Recognition of Ancient Egyptian Artifacts using a Feature Points Extraction Methodology

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Abstract

Ancient Egyptian Artifacts represent significant reflections of ancient Egyptian heritage as they represent valuable knowledge about the life and culture of Egyptian people in times long past. Over the past two decades, the use of computer vision techniques for archaeological artifacts has been applied for ancient artifacts. In the present work, we aim to be able to recognize images of a limited dataset of small ancient Egyptian artifacts for the purposes of labeling and subsequent retrieval of content information. We present the methodology and the results obtained for the recognition of a sample of small ancient Egyptian artifacts. Our work uses the collection of artifacts images as input data and uses recent image processing and feature point extraction methodologies for the recognition and identification of these artifacts.

Our methodology for recognition relies on a feature point extraction approach using the FAST (Features from Accelerated Segment Test) corner detection algorithm. Using a dataset of 254 artifacts images, we investigated the dependence of the recognition rate on various factors including number of strongest feature points, the threshold for the nearest neighbor metric, and the image scale factor. Using the FAST algorithm with the optimal factors found in our study, we achieve a recognition rate for the artifacts of around 90% accuracy. We find our methodology to be robust and to provide good means of recognizing small ancient Egyptian artifacts.

Keywords: Ancient Artifacts, Image Recognition, Feature Points Extraction, Image Processing.

1. INTRODUCTION

Ancient Egyptian Artifacts are considered significant reflections of ancient Egyptian heritage. Today, archeologists, researchers and even ordinary people consider such artifacts to convey valuable knowledge about the life and culture of Egyptian people in ancient times. Ancient artifacts are objects created or shaped by ancient people to show their art, tools used in ordinary life or religious practices, and to glorify their achievements. Examples are Pottery, Palettes, Canopic jars, statuettes, etc. The Egyptian Museum holds a very large collection of magnificent ancient artifacts.

For a long time, artifact classification has been performed by visual inspection. However, the current advancement in Image Processing, Computer Vision and AI computerized tools has generated fast growing research and applications in the identification, classification and reconstruction of ancient artifacts. Over the past two decades, the use of computer vision techniques for archaeological artifacts has been applied in content-based image retrieval for historical glass and for medieval coin classification (Van der Maaten et al., 2006). The work ofKarasik & Smilansky (2011) presents a morphological analysis of ceramic assemblages using objective, automatic and computerized method for clustering and classification. Image processing methods have also been used for the recognition and classification of coin-type ancient artifacts (Vasile et al. 2017). More recently, existing image recognition services (Google Vision API and Clarifai Predict API) have been applied for an image repository from the Çatalhöyük Archaeological Project (Engel et al.,2019). Very recently, Neural Networks have been used for the automatic recognition of ancient pottery (Gualandi et al, 2021)and for the automatic reconstruction of ancient pottery fragments (Rasheed & Jan Nordin, 2020; Eslami et al., 2021). Moreover, machine-learning algorithms proved to be highly successful in identifying the ancient artifacts found throughout China (Zhao, 2021).

In the present work, we aim to be able to recognize images of a limited dataset of small ancient Egyptian artifacts for the purposes of labeling and subsequent retrieval of content information. We present the methodology and the results obtained for the recognition of a small sample of such artifacts. Our work uses the collection of artifacts images as input data, applies recent image processing methods, and uses feature point extraction methodologies for the recognition and identification of these artifacts.

For the feature extraction method, we adopt the FAST (Features from Accelerated Segment Test), corner detection algorithm. The basic goal of this algorithm is the detection of corners, which proved to be efficient features for matching due to its ability to show two dimensional intensity changes (Baruah & Saikia, 2020, Wu, 2018). A comparison of different methods for detection and extraction of features in images(e.g. Alsuhimat et al, 2019) shows that the FAST algorithm has the best results among the feature detection algorithm in terms of run time.

A variety of recent machine learning applications has successfully used the FAST algorithm for feature extraction. Examples are applications in Face Recognition (e.g. Anil & Suresh, 2019, Qasim & Salman, 2021), Signature Images (Mohamed et al, 2018, Alsuhimat et al, 2019), Image Mosaicing (Bheda et al, 2014, Ghosh et al, 2015), Text Detection in images (Mathur & Rikhari, 2017) and various Biometric problems (e.g.Bader & Sagheer, 2018).

Although some of the recent methodologies used in our work may have been used in the archeological field, to our best of knowledge no comparable research work has been done on small Egyptian Artifacts. The rest of the paper is organized as follows: section 2 introduces our main methodology, section 3 describes the experimental setup for the obtained artifacts image dataset; section 4 presents the obtained results and their analysis; finally, section 5 presents the summary and conclusion of our work.

2. METHODOLOGY

Our main objective is to be able to recognize an ancient Egyptian artifact that is initially presented as an image. Many of the artifacts dealt with in our work are basically statuettes or jars, which often bear hieroglyphic inscriptions on them. In addition, many of such artifacts have boundaries that are close in shape, which would make confusions if boundary extraction were used. To avoid such possible confusion, we have adopted to use a feature point extraction methodology.

In our design methodology, we use a limited dataset of images of small-sized Egyptian Artifacts, acquired using smart phone photography, which is allowed for tourist photography in the Egyptian Museum. The objective of our system is to be able to recognize such images for the purposes of labeling and subsequent retrieval of content information. Our methodology relies on extracting features from images using the efficient FAST corner extraction algorithm. In most applications of such algorithm, preprocessing of images is used to improve their quality and to ensure the effect of feature extraction by FAST (e.g. Chen et al, 2019, Song et al, 2020).

For this purpose, the present methodology uses three stages, which are image preprocessing, segmentation then the feature extraction process. This is detailed in the following sub-sections. In the process of recognition of an artifact sample amongst those in the dataset, we utilize a nearest-neighbor approach using the Manhattan Distance as a distance metric.

2.1 Stage I: Image Preprocessing

The first stage starts with taking a sample colored image of an Egyptian Ancient Artifact then removing all features smaller than the structuring element to ensure an accurate removal of background noise that would affect the feature extraction process negatively. In addition, the sampled image is converted from RGB to grayscale then adjusted by stretching it to make it clear for the next step in the preprocessing stage which is image binarization. Such step aims at enhancing the contrast and important features in the image for the next stage of segmentation. Binarizing the image converts the grayscale of the original image to black-and-white only, essentially reducing the information contained within the image from 256 shades of gray to two shades: black and white. Image binarization plays an important role in the image preprocessing stage (Choras, 2006).Then comes the complementation process which is the final step in the image preprocessing stage before moving to the segmentation stage, where the image iscomplemented in order to make the image black and the background white to be used in calculating the distance transform by finding the nearest non-zero values within the image (Singh et al, 2012). Figure 1 shows an example of an artifact image throughout the different preprocessing stages.

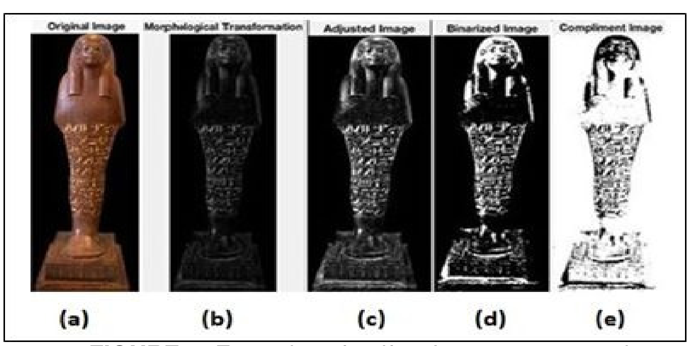

FIGURE 1: Examples of artifact Image preprocessing:
(a) Sample original image, (b) Grayscale image conversion, (c) Adjusted Grayscale image, (d) Binarized image, (e) Compliment Image.

2.2 Stage II: Segmentation

The objective of the segmentation process is to simplify or change the representation of the image into elements or objects that can be easier to analyze and locate. For this purpose, we use the Watershed algorithm.

The Watershed segmentation algorithm is considered a classical algorithm that works on a grayscale image, and also on binarized images. Watershed algorithm works by filling the object in the image with water to perform the segmentation process afterwards (Meyer, 1994). In this process, the compliment binarized image is used as a mask for the watershed. The watershed function takes the image as an input and it is stored in a labeled matrix image having positive integer values at different regions and 0 at the watershed ridge lines(Preim & Botha,2014).

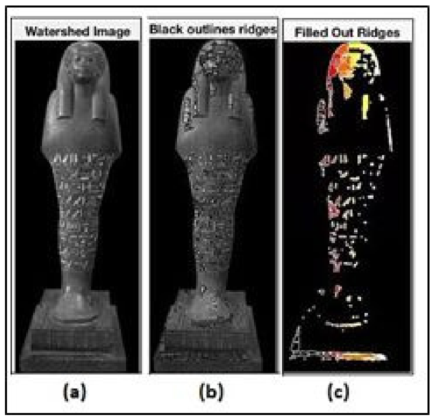

FIGURE 2: Image segmentation with Watershed algorithm.

Figure 2 shows an example of an artifact image throughout the watershed segmentation process. Figure 2(a) shows the watershed image. Figure 2(b) shows the black outline ridges during the segmentation process, and Figure 2(c), shows the filled-out ridges for the segments.

2.3 Stage III: Feature Points Extraction

In general, the main goal of a feature extraction process is to obtain the most relevant and distinctive information from the original data and represent that data in a lower dimensionality space. Appropriate distance measures in the feature space can then be used in classification and recognition of objects.

For images of one or few objects, it would seem convenient to extract object boundaries and map them to the feature space. However, many of the artifacts dealt with in our work are basically statuettes or jars which often bear hieroglyphic inscriptions on them. In addition, many of such artifacts have boundaries that are close in shape, which would generate less distinctive features if boundary extraction were used. To avoid such possible confusion, we have adopted to use a feature point extraction methodology. The preprocessing stages outlined earlier actually streamline with such methodology.

There are several well-known algorithms for finding points in images with distinctive image features. Among these we mention the SIFT algorithm (Lowe, 2004) in which the initial detection of interest points (scale-space extrema) is based on the differences-of-Gaussians (DoG) operator (Lindeberg, 2015). An algorithm that proved to be faster than many other well-known feature extraction methods such as the SIFT algorithm is the FAST algorithm. The FAST (Features from Accelerated Segment Test) algorithm is a fast algorithm for corner detection (Rosten & Drummond, 2005, 2006; Wadhai & Kawathekar, 2017) that proved to be highly efficient.

In the present work, we use the FAST algorithm for feature point extraction from watershed images. The FAST algorithm requires a ring of contrasting pixels more than halfway around the center of a corner. Basically, the algorithm checks whether a candidate point is really a corner point by examining a circle of radius 3 pixels around it (16 pixels on the circle). Using a threshold intensity difference (*t*), and a majority number of pixels (usually 12), a point with intensity *Ip* is classified as a corner point if the majority of contiguous pixels have intensities greater *Ip + t*, or if the majority of contiguous pixels have intensities less than *Ip – t*. This is then followed by a high-speed test for few pixels to verify that the point is actually a corner point.

In the present application of the FAST algorithm on watershed images, the algorithm gives the position (*x,y*) of the feature points together with a metric representing its relative strength. As an example of such method for feature points extraction, Figure 3 shows a sample image of an Egyptian artifact with the extracted corner points superimposed on the grayscale image.

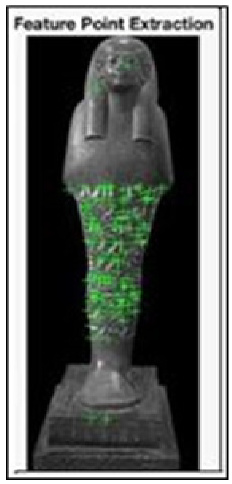

FIGURE 3: Example of FAST feature points extraction (marked in green).

3. EXPERIMENTAL SETUP

In our experiments on the recognition of ancient Egyptian artifacts, we consider different factors such as the dataset used, the distance metric for recognition, the number of feature points used, the image size (scale) and its orientation (image axis).

3.1 Building the Dataset

Our dataset contains 254 images, five of which were from public sources (Public Sources, 2021). As for the remaining 249 pictures, we took them all from the Egyptian Museum. This museum has over 160,000 artifacts that date from the Niqada 3 period (from 3200 BC to 3000 BC). These pictures were acquired using mobile devices, which is allowed for tourist photography in the museum.

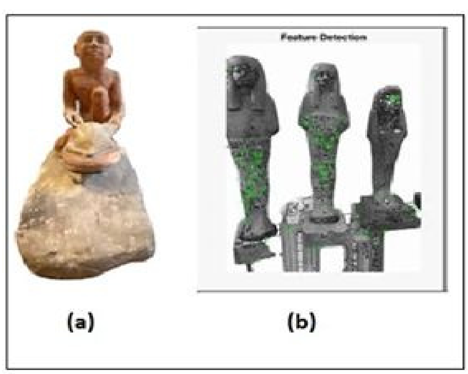

FIGURE 4: Clean image of an artifact after removal of background.

In order for us to build our dataset, we needed to clean all of our pictures. To do so, we removed the background of the imagessuch that each images contains only the artifact itself with no other object in the background in order to have a clean dataset. An example of an artifact image after background removal is shown in Figure 4a. If the images are not clean, this can cause the unwanted addition of corners of irrelevant objects instead of the detection of the features of the artifact itself (Figure 4b).

The artifacts in the current dataset were categorized as follows:

- Head-rest
- Horus's eye
- Faces
- Miniature coffins
- Palettes
- Pottery
- Sandals
- Seated statuettes and Statuettes from Karnack
- Tablets
- Wooden statuettes
- Canopic jars
- Wooden limbs
- Pictures of Nefertiti's statues.

3.2 Distance Metric for Recognition

In the process of recognition of an artifact sample amongst those in the dataset, we utilize a nearest-neighbor approach using the Manhattan Distance as a distance metric. For two images ***P*** and ***Q*** with the same number *N* of strongest feature points, we compute the Manhattan Distance (***D***) defined as:

$$D = \sum_{i=1}^{N} \left| P_{x_i} - Q_{x_i} \right| + \left| P_{y_i} - Q_{y_i} \right| \qquad (1)$$

where (x_i , y_i) are the coordinates of a feature point (i).

For convenience, we normalize ***D*** using a Maximum Manhattan distance obtained by comparing the sampled image with a black image. The reason for that is the fact that different images might have the same threshold and a black image is considered to have zero corners; thus, zero feature points. Therefore, when *N* feature points are taken from the black image, it is considered that there are *N* feature points of zeros.

A test of the use of the normalized Manhattan Distance metric shows that it can clearly distinguish between similar objects and between different objects using the strongest feature points in the images.

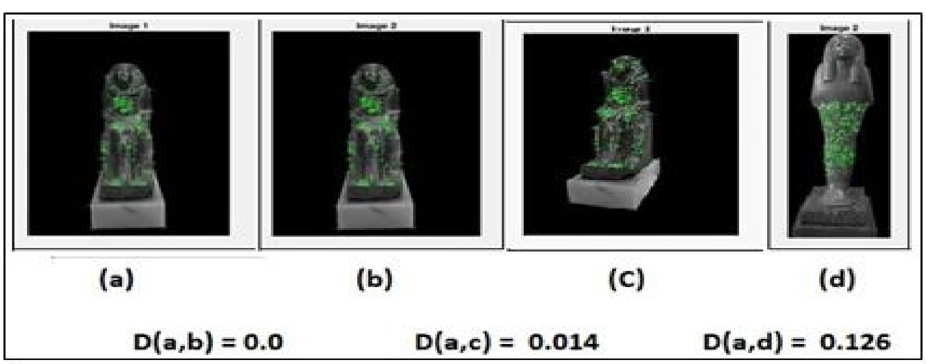

FIGURE 5: Normalized Manhattan Distance between: Similar images (a, b), one differently oriented (a,c), and completely different images (a,d).

Figure 5 shows an artifact in (a), the same artifact in (b), and the same artifact but in a different orientation in (c). Figure 5(d) shows a completely different artifact.

Test on these images showed how the Manhattan distance is sensitive to the change in objects. For completely similar objects (a and b), the distance was found to be zero, as should be expected. In fact, as the objects become more similar, the distance between them will approach zero. However, when the normalized Manhattan distance approaches 1, then this means that both objects compared are relatively distinct. This was clearly seen in the case of the objects shown in Figure 5, where the normalized Manhattan distance was 1.4% in the case of the same object but with one differently oriented (a with c), whereas the distance was 12.6% in case of two different objects (a and d).

4. EXPERIMENTAL RESULTS

We have performed a number of experiments to test the present methodology for recognition of Egyptian Artifacts in the constructed image dataset. In these experiments, we use the normalized Manhattan distance to determine whether a test image is recognized or not. For a given test image the image's strongest number of feature points are compared to all those 254 images in the dataset. The normalized Manhattan distance of each comparison is compared to the threshold chosen; if the normalized Manhattan distance is more than the threshold, the image is rejected. However, if the number is below the threshold chosen, the image detected is added to a list of the recognized images. In this way, a test image is defined to be either recognized or rejected. Basically, the recognition rate is the rate for which test images have been recognized correctly. The rejection rate, on the other hand, is the opposite of the recognition rate; it is the rate for which a test image is either not recognized or wrongly recognized.

4.1 Preliminary Tests

In our preliminary tests, we have used a small dataset of artifacts of about 10-14 images. The images in this small dataset had variances due to the presence of background impurities and also from small angle deviations (such as those in the sample images shown in Figure 5(a) and (c)). The images were typically 500-600 pixels of width on average.

In these tests, we have measured the true positive rate for different numbers of strongest feature points. True positive is the case when the desired image (correct image) is the one with least normalized Manhattan distance among all detected images for a certain input image. We have varied the numbers of strongest feature points from 20 to 200 points using normalized Manhattan distance thresholds in the range from 0.03 (3%) to 0.12 (12%). Results of these preliminary tests are shown in Figure 6, (labeled TP1).

We have been able to attribute the low True Positive rates we obtained in these preliminary tests (shown in Figure 6: TP1) to the presence of background impurities and orientation angle variances in the vertical axes of the images. The effect of the axis of the angle of orientation was determined after redoing the test on another set of images allowing only small angle variances in the horizontal axes of the images (such as the images shown in Figure 5(a) and (c)).

In Figure 6, (Labeled TP2), we show the results for the True Positive rate after removal of background impurities and maintaining only small angle deviations in the horizontal plane. It can be seen from that figure that such adjustments have significantly improved the True Positive rates for the small dataset used. From the comparison of the graphs TP1 and TP2 in Figure 6, we may conclude that both background impurities and orientation angle variances in the vertical axes of the images are quite undesirable and tend to reduce the recognition rate.

Another test on the small datasets has showed that the recognition rate is not significantly affected by the change in the number of strongest feature points so long as there is no change in the image size.

4.2 Effects of the Number of Feature Points and the Normalized Distance Threshold

Here, we report experimental results related to our full dataset, which contains 254 images, and using 199 test images. The images had pure backgrounds and their orientation variances were mostly angled in the horizontal direction.

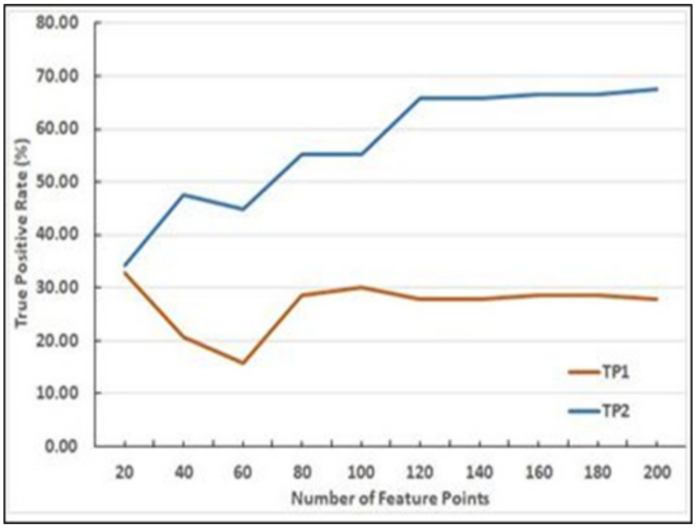

FIGURE 6: Preliminary test on small (~10) images.
TP1: images include B.G. impurities and small angle variants, TP2: cleaned and adjusted images.

In experimenting the effect of both the number of feature points and the normalized distance threshold, the range of numbers of feature points was narrowed to accommodate 10 numbers (starting with 10 to 100 with step 10). This range of number of feature points was found adequate; since in widening our dataset, some images had much less details than the range of images we used in the preliminary tests. Images with fewer details eventually gave less feature points using the fast feature extraction.The least number given by an image was 107 feature points, leaving us with the limitation of not exceeding this number while experimenting to accommodate the whole dataset. On the other hand, the range of thresholds was widened to 20 threshold valuesextending the thresholds to 0.20 (20%) and starting from 0.01 (1%) with step 0.01.

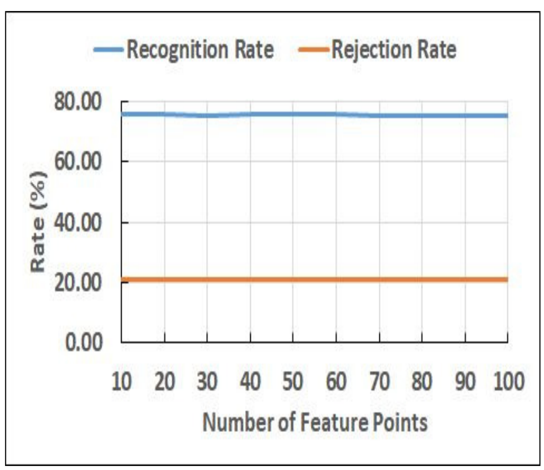

FIGURE 7: Effect of number of feature points on recognition and rejection rates.

Similar to the case of the small dataset in the preliminary tests, we find that the recognition rate is not significantly affected by the change in the number of strongest feature points so long as there is no change in the image size. This is illustrated in Figure 7, where one may observe a markeddistinction between recognition and rejection rates over a wide range of the number of feature points. Such distinction can be taken as a measure of robustness of the present methodology.

With regard to the effect of the normalized Manhattan Distance threshold, we show in Figure 8 the results obtained from the whole dataset. In that figure are shown the dependences of both the recognition and rejection rates on the distance threshold used.

The graphs in Figure 8 show the general rise/decline of the recognition/rejection rate as the distance threshold increases. Below a threshold of about 0.08, there is a fast rise with increasing threshold. A relatively steady and slow rise is observed beyond this threshold value. In general, in the threshold range 0.07-0.15, the recognition rate is 80 – 93%, which is quite acceptable.

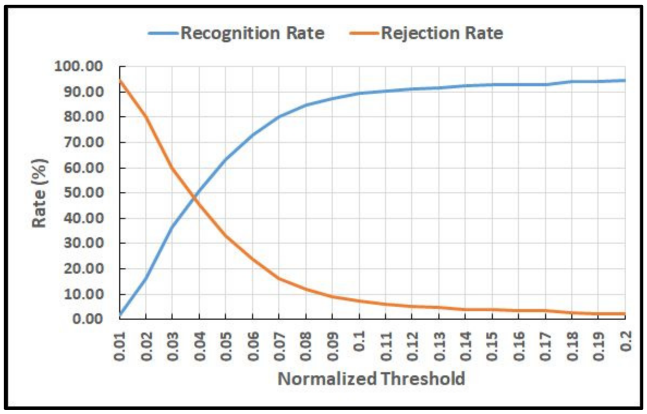

FIGURE 8: Effect of distance threshold on recogition and rejection rates.

4.3 Effect of Image Size Scaling on Recognition Rate

We have also investigated the effect of image scale (size) on the recognition and rejection rates. Experiments for the scale effect also used the full dataset, which contains 254 images and using 199 test images. The images had pure backgrounds and their orientation variances were mostly angled in the horizontal direction. In these experiments, the number of strongest feature points was fixed to 20 only; the choice of this number was, again, based on limitations due to the widened dataset. Images with less details,as discussed earlier, when scaled down to half their original size (scale = 0.5), could not give more than 23 feature points only. Consequently, we have reduced the number of feature points to 20 to accommodate the whole dataset. This is illustrated in the example of Figure 9 where an artifact is shown with scales of 0.5, 1.0 and 2.0 together with the feature points detected in each.

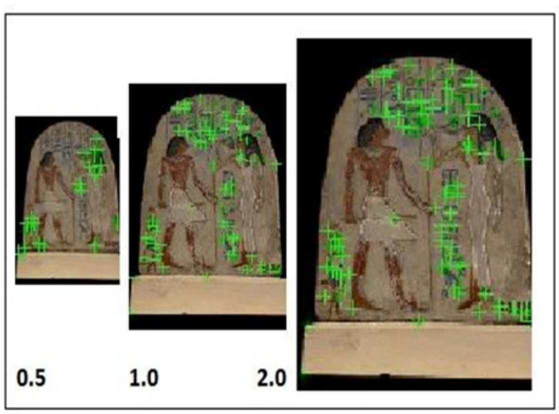

FIGURE 9: Feature points in scaled images.

Regarding the threshold for the normalized Manhattan distance, this was fixed to 0.08, considering it as a point when the recognition rate starts the saturation phase (see Figure 8).

The image scale/size generally affects the maximum number of strongest feature points that could be detected in some image. Having small scales of images, means having less details/features, therefore less number of strong feature points. The scale has the opposite effect with higher scales, obviously. As shown in Figure 10, there is an increase/decrease in recognition/rejection rate by the increase of image scale factor. This behavior is expected since having larger images means having more pixels in the image and thus more pixels per details leading to an increase of features. Having more features gives more choices of the features points and giving the opportunity to choose more unique features.

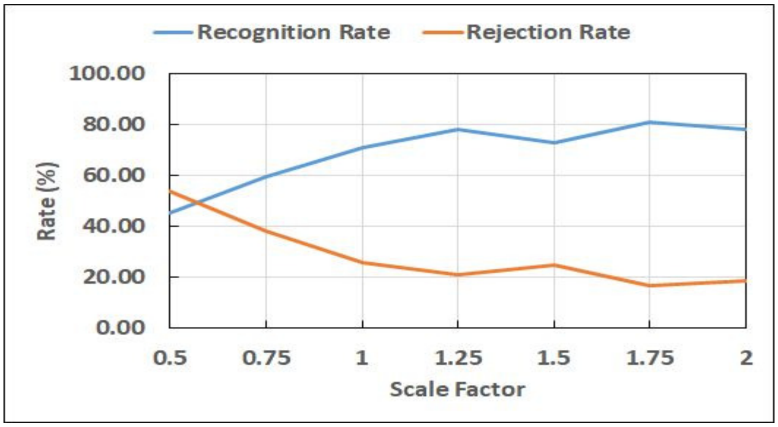

FIGURE 10: Effect of image scale on recogition and rejection rates.

4.4Effect of Image Size Scaling on Execution Time

The average execution time is the time taken to recognize one image. The average execution time might be affected by many factors; for instance, it can be affected by the number of feature points, but since the number of feature points is dependent on the scale factor, it was chosen to study the effect of the scale on the average execution time. It should be noted that the process of detecting the strongest feature points by the FAST algorithm is supposed to be linear in the number of pixels in an image. The computation of the normalized Manhattan distance is also linear in the number of feature points matched.

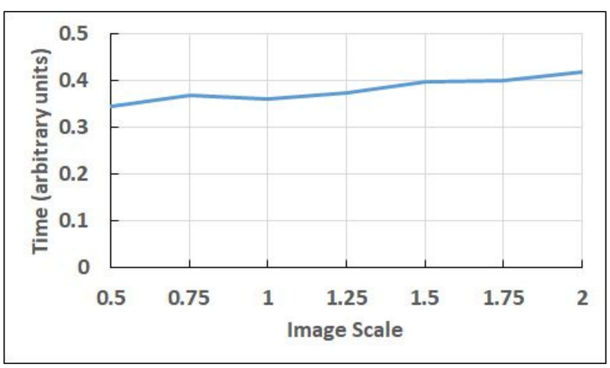

FIGURE 11: Effect of image scale on execution time.

The effect of the scale of the average execution time is shown in Figure 11. It is expected that the time of execution would increase linearly by the increase of the size of the images because larger images would need more time to be processed.

4.5 Analysis of Results

The preliminary experimentation on the small dataset of 10-14 artifact images has indicated the effect of background impurities and orientation angle on the recognition process. We find from these experiments the importance of removing such impurities while keeping orientation to small angles to the horizontal axis of the image. As mentioned earlier, most applications of the FAST algorithm require preprocessing of images improve their quality and to ensure the effect of feature extraction by FAST (e.g. Chen et al, 2019, Song et al, 2020). The preprocessing method used in our work may be considered as an improvement on the application of the FAST algorithm in our work.

Our experiments on the full dataset of 254 artifacts images show that the change in the number of strongest feature points does not significantly affect the recognition rate so long as there is no change in the image size. When images are adequately preprocessed, corner detection becomes more accurate and the number of significant feature points does not necessarily influence the matching process. Naturally, the true recognition rate exhibits an increase with increasing the threshold used for the distance metric.In the threshold range 0.07-0.15, the recognition rate is found to be 80 – 93%, which is quite acceptable given the nature of the artifacts images used.

For the effect of image scale (size) on the recognition and rejection rates, we find that there is a slow increase/decrease in recognition/rejection rate by the increase of image scale factor. This is due to the increase in accuracy of feature point extraction by increasing the image size and details. Although FAST is a fast algorithm compared to other feature extraction algorithms (e.g. song et al, 2020), one should expect that more details caused by increasing scale for preprocessed images would lead to an increase in the feature extraction time.

Although some of the recent methodologies used in our work may have been used in the archeological field, to our best of knowledge no comparable research work has been done on small Egyptian Artifacts. This limits our comparison with other works to the methodology used. In this respect, the recent work of Zhao (2021) on ancient artifacts found throughout China uses a decision tree algorithm for recognition and gradient boosting for perception aspects. According to the findings of that study, the algorithms produced 98% accuracy. On the other hand, the study ofMohamed et al (2018) on Images Signatures utilizes the FAST algorithm among other feature extraction algorithms. Their results showed that the FAST algorithm got the best results among the feature detection algorithm in terms of run time. Ghosh et al (2015) made a comparison of different feature detection techniques for image mosaicking. Their results for 10 images show that the FAST algorithm gives 52.7% accuracy, but exhibits very small run time compared with the SURF algorithm. In the work ofMathur&Rikhari (2017), the FAST algorithm has been used in text detection in document images. They report that the precision of this method is closer or higher than 90%. .Therefore, our results and a recognition rate of around 90% seem to be quite adequate given the nature of the artifact images in the present dataset.

5. SUMMARY AND CONCLUSION

The main aim of the present work is to be able to recognize images of a limited dataset of small ancient Egyptian artifacts for the purposes of labeling and subsequent retrieval of content information. In the present work, we present the methodology and the results obtained for the recognition of a sample of small ancient Egyptian artifacts. Our work uses the collection of artifacts images as input data and recent image processing and feature point extraction methodologies for the recognition and identification of these artifacts. For that purpose, we have constructed a dataset of 254 artifacts images. Most of these images were acquired using mobile devices, which are allowed for tourist photography in the Egyptian Museum.

Our methodology for recognition rely recent image processing methods and a feature point extraction approach using the FAST corner detection algorithm. For this purpose, the present methodology uses three stages, which are image preprocessing, segmentation then the feature extraction process. In the preprocessing stage, we use image enhancement and binarization methods while the segmentation uses a watershed algorithm. The FAST algorithm is then used to extract the strongest feature points present in an artifact image.

From preliminary experimentation on a small dataset of 10-14 artifact images, we have studied the effect of background impurities and orientation angle on the recognition process. We find from these experiments the importance of removing such impurities while keeping orientation to small angles to the horizontal axis of the image.

In our main experimentation, we use the full dataset of 254 artifacts images. The recognition process relies on extraction of strongest feature point and utilizing a nearest-neighbor approach using a normalized Manhattan Distance as a distance metric.

We have performed a number of experiments to test the present methodology for recognition of Egyptian Artifacts in the constructed image dataset. Using the full dataset and 199 test images, we find that the recognition rate is not significantly affected by the change in the number of strongest feature points so long as there is no change in the image size. However, the recognition rate is found to be dependent on the threshold used for the distance metric. In general, in the threshold range 0.07-0.15, the recognition rate is found to be 80 – 93%, which is quite acceptable. We have also investigated the effect of image scale (size) on the recognition and rejection rates. We find that there is a slow increase/decrease in recognition/rejection rate by the increase of image scale factor. The execution time for recognition is also found to be linearly dependent on the image scale factor.

From the experimental results we obtained, we have good indicators of the robustness of the image processing and feature extraction methodologies used. Moreover, a recognition rate of around 90% seems to be quite adequate given the nature of the artifact images in the present dataset.

A practical implication of the current work allows the design a smartphone application to recognize and identify small Ancient artifacts from their captured images. Visitors to the Egyptian Museum where internet resources are available can use such application easily. For future work, we hope to be able to expand the full dataset of small Ancient Egyptian Artifacts available in the Egyptian Museum beyond the current size. However, the Egyptian Museum is currently in the process of moving to a new site and we have to wait until all its facilities become available to the public.

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