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Research Article

Classification Archaeological Fragments into Groups

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Abstract: The objective of this study is to suggest a method for classifying archeological fragments into groups. For this task, the method suggested begins with conversion of images from their original RGB color to a Hue, Saturation and Value (HSV) color. From that point forward, a 2D median filtering algorithm is implemented to remove any resultant noise. Next, each image is separated into six sub-block of equivalent size. In order to extract the feature for each sub-block, it is represented as a vector intersection of colors between each part of the image and the corresponding parts of the five remaining images. At this stage, we obtain a vector that consists of the six values for each image. For the last stage, a Self-Organization Map (SOM) Neural Network classifies the fragments into groups relying upon their HSV color feature. The algorithm was tested on several images of pottery fragments and the results achieved demonstrate this approach is promising and is able to cluster fragments into groups with high precision.

Keywords: Archaeology, fragments, HSV color, SOM, sub-blocks

INTRODUCTION

Technology has effectively contributed to the preservation of cultural wealth through complex automated image processing procedures and several authors have participated in providing many of the approaches for the (semi/automated) reconstruction of unknown broken or torn objects from a large number of irregular fragments (Zhu, 2013; Zhou *et al*., 2007), such as archeology, forensics and medical imaging (Papaodysseus *et al*., 2012; Youguang *et al*., 2013). In particular, several researchers are interested in reassembling archaeological fragments, especially when exploring archaeological objects that have high archaeological value for the scholars such as (Papaodysseus *et al*., 2012; Leitão and Stolfi, 2005). Therefore, it is of great interest that the objects are reassembled before they are lost or damaged. Artifacts are often found in archaeological excavation sites and are randomly mixed with each other. Therefore, classifying them manually is a difficult and time consuming task, because they commonly exceed thousands of fragments. Thus, only a few previous research works focused on the classification of fragments (Makridis and Daras, 2012) such as (Papaodysseus *et al*., 2012; Karasik and Smilansky, 2011):

The work by Maiza and Gaildrat (2005) presented a method based on the profile of the object and classified it based on a genetic algorithm to evaluate and determine the optimum position between the fragment and the tested model. The work by Ying and Gang (2010) proposed an approach for the classification of ancient ceramic fragments by relying on surface texture features that were extracted using a Gabor wavelet transformation. The classification of ceramic was performed through applying a non-supervision kernel- based fuzzy clustering algorithm. Also, the study of Smith *et al*. (2010) suggested a method depending on the color and texture features and they classified fragments on the basis of the *K*-Nearest Neighbor method. The work by Zhou *et al*. (2011) involved the classification of ancient porcelain based on features of color and texture; the fragments were classified by using the *K*-Nearest Neighbor method. Moreover, the work by Makridis and Daras (2012) focused on the automatic classification of ceramic and pottery fragments that contain little textual information. The technique is based on chromaticity and chrominance (color), the low and medium level features, as well as the *K*-Nearest Neighborhood classifier to classify the fragments.

The main objective of this study is to propose a novel algorithm for classifying ancient pottery fragments depending on global feature, specifically the

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color feature. The main contributions of the research work can be summarized as:

- Replacing manual classification of fragments and automate the task of classifying the fragments into groups by proposing a method that depended on color characteristics.
- Reduce the human resources necessary for the task of classifying irregular fragments. This reduces the time and effort by laborers and archaeologists.

MATERIALS AND METHODS

This study consists of a set of procedures, each one responsible for a specific job. This can be summarized in the following steps:

Image acquisition and pre-processing: This procedure is responsible for loading the image files into memory in *JPG* format. The dimensions of each image in this study are 300×210 pixels. All images are converted from RGB color to the HSV color. A 2D median filtering algorithm (Huang and Yang, 1979) was employed to remove noisy objects of various shapes and sizes. Finally, each image is divided into six parts, each of which has a size of 50×35 pixels.

Feature extraction: Extract the features of an object to be classified is an important part of pattern recognition, where the feature vector is a list of descriptions that includes sufficient information to identify a pattern. In this study, the features were extracted from fragments depending on their color, which is an important feature in image recognition (Kavitha *et al*., 2011; Rui *et al*., 1999). The author, Jack (2005) mentions that Hue, Saturation and Value (HSV) color spaces was developed to be similar to the human vision, so this study depended on HSV feature to classify the fragments. In order to extract the HSV feature, we rely on the mathematical method that is similar to the one used in Rasheed and Nordin (2015), which includes the intersection of HSV colors between the matrices of each sub-block of one image with the corresponding sub-blocks of the other images.

Step 1: Determine the values of the HSV in each pixel. Let $F(x, y)$ be a $2D$ image pixel array of color images with size of 300 × 210 pixels:

$$\{F(x,y);\ \mathrm{x}=1,2,...,300\ ,\ \mathrm{y}=1,2,...,210\}; \tag{1}$$

To denote the HSV value of the pixel (x, y):

$$F(x,y)=\{F_H(x,y),F_S(x,y),F_V(x,y)\}; \tag{2}$$

Step 2: For each image, all the surface points are stored in an array which is obtained as a set of values arranged in a parallel manner:

$$F(x,y)=\{\forall P(F_H(x,y),F_S(x,y),F_V(x,y))\}; \tag{3}$$

Step 3: $F_1(x, y)$ is a set, each element consist of three values [Hue, Saturation, Value] regarding to the first image. Similarly, $F_2(x, y)$ is a set each element represents three variables regarding to the second image:

$$F_1(x,y)=\{\forall P_1(F_H(x,y),F_S(x,y),F_V(x,y))\}; \tag{4}$$

$$F_2(x,y)=\{\forall P_2(F_H(x,y),F_S(x,y),F_V(x,y))\}; \tag{5}$$

where, P_1 and P_2 denotes the number of the elements in the set $F_1(x, y)$ (first image) and set $F_2(x, y)$ (second image) respectively.

Step 4: Obtain the set S that represents the results of the intersection between two images:

$$S=F_1(x,y)\cap F_2(x,y) \tag{6}$$

Step 5: This procedure is repeated for another two images, until obtaining all intersections between all images, each element of each set is a vector representing the values of HSV.

Classification technique: This explains the clustering of the images into similar groups by computerized guidance. Therefore, after converting each image to six vectors with a fixed length, it becomes a matrix of size 6×36 for clustering. Consider the Neural Networks is an area of Artificial Intelligence (AI) that simulates the human neurons in both perception and learning (Willow, 2005). It can be a fast and powerful technique which can be used to solve many real world problems and have the ability to learn from experience. In addition to that it is able to deal with incomplete information or noisy data; also it can be very effective, especially in complex situations where it is possible to define the rules or steps that lead to the solution of the problem. One of Neural Networks is Self-Organization Map (SOM), or a Kohonen Neural Networks. Therefore, in this study the clustering is performed by using SOM, which is a single layered neural network and it is considered an unsupervised learning process that uses competitive learning techniques to train the network. It is a set of high-dimensional data items, where each item is assigned to one node within the map and the similarities between the items are based on the distance between them (Kohonen, 2014). This network has been applied in many domains, including statistical, industrial, biomedical and financial applications. It has achieved remarkable performance (Kohonen, 2014). The algorithm of SOM is (Bação and Lobo, 2005):

Suppose x_k be the input with n-dimensional training patterns and w_{ij} represent the neurons in position (i, j). Neighborhood Function $h(w_{ij}, w_{mn})$ that

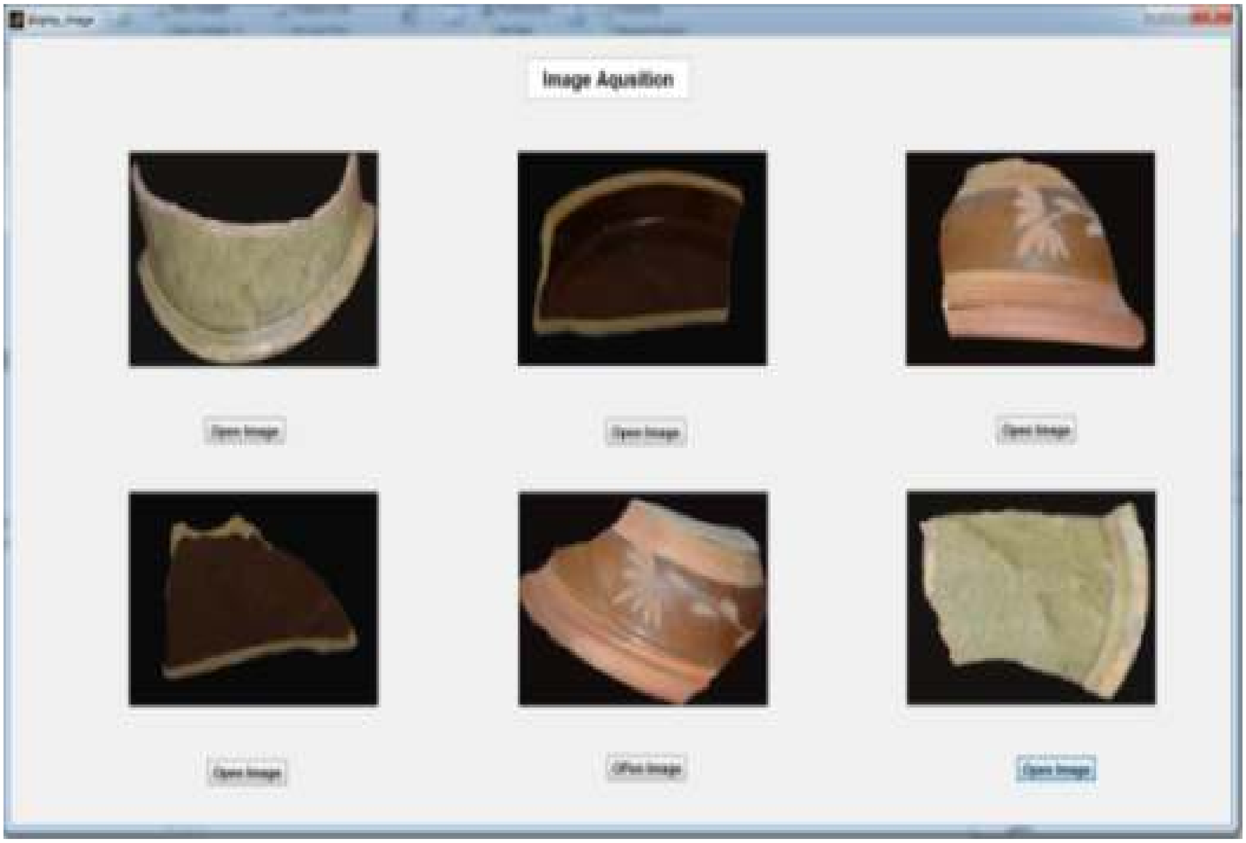

Fig. 1: Six images of the fragment are loading

have values of range [0,1], where it is high for the neurons that has achieved best matching (w_{winner}) and small or zero for the remote neurons. Also w_{winner} represents winner neuron for a given input pattern and the learning rate α has value $0\leq \alpha \leq 1$. At last the Neighborhood radius is r, so the algorithm for training the network is:

Step 1: Initialize the grid.

Step 2: Compare each input with all nodes, that's mean calculated the distance between the pattern and all neurons:

$$d_{ij}= \| x_k - w_{ij} \| \tag{7}$$

Step 3: Select the nearest neuron as winner w_{winner}:

$$w_{ij}:d_{\mathrm{ij}} = \min(d_{mn}) \tag{8}$$

Step 4: Update each neuron according to the rule:

$$w_{ij} = w_{ij} + \alpha h(w_{winner},w_{ij}) \| x_k - w_{ij} \| \tag{9}$$

Step 5: Repeat the process until the full number of epochs has reached.

Experimental setup: The aim of this experiment is to use HSV color feature to cluster ancient fragments. The following steps explain the experiment carried out in details:

Image acquisition: The algorithm starts by loading six image files, as shown in Fig. 1. Each image is converted from RGB to HSV color, as depicted in Fig. 2 part 1. Next, two procedures are applied, one for noise removal and the second for dividing each image into six equal sized sub-blocks, as shown in Fig. 2 - parts 2 and 3 respectively.

Feature extraction: In order to derive the color feature, we apply the algorithm that has been mentioned in the materials and methods section feature extraction. Fig. 3 and 4 shows the HSV vectors for the six images, as well as it can be observed the results of the first fragment in Fig. 2- part 4 that represents the first row. The first column represents the total Hue color in the first sub-blocks of all of the images after unification of colors in each image, as well as the Saturation and Value. Therefore, we have six vectors for all images, each of which consists of the Hue, Saturation and Value according to each sub-block.

On the basis of the aforementioned results, we applied the proposed algorithm based on the intersection of HSV colors between the six sub-blocks

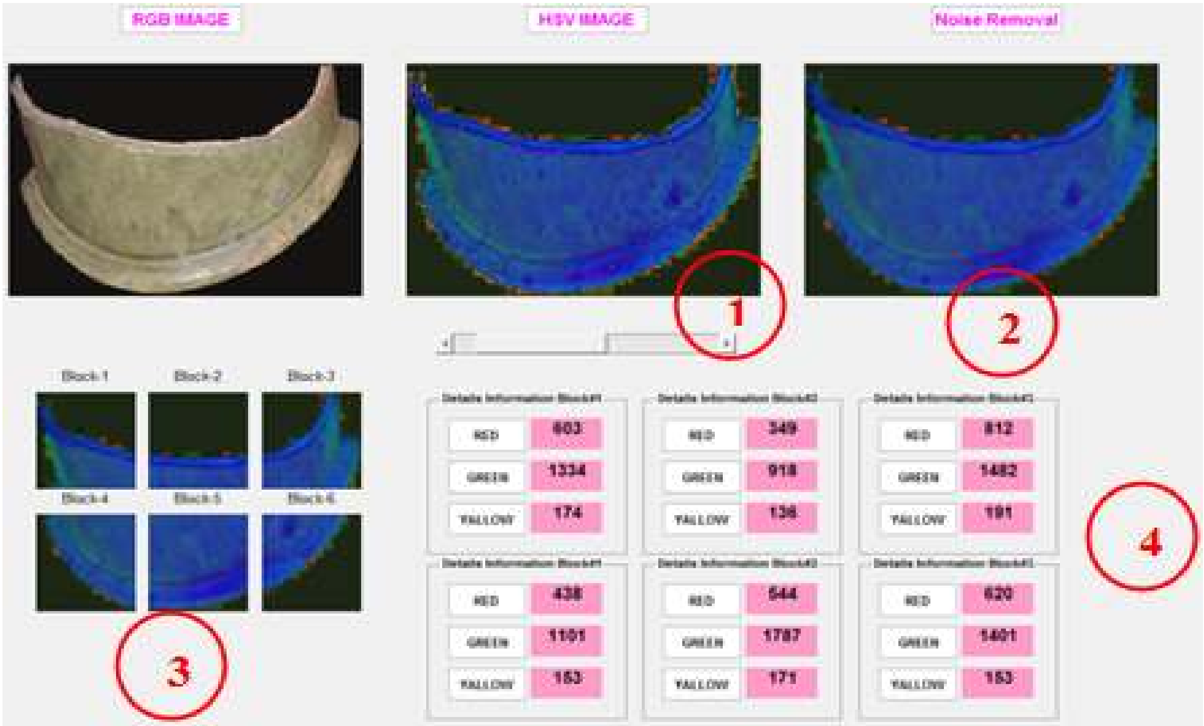

Fig. 2: Noise removal and divide the image into six blocks equal sized

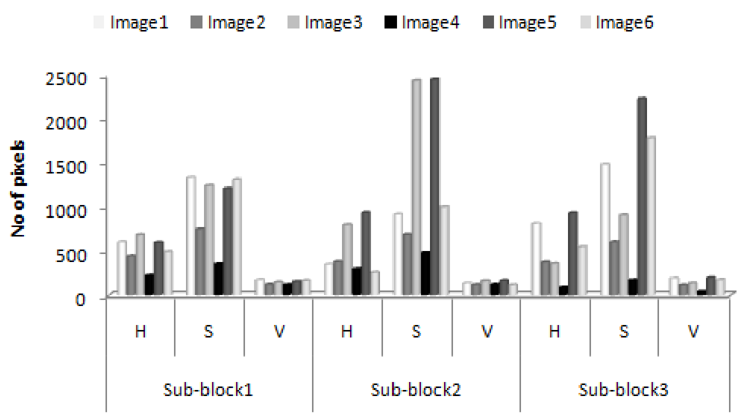

Fig. 3: Demonstrates hue, saturation, value for each the sub-block1 to sub-block3 for all images

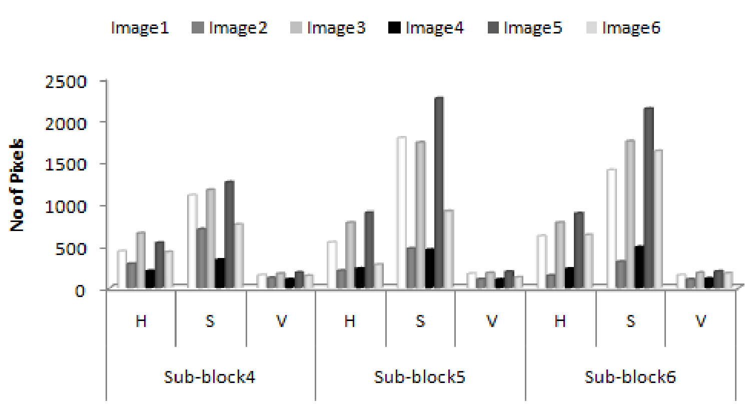

Fig. 4: Demonstrates hue, saturation, value for each the sub-block4 to sub-block6 for all images

Table 1: Demonstrates the intersection between image 1 and all sub-blocks for five images

Image No.	Image 1 b1	b2	b3	b4	b5	b6
2	1	1	2	1	1	1
3	1	1	1	1	1	1
4	2	1	1	1	1	2
5	1	1	1	1	1	1
6	66	43	65	52	77	81

Table 2: Demonstrates the intersection between image 2 and all sub-blocks for five images

Image No.	Image 2 b1	b2	b3	b4	b5	b6
1	1	1	2	1	1	1
3	2	3	1	2	1	1
4	25	16	14	50	142	24
5	2	1	1	1	1	2
6	1	1	1	1	1	1

Table 3: Demonstrates the intersection between image 3 and all sub-blocks for five images

Image No.	Image 3 b1	b2	b3	b4	b5	b6
1	1	1	1	1	1	1
2	2	3	1	2	1	1
4	1	1	1	1	1	1
5	38	48	24	13	30	39
6	1	1	1	1	1	1

Table 4: Demonstrates the intersection between image 4 and all sub-blocks for five images

Image No.	Image 4 b1	b2	b3	b4	b5	b6
1	2	1	1	1	1	2
2	25	16	14	50	142	24
3	1	1	1	1	1	1
5	1	1	2	1	1	1
6	1	1	1	2	1	1

Table 5: Demonstrates the intersection between image 5 and all sub-blocks for five images

Image No.	Image 5 b1	b2	b3	b4	b5	b6
1	1	1	1	1	1	1
2	2	1	1	1	1	2
3	38	48	24	13	30	39
4	1	1	2	1	1	1
6	1	1	1	1	1	1

Table 6: Demonstrates the intersection between image 6 and all sub-blocks for five images

Image No.	Image 6 b1	b2	b3	b4	b5	b6
1	66	43	65	52	77	81
2	1	1	1	1	1	1
3	1	1	1	1	1	1
4	1	1	1	2	1	1
5	1	1	1	1	1	1

for all six images. Table 1 to 6 summarize the results of the experiment. The results clearly show that the images have been categorized before conducting the clustering process.

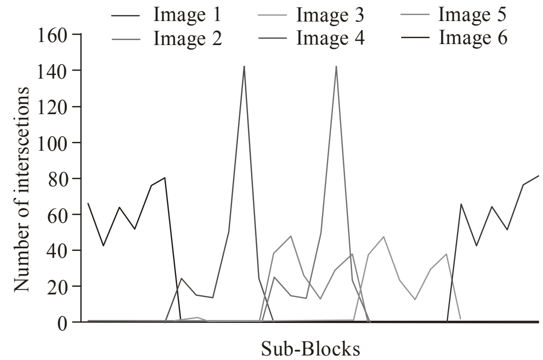

Fig. 5: Shows the intersections between six images

In Fig. 5, the first image is classified with the sixth image, because the total intersecting colors between the two images are higher than the rest of the images according to all sub-blocks. Also, the curves that represent the second and fourth images are similar. Furthermore, the curves of third and fifth images also similar. This demonstrates the efficiency of the proposed method.

Classification technique: In order to classify the fragments on the basis of the HSV features, we applied the SOM algorithm on all the intersection vectors for all the available sub-blocks. Image clustering was implemented using the MATLAB software application.

The inputs are 36×6 matrices representing 6 samples of 36 elements. So the input will be 6×6 for each sub-block. Thus, the output for each sub-block is being 1×6, so should combine them to obtain one result. Furthermore, the size of the two-dimensional map is 15×15 and training runs for the maximum number of epochs is 200 iterations with a time of 1 sec. Finally, the SOM topology used is hexagonl. Therefore, the experiment implemented on a set of fragments captured by a camera. The results of the classifying process are shown in Fig. 6 that shows SOM neighbour weight distances, Fig. 7 depict SOM weight plans and Fig. 8 represents SOM weight positions.

According to the SOM neighbor weight distances figure, which represents the distances between neurons, it seems that the neighbor patches are colored from dark to light. In Fig. 6, the patches are smooth. This means that the weight vectors of the neurons are close to their neighbors, with the exception of some regions that have dark coloring between the neurons and thus, a gap between the HSV values in the input space. Moreover, in Fig. 7, it is clear that the connection patterns of six inputs are very similar, which means that they are highly correlated. In this case, there were similar connections between Inputs 1 and 6; Inputs 2 and 4; also Inputs 3 and 5. The last Fig. 8 represents the network of input data, which has been configured during the training process.

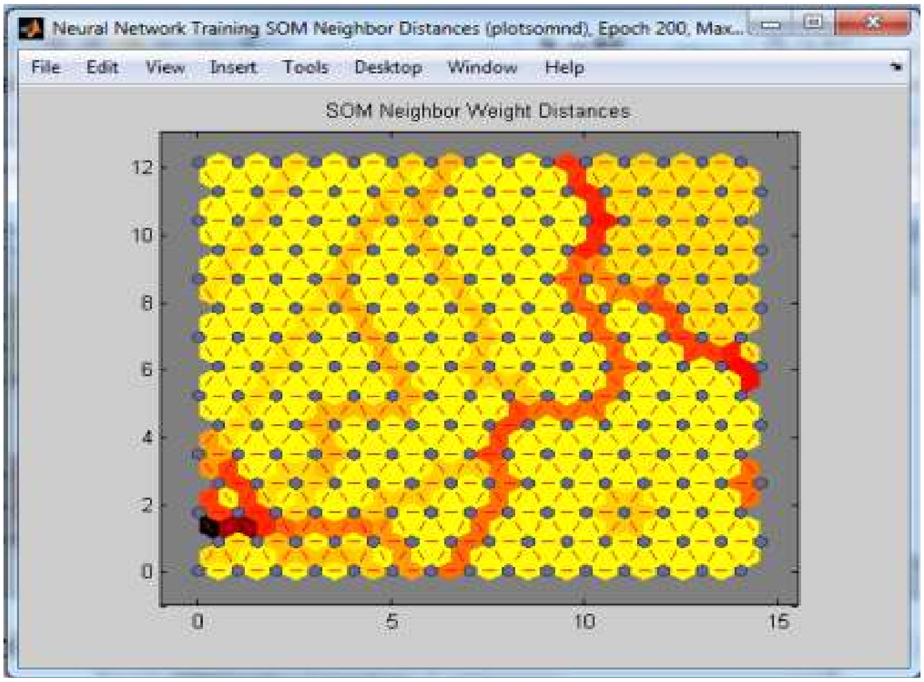

Fig. 6: SOM neighbour weight distances

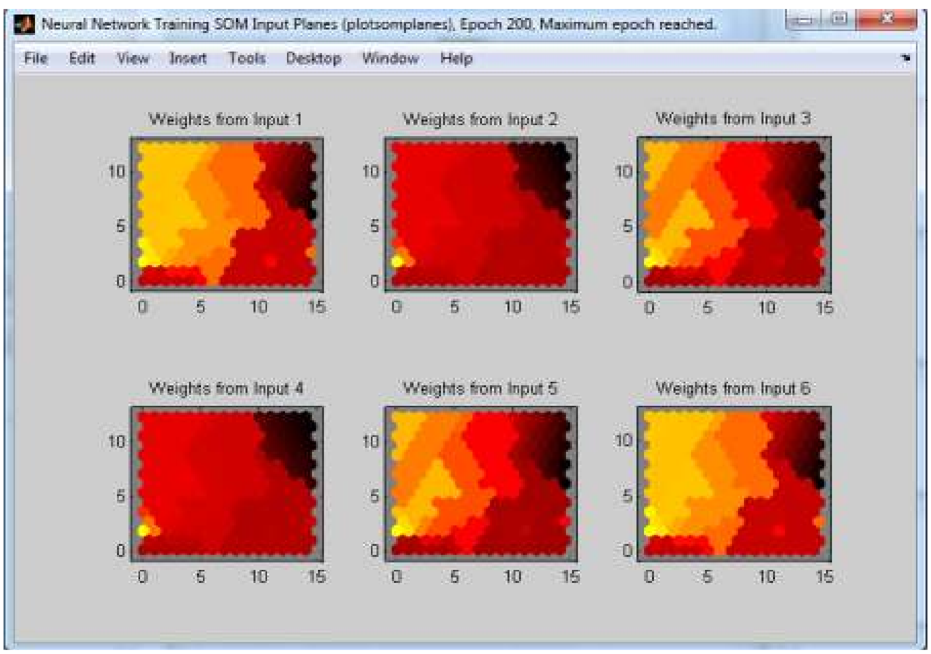

Fig. 7: SOM weight plans

Finally, the results were saved in order to use them as inputs for the next phase, which is responsible for the task of the reconstruction of archaeological objects.

The output of the classification technique is sorted and displayed, in Fig. 9 that used fragments picked by the camera, which contain several icons, in the far left of the model display the six input images, while the classification technique was applied to the right of the model. Therefore, the fragments are classified successfully and the results were saved in order to use them as inputs for the next phase, which is responsible for the task of the reconstruction of archaeological objects.

RESULTS AND DISCUSSION

This part focuses on the evaluation, analysis and compare the performance of the proposed method based

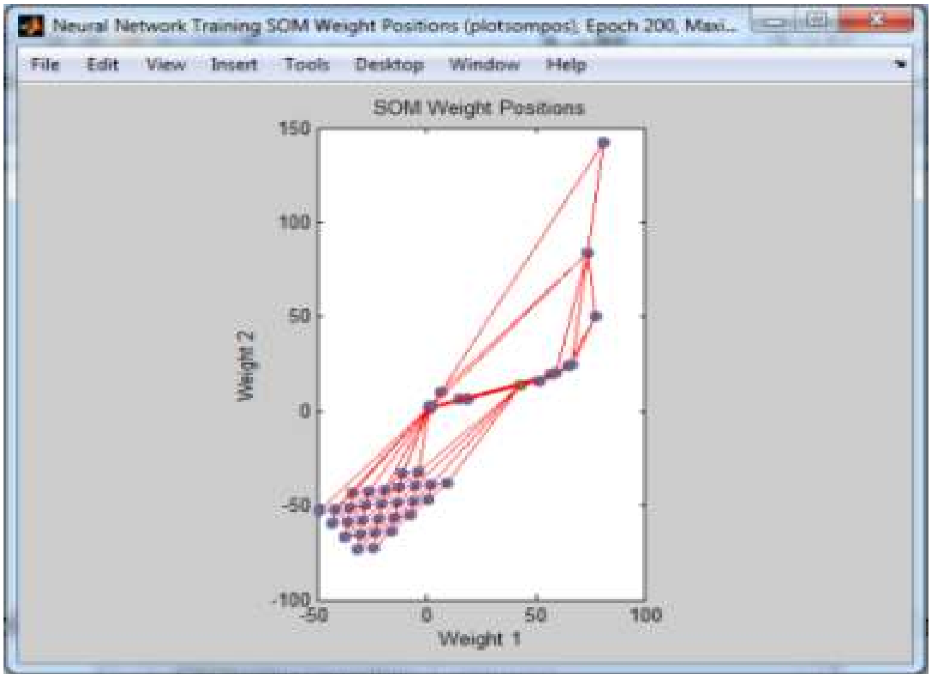

Fig. 8: SOM weight positions

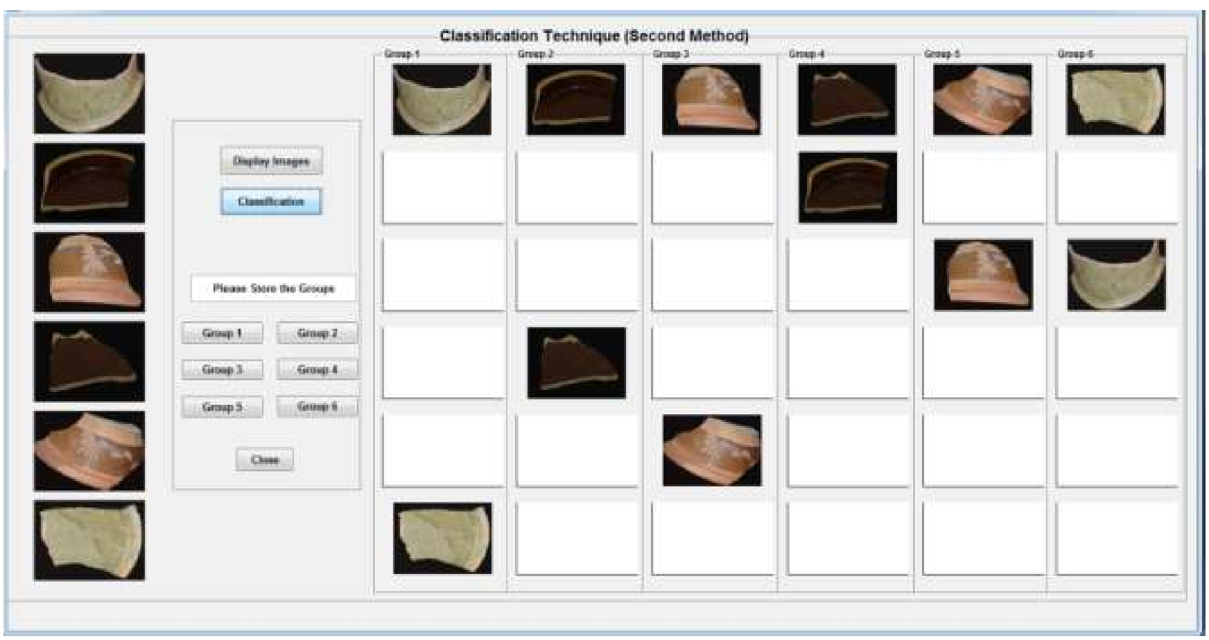

Fig. 9: Classification technique depending on HSV color

Table 7: Demonstrates the database of ceramic fragmented

Group A	Group B	Group C	Group D	Group E	Group F	Group G
						
3	4	3	3	4	11	2

on individual experiments. Therefore, to evaluate the performance of the proposed algorithm, several tests were conducted on the images dataset that consists of seven classes obtained by a camera, which are shown in Table 7 and eight classes were found in the database available on the website (Ceramic Sherd Database, 2010).

Initially, for the purpose to evaluate the performance of the proposed method there are several steps should follow:

Table 8: Classification results for Smith *et al*. (2010)

		SIFT		TVG		Method	
Clas	Piec.	#[1]	%	#	%	#	%
A	9	7	78	6	67	7	78
B	9	6	67	5	56	7	78
C	9	7	78	7	78	9	100
D	16	11	69	11	69	13	81
E	2	1	50	1	50	2	100
F	10	6	60	7	70	9	90
G	7	5	71	5	71	5	71
H	18	18	100	18	100	17	94
A11	80	61	76	60	75	69	86.2

Step 1: Compute the accuracy rate: In order to compute the accuracy rate for the proposed method using the dataset that mentioned before, this study will use two types of methods according to the methods that should be compared with it:

- Smith *et al*. (2010) method: They've been testing method several times using ceramic fragments of Dataset 2010. The accuracy was calculated by dividing the number fragments classified correctly on the total number of the fragments per group.
- Makridis and Daras (2012) method: The authors relied on Confusion Matrix to compute the accuracy, which includes two factors: True Positive Rate (TPR) and False Positive Rate (FPR).

Step 2: Compare the method with the other methods: Several experiments were conducted using the dataset that obtained from the website (Ceramic Sherd Database, 2010). Total eighty artifact fragments used by Smith *et al*. (2010) and the opinion of Makridis and Daras (2012) that the dataset "it is ideal for evaluation".

A series of experiments was run upon the fragments that obtained and its results demonstrate in Table 8.

To compare the performance of the proposed system with the method of Smith *et al*. (2010) in classifying archaeological fragments, it found clear the progress of results for the proposed method against the Smith method. As depicted in Table 8, the SIFT and TVG columns represent the results of Smith *et al*. (2010) relied on color and texture features to classify the ceramic fragments, they were achieved 76% and 75%. Whereas the proposed method achieved 86.2%, using the method of intersection HSV. The cause of achieving the progress that the method was applied procedure of image segmentation and separate the object from the background, this gab mentioned in the work of Smith *et al*. (2010) as follow:

"It should be noted that the descriptors were defined over the entire image, occasionally resulting in feature descriptors located in the background of the image describing the outer boundary of an artifact. In future work, the descriptors located in the background will not be considered". It would like to point out that the authors Makridis and Daras (2012) noted that the algorithm of Smith *et al*. (2010) poor classification rates when the fragments have low textured with small intensity and color variations. As it has been noted the solutions are not accurate enough and the results they achieved after testing their models are limited. While as mentioned previously the artifacts are often found in a large amount in different excavation sites. Therefore, in this study has been proposed the method in order to get results better than the results of previous methods.

Step 3: Based on Confusion Matrix that is also called contingency table, the study enables to compute the accuracy rate of the fragments that classified correctly. Where the diagonal of the table represents the number of fragments that have been classified correctly. Therefore, the sum of the diagonals indicates to the total number of the fragments that were classified into groups correctly. The rows represent total tested of the fragments within each class, where the last row represents the fragments that correctly classified. Hence, the accuracy is computed by dividing the sum of correctly classified/total tested. Thus, it calculated according to the following formula :

$$Rate = \frac{36}{46} \times 100 \tag{10}$$
$$Rate = 78.26\%$$

$$Rate = \frac{69}{77} \times 100$$
$$Rate = 89.6\% \tag{11}$$

As demonstrate in Table 9 the method of Makridis and Daras (2012) achieved accuracy rate 78.26%, while according to the multi-experiments and the Table 10 the proposed method achieved 89.6%. In fact, the method of Makridis and Daras (2012) managed to classify 36 of 80 fragments, whereas the proposed method was classified 69 of 80 fragments. This is because the proposed method relies on a novel styles to extract the set of features, namely, the intersection of colors between the sub-blocks of the images. Makridis and Daras (2012) said that his proposed method were not an alternative to the manual method, as their text below. Also the authors point out that their proposed work contribute 50% to help for manual classification.

"It should be clearly stated that, the aim of the proposed work is not to replace the experts but to facilitate their work. As it can be assumed, automated classification of archaeological sherds cannot be more successful than manual classification. However, a rough classification with over 50% success rate would be very useful, in terms of speeding up the manual classification procedure. This is exactly the aim of the article" (Makridis and Daras 2012).

Along these lines, this study plans to find a solution for classification the archaeological fragments based on the development of the sciences. They were tried with many features to extract such as Hue,

Table 9: Confusion matrix for Makridis and Daras (2012) method

Classes	A	B	C	D	E	F	G	H	Sum
Class A	5	0	0	0	0	0	0	0	5
Class B	0	5	0	0	0	0	0	0	5
Class C	1	0	6	0	0	0	0	0	7
Class D	0	0	0	4	0	1	3	0	8
Class E	0	0	0	1	0	0	0	0	1
Class F	0	1	0	0	0	2	0	0	3
Class G	0	0	0	0	2	1	1	0	4
Class H	0	0	0	0	0	0	0	13	13
Correctly classified	5	5	6	4	0	2	1	13	36
Total tested	46	Rate	78.26%						

Table 10: Confusion matrix for the proposed method

Classes	A	B	C	D	E	F	G	H	Sum
Class A	7	1	0	0	0	0	0	0	8
Class B	1	7	0	0	0	0	0	0	8
Class C	0	0	9	0	0	0	0	0	9
Class D	0	1	0	13	0	1	0	0	15
Class E	0	0	0	0	2	0	0	0	2
Class F	0	0	0	1	0	9	0	0	10
Class G	0	0	0	1	0	0	5	1	7
Class H	1	0	0	0	0	0	0	17	18
Correctly classified	7	7	9	13	2	9	5	17	69
Total tested	77	Rate	89.6%						

Saturation, Value, YIQ, RGB, Standard deviation, Contrast, LBP without focus on the important features so this will cause confusion. Also, they used many classifiers such as KNN, SVM, Naive Bayes, SMO, Simple logistic and they compared between them. Although they used bag of words BOW to reduce the complex calculations, but their method relies on many features that consumes a lot of time and delays. Furthermore, in order to enhance the classification accuracy, they were used both the front and back characteristics for the ceramic fragments, but their method not achieve a high precision. In fact, the classification process depends mainly on the surface of the fragment, so used the back of fragment be no avail.

CONCLUSION

Archaeological objects are usually found in excavation sites broken and mixed with each other. So, classifying them manually is a difficult process and time consuming, because they commonly exceed thousands of fragments. Hence, this study aims to propose a novel approach to classify archeological fragments into groups. In the first step, six images are acquired into memory and converted to the HSV color space. Next, the pre-processing procedure is applied to remove noise caused by the conversion process. Moreover, each image is divided into six sub-blocks and the HSV color feature is extracted from each sub-block. Each HSV color of the sub-block vector was intersected with the corresponding sub-blocks of the other images. As a result, we obtain six vectors for each image. At the final stage, on the basis of the results we obtained, the fragments were classified by using the SOM method. The algorithm was tested on several images of 2D ceramic fragments and achieves accurate results. We conclude that the proposed classifying technique is effective and achieves promising results. The proposed method adopted the color of the surface information of fragments and when evaluating the method for accuracy, it achieves value of 89.6% for classification of the fragments into similar groups. In future work, an integration of the RGB color space and the HSV color space is performed to extract the features and classify the images based on the SOM classification model.

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