this study, we propose a method based on Multidimensional Scaling (MDS) to reduce the dimensions of ancient ceramic fragment features. This method focuses on selecting the most important features based on the density of the grayscale image and texture. Finally, we use the Euclidean distance equation to classify objects into similar groups. With a database containing more than 300 images, the experiment achieved an impressive 90% success rate in accurately categorizing fragments as either similar or non-similar. These results demonstrate the effectiveness and promise of the proposed approach for image classification tasks, emphasizing the potential of statistical methods and image processing techniques for addressing complex computer vision challenges.

***Keywords*: Feature extraction; multidimensional scaling; fragments classification.**

1. Introduction

Ceramics were one of the earliest materials used by humans, dating back to prehistoric times. As such, they offer a unique perspective into the evolution of human civilization, from the development of agriculture and trade to the rise of complex societies and the emergence of art. The automatic classification of ancient pieces into similar groups and their subsequent reconstruction into original objects is crucial for archaeologists to derive meaningful insights about ancient civilizations [1]. Excavations often yield large amounts of broken fragments, which are difficult to reassemble into archaeological objects [2-3]. Despite rapid technological development, many artifacts have not yet been repaired and assembled [4].

Although several methods have been proposed to solve this problem, archaeologist's have not utilized them to facilitate their work [5]. Statisticians have presented hypotheses, theories, and statistical methods to help researchers reach accurate conclusions from available data. This paper uses MDS to reduce the dimensions of all fragments' features [6] and selects important features to classify the similar fragments.

The following is the structure of the paper: Section 2 presents the significant papers that have been previously presented, while Section 3 provides a brief overview of MDS. Section 4 outlines the materials and methods used in conducting the experiments and presenting the results. Finally, Section 5 presents the critical conclusions.

2. Literature Survey

In the feature extraction stage, a suitable statistical method is utilized to measure unique attributes of patterns, ensuring that they do not overlap. The objective is to obtain features that are either invariant or less prone to being affected by variations and distortions. This stage holds immense importance in object classification, leading researchers to explore different techniques for extracting crucial features for object representation. The field of feature extraction is vast, comprising multiple approaches. As the paper concentrates on artifact classification, the emphasis is on the most significant features that researchers have utilized to group artifacts into similar categories post-excavation. In the early 1970s, studies began to focus on the dimensions of fragment features, such as the width and height of the neck, as well as the width of the artifact's base [7]. During the 1990s and 2000s, numerous attempts were made and a variety of algorithms proposed to extract features, such as [8-11] that relied on the profile (primitives, B-splines, and rotation estimation).

Kampel & Sablatnig [12] developed an automated system based on prior information. Another method was proposed by [13], which relied on multiple measurements as features. Several authors [14-16] focused on the contour, thematic content, and geometry of fragments.

On one hand, several authors [3][17-19] utilized a selection technique primarily based on the color and texture of archaeological fragments. On the other hand, other methods have been employed to classify such fragments, including the use of 3D models. These approaches relied on the fragment's profile to estimate parameters such as diameter and perimeter [20-21] proposed an estimated rotation axis. During the 1990s and 2000s, several algorithms were proposed to extract features, such as [8-9][10-11], which were based on the fragment's profile (primitives, B-splines, and rotation estimation). Mara & Sablatnig 2006 performed a study based on profile lines of fragments [22]. Studies have continued to use different characteristics to represent objects [23], including geometry and photometry. The utilization of 3D contour curves was employed by Zheng and colleagues in their work [24].

3. Multidimensional scaling

The statistical approach is widely used in pattern recognition systems because of its ease of application [25]. Each pattern is represented by an n-dimensional feature vector, and effective procedure is needed to reduce it. Therefore, this paper aims to apply the MDS method to obtain important features. The MDS is a general technique that consists of numerous various and special types. The classification of these types depends on the similarities in information, whether they are quantitative or qualitative [26]. This technique consists of many geometric objects to represent the data in one, two, or more dimensions and an analogous group of methods to appropriate the models to real data [27]. The MDS method can be used when the data is in a matrix of similarity or difference or is derived from other rectangular data with correlations [28]. The aim of applying the MDS method is to transform the data into a set of points with coordinates that match the estimated distance between the points with the observed distances among the variables. The algorithm of MDS is as follows [29]:
Input: A square matrix that is symmetric.
Output: The matrix is rectangular with respect to the stimuli coordinates.

Assume a linear relationship between the distances and the dissimilarities, so the MDS formula is:

$$\delta_{ij} = f(d_{ij}) = f[[\sum_{k=1}^{n}(x_{ik} - x_{jk})^2]^{1/2}]. \quad (1)$$

where:
x_{ik} – represents the coordinates of the stimuli i on dimension k
x_{jk} – represents the coordinates of the stimuli j on dimension k
δ_{ij} – represents the dissimilarities between stimuli i and j
d_{ij} – represents the distances between stimuli i and j
n – represents the total number of dimensions
The algorithm of MDS consists of the following steps:

Step 1: Estimate the additive constant by converting the dissimilarities into absolute distances.

Step 2: Calculate scalar products by converting the absolute distances.

Step 3: Estimate the coordinates of the stimuli using the principal component analysis (PCA) method.

4. Materials and methods

This paper presents a proposed method for solving the problem of classification of archaeological fragments based on statistical tools. The methodology of this paper consists of a set of procedures, as shown in the following steps:

4.1. *Image acquisition*

The proposed method was applied to two sets of images: one captured by a Nikon camera and the other obtained from the region of Independence National Historical Park in Philadelphia, Pennsylvania, the National Constitution Center was established between 2002 and 2003. During the excavation process, more than one million artifacts were unearthed, dating back to the late 1700s and early 1800s, as stated in[30-31]. Each image had dimensions of 210 × 300 pixels. The resulting images were used to extract features, which were then used as input to the MDS algorithm for dimensionality reduction and classification. The proposed method can be applied to numerous ceramic fragments of different sizes and shapes, as shown in Figures 1 and 2.

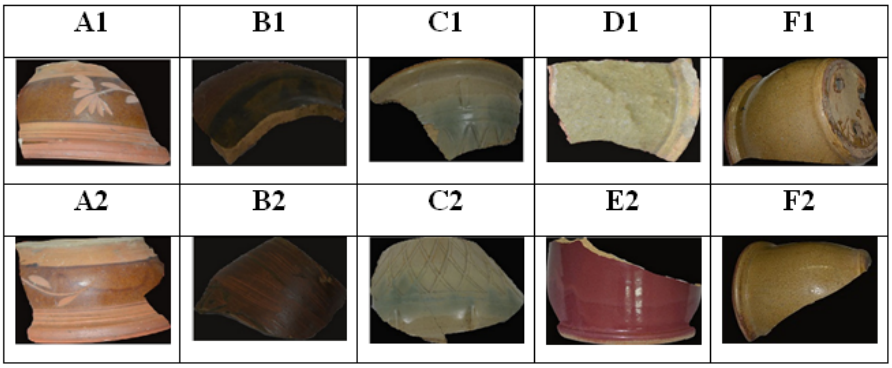

Fig. 1. Demonstrates the database (First set) of ceramic fragments captured by Nikon camera.

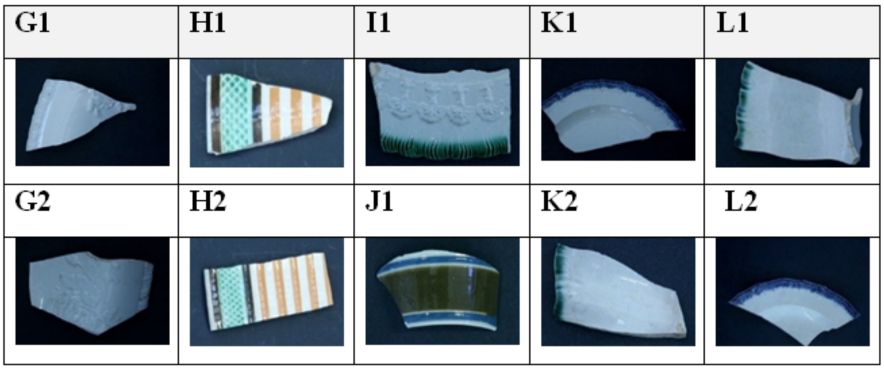

Fig. 2. Demonstrates the database (Second set) of ceramic fragments.

4.2. *Feature extraction based on the color and texture of the fragments*

The choice of object properties for feature extraction is a critical aspect of computer vision. Extracting features from two-dimensional images and identifying points that represent objects in the image requires specialized calculations [32-33]. Choosing the Feature of an object is not easy task [34].

Researchers are attempting to reduce the number of features used in their proposed method. To achieve this goal, they are exploring methods to decrease the dimensionality of the extracted features. In this paper, we relied on two key properties of images - gray level and texture - to form important features [35] for inference and to classify image fragments into similar groups [36].

After reading all the images, we calculate the average color intensity of all pixels for each line in each image. This results in 120 average values for each image. In addition, we obtain additional features by applying the

Haralick method, which utilizes the Gray Level Co-occurrence Matrix (GLCM) [37]. This method is widely used as it provides many features, such as correlation, contrast, energy, and homogeneity based on each pixel and its neighboring pixel [38]. Tables 1 and 2 contain the GLCM texture features of the two databases mentioned earlier.

Fragment	A1	A2	B1	B2	C1	C2	D1	E1	F1	F2
Correlation	0.9846	0.98	0.951	0.9338	0.9774	0.9746	0.9587	0.9636	0.9329	0.9545
Contrast	0.1041	0.1193	0.0349	0.0362	0.0673	0.0949	0.3513	0.0925	0.215	0.1814
Energy	0.2054	0.2105	0.4346	0.4604	0.3039	0.4064	0.2517	0.3228	0.1897	0.2355
Homogeneity	0.9601	0.9525	0.9827	0.9823	0.9709	0.9658	0.9337	0.9628	0.906	0.9412

Table 1. Represent the texture features for the First set .

Fragment	G1	G2	H1	H2	I1	J1	K1	K2	L1	L2
Correlation	0.9936	0.978	0.9726	0.9855	0.9671	0.979	0.9832	0.9846	0.9843	0.9859
Contrast	0.0707	0.1056	0.2777	0.1342	0.2088	0.0943	0.1703	0.1616	0.1438	0.13
Energy	0.315	0.2157	0.1256	0.1749	0.3237	0.2576	0.2767	0.299	0.2421	0.1778
Homogeneity	0.9702	0.9506	0.9011	0.9426	0.9327	0.9561	0.9301	0.9384	0.9421	0.9475

Table 2. Represent the texture features for the Second set.

To reduce the dimensionality of the features and minimize their number, we adopted a statistical method called Multidimensional Scaling. We used the Statistical Package for the Social Sciences (SPSS) system to achieve highly accurate results. Tables 3 and 4 represent the results obtained after applying this method to the first and second sets of fragments, respectively:

Dimension	A1	A2	B1	B2	C1	C2	D1	E1	F1	F2
Dimension 1	-0.214	-0.506	0.904	0.88	0.38	0.061	-0.76	0.453	-0.398	-0.801
Dimension 2	-0.487	-0.438	0.111	0.014	0.244	0.142	0.511	-0.221	0.119	0.005

Table 3. Represent the texture features for the First set .

Dimension	G1	G2	H1	H2	I1	J1	K1	K2	L1	L2
Dimension 1	-0.113	-0.327	0.844	0.864	0.18	-0.794	-0.719	-0.497	0.433	0.13
Dimension 2	-0.017	-0.059	-0.156	-0.033	-0.374	0.645	-0.354	-0.464	0.422	0.389

Table 4. Represent the results after applying the method on the Second set.

Fig. 3 and 4 display the results obtained after applying the MDS method to the two databases, which include the locations of each fragment. The proximity of fragments in the resulting figures indicates the similarity of their features. Fig. 3 can be used to identify similar and non-similar fragments before applying the classification tool. For example, pieces (A1 and A2), (B1 and B2), (C1 and C2), and (F1 and F2) form similar groups, while fragments E1 and D1 are far from similar groups. Similarly, Figure 4 shows that fragments (G1 and G2), (H1 and H2), (K1 and K2), and (L1 and L2) form similar groups.

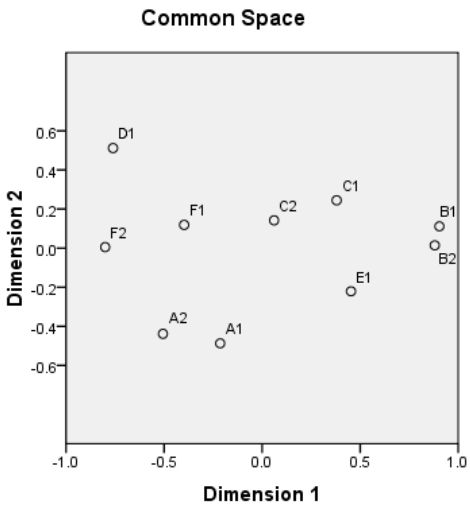

Fig. 3. Displaying the outcomes post MDS implementation on the first set.

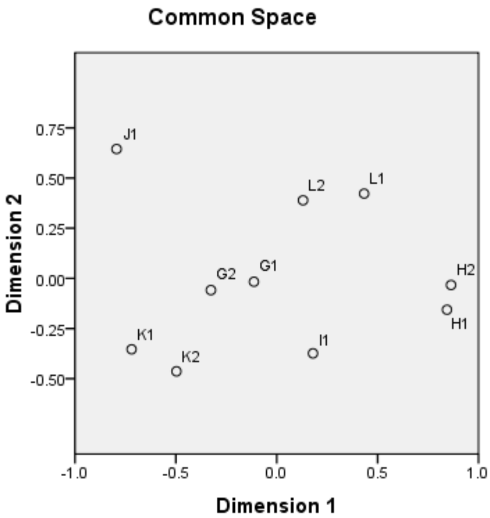

Fig. 4. Displaying the outcomes post MDS implementation on the second dataset.

4.3. *Applying the classification technique using Euclidean distance*

To successfully classify the fragments, we used the Euclidean Distance equation based on texture features, as shown in Eq. (2):

$$D(x, y) = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2} \, . \tag{2}$$

where:
D - distance;
x and y = the dimensions of two features of fragments.

After applying the minimum Euclidean Distance Formula to each vector of image features in the database, the results were presented in Tables 5 and 6. These tables represent the output of the classification for the set captured by the Nikon camera and the set obtained from the website, respectively.

Before analyzing the results, it is important to note that we considered the lowest value between the dimensions of the two fragments to determine similarity. Specifically, in Eq. (2), D represents the distance, and *x* and *y* represent the dimensions of two features of fragments.

Table 5 shows that the lowest value in the fourth column, representing the first fragment (A1), is 0.296, which indicates the distance between it and the second fragment (A2). This suggests that the two fragments belong to the same object. On the other hand, fragment D1 achieved the lowest value (0.508) between it and the last fragment F2, while F2 achieved a difference value of 0.419 with fragment F1. Therefore, we conclude that fragments D1 and F1 do not belong to the same object and should be classified with other groups. Additionally, fragments F1 and F2 are part of the same object.

Also, in Table 6, the fourth column represents the difference between the dimensions of the first fragment (G1) and the dimensions of the remaining nine fragments. It has achieved the lowest value (0.217) which corresponds to the second fragment (G2). That means the two fragments (G1 and G2) are similar and they belong to the same object. The same goes for the fragments (H1 and H2), (K1 and K2), and (L1 and L2). However, the dimensions of the pieces (I and J) are far from the dimensions of other fragments, so they would be returned to the second set to be compared with other pieces.

Fra.	Dim.1	Dim.2	A1	A2	B1	B2	C1	C2	D1	E1	F1	F2
A1	-0.214	-0.487	0.000	0.296	1.268	1.204	0.942	0.687	1.139	0.718	0.634	0.766
A2	-0.506	-0.438	0.296	0.000	1.513	1.458	1.118	0.811	0.983	0.983	0.568	0.533
B1	0.904	0.111	1.268	1.513	0.000	0.100	0.541	0.844	1.712	0.560	1.302	1.708
B2	0.880	0.014	1.204	1.458	0.100	0.000	0.551	0.829	1.714	0.488	1.283	1.681
C1	0.380	0.244	0.942	1.118	0.541	0.551	0.000	0.335	1.171	0.471	0.788	1.205
C2	0.061	0.142	0.687	0.811	0.844	0.829	0.335	0.000	0.901	0.534	0.459	0.872
D1	-0.760	0.511	1.139	0.983	1.712	1.714	1.171	0.901	0.000	1.417	0.534	0.508
E1	0.453	-0.221	0.718	0.983	0.560	0.488	0.471	0.534	1.417	0.000	0.916	1.274
F1	-0.398	0.119	0.634	0.568	1.302	1.283	0.788	0.459	0.534	0.916	0.000	0.419
F2	-0.801	0.005	0.766	0.533	1.708	1.681	1.205	0.872	0.508	1.274	0.419	0.000
Minimum each column			0.296	0.296	0.100	0.100	0.335	0.335	0.508	0.471	0.419	0.419

Table 5. Illustrates the outcomes obtained from calculating the Euclidean Distance for the first set.

Fra.	Dim.1	Dim.2	G1	G2	H1	H2	I1	J2	K1	K2	L1	L2
G1	-0.113	-0.017	0.000	0.217	0.967	0.977	0.461	0.950	0.693	0.589	0.701	0.473
G2	-0.327	-0.059	0.217	0.000	1.174	1.191	0.596	0.845	0.491	0.439	0.899	0.640
H1	0.844	-0.156	0.967	1.174	0.000	0.125	0.699	1.823	1.576	1.376	0.709	0.898
H2	0.864	-0.033	0.977	1.191	0.125	0.000	0.765	1.791	1.616	1.428	0.627	0.847
I1	0.180	-0.374	0.461	0.596	0.699	0.765	0.000	1.409	0.899	0.683	0.835	0.764
J1	-0.794	0.645	0.950	0.845	1.823	1.791	1.409	0.000	1.001	1.147	1.247	0.959
K1	-0.719	-0.354	0.693	0.491	1.576	1.616	0.899	1.001	0.000	0.248	1.389	1.128
K2	-0.497	-0.464	0.589	0.439	1.376	1.428	0.683	1.147	0.248	0.000	1.285	1.059
L1	0.433	0.422	0.701	0.899	0.709	0.627	0.835	1.247	1.389	1.285	0.000	0.305
L2	0.130	0.389	0.473	0.640	0.898	0.847	0.764	0.959	1.128	1.059	0.305	0.000
Minimum each column			0.217	0.217	0.125	0.125	0.461	0.845	0.248	0.248	0.305	0.305

Table 6. Illustrates the outcomes obtained from calculating the Euclidean Distance for the second set.

5. Conclusions

The paper introduces a technique for grouping image fragments into similar categories, which involves feature extraction based on fragment color and texture, dimensionality reduction via Multidimensional Scaling, and classification using the Euclidean Distance formula. The experiment involved over 300 images in the database, yielding a high success rate of 90% in correctly categorizing fragments as either similar or non-similar. Based on the findings, the authors deemed the proposed approach as effective and promising for image classification tasks, highlighting the potential of statistical methods and image processing techniques in solving challenging computer vision problems. Overall, the paper demonstrates the potential of statistical methods and image processing techniques for solving complex problems in computer vision.

Conflicts of Interest: The authors have no conflicts of interest to declare that we have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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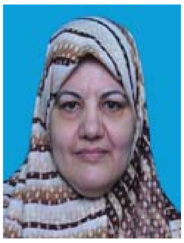
Author's Profile



Nada A. Rasheed, I am currently employed as an assistant professor at the Department of Medical Physics within the College of Science at Al-Karkh University of Science. My doctoral degree is focused on computer science and information technology. In essence, my professional background encompasses several years of experience in research, teaching, and academic engagements. My PhD research primarily centered around image processing and artificial intelligence. I possess expertise in classification and reconstruction algorithms of archaeological fragments using colour and slope features. In addistion, the processing and analysis of medical images. Also, I have facilitated several scientific workshops. Moreover, I have supervised undergraduate research students and projects, guiding them through endeavors such as medical image analysis, computer vision, and image processing.

Osama Mohammed Qasim, an Assistant Lecturer with a background in Computer Science, serves as a Lecturer and Researcher at Al-Karkh University's IT Department. Prior to his current position, he held roles as a travel agent at Om Alqura Company for tourism and an IT engineer at Alkoukh Company for fashion. His research interests primarily revolve around the study of Data Mining Techniques, with a specific focus on disciplines such as Data Mining, Artificial Neural Network, and Artificial Intelligence. Osama possesses a diverse skill set and expertise in areas including Data Mining, Algorithms, Classification, Machine Learning, and Bayesian methods. He is proficient in both Arabic and English languages.