A New CBIR Technology to Help Reassembling Moorish Ornamental Carvings

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In this paper, we present a new Content Based Image Retrieval technology specially designed to help reassembling archaeological pieces. The method finds similar fragments based in the fragment content and not the shape of the fracture. A texturization method is proposed to enhance this content. Futhermore, classical Fourier features computation is modified to increase the success matching, and preserve the scale information. The results show that this technology is suitable to filter candidates in a puzzle-solving tool when the number of fragments are huge.

Keywords: CBIR, reassembling, puzzle solving.

1. Introduction

The reassembly of fragments to recompose images and objects is a common problem in archeology (CARLINI, 2008). Many of the developed algorithms solve the reconstruction problem as a puzzle composition by using different techniques: (1) pairwise geometric matching (shape of fractures), (2) matching content properties like color, drawings or figures, (3) or both. In the case of objects like vessels or statues, a 3D model can be used to enhance the results.

The number of fragments plays a relevant role in these problems. Most of the puzzle based techniques drastically reduce the performances or fail with hundreds of fragments. In our case, there are hundreds of thousands of fragments in the image database. A successful pairwise matching requires both: fracture and content analysis. But an exhaustive image processing procedure can not be applied because of the time required, so the initial set of candidates must be reduced. In this work, we propose to use a modified release of general-propose Content-based Image Retrieval techniques (CBIR) to achieve it.

Because of the conservation state and the number of fragments, in a first stage the fracture shape and the color should not be taken into account. In a second stage, if the reduction is significant, the reconstruction can continue by geometric pairwise matching. The first stage is the main goal of this work, this is, to obtain a reduced and likely subset of candidates based on content similarities. But, to achieve successful results, many aspects of these algorithms must be adapted to our specific reconstruction problem.

In section 2 we outline the main aspects of CBIR technologies. Section 3 is dedicated to describing specific aspects of the reconstruction of the Atauriques (Moorish ornamental carvings). Section 4 shows the proposed CBIR algorithm. In section 5, results are analyzed, and finally, in section 6, we outline current works to enhance the algorithm performances.

2. CBIR technologies

CBIR techniques were initially design for retrieving the most visually similar images to a given query image from a database (FALOUTSOS, 1994; CARSON, 1999). The features normally involved in the matching are colors, shapes and textures. These properties are abstractly related to mathematical characteristics or descriptors, such as hue histograms, fourier transform, fourier descriptors, haar coefficients, etc (DESELAERS, 2004).

CBIR algorithms must be computationally efficient in order to obtain results to a query quickly. To achieve this, each image must be processed and stored in the database saving its extracted features. The most complex and time consuming algorithms are applied in this stage. Thanks to that, a query only has to compare the features of two images using theirs CBIR descriptors. Many techniques have been proposed (REDDY, 1996; KEYSERS, 2004; TAMURA, 1978).

Figure 1: *Picture (b) is a brightened version of the picture (a), but CBIR classifies (a) closer to the picture (c).*

But similarities in the human sense are related to the semantic information of the image content. Many authors have pointed out a semantic gap in CBIR descriptors (ESNER,2003; TRAINA, 2006; WANG, 2008) as the main lack of this technology. For example, two scenes with little differences (figures 1a, 1b) can be considered by CBIRs as very different, and conversely, two different scenes can be appreciated as similar (figures 1a, 1c).

Many error sources can be removed by controlling picture illumination and background. Other errors require algorithm modifications that depend on the objects characteristics. This work shows that CBIR can be considered as a suitable technology for our reconstruction problem, and customizing the algorithms, there is a high probability that the selected subset contains many similar fragments.

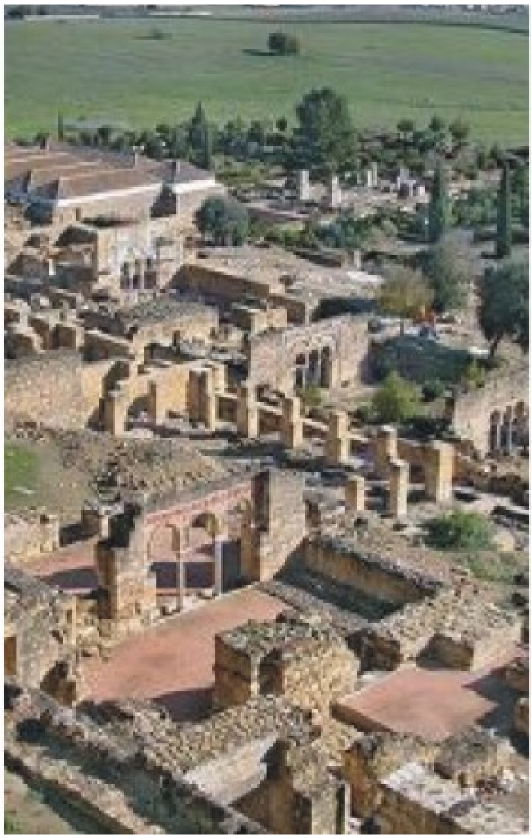

Figure 2: *Madinat al-Zahra. ©Junta de Andalucía.*

3. Atauriques: image-related properties

Atauriques are plasterworks or stuccos wall facings decorated with vegetal and other motifs. They are very common in Spanish Moorish architecture.

The images of the atauriques in this work belong to a catalog of Madinat al-Zahra, the ancient city just outside Cordoba (Spain). The ruins of Madinat al-Zahra represent a powerful, flowering of Islamic art, architecture and urban design. It was effectively the capital of al-Andalus, the powerful Muslim-occupied territory in the Iberian Peninsula. So far, hundreds of thousand of fragments have been cataloged. But this is just a little percent of the real number.

Luminance and color histogram analysis show that the images of the fragments have low contrast, and the colors are very uniform. As a consequence, it is almost impossible to extract local significant properties like corners or edges, no matter the selected algorithm and threshold. Therefore, the identification of ornamental drawings from local analysis becomes a pretty difficult problem. Figure 3 shows these ideas. The modified CBIR algorithm proposed in this paper works with either local or global features, so the probability of a successful match increases.

The state of conservation of the fragments influences critically in the results. The fragments are very deteriorated. Algae change the color in several areas, creating shadows, edges and false textures. To reduce matching errors, algae should be physically removed. Moreover, after cleaning, it is very common to label the fragments with an identification number. Most of image processing algorithms can find false contours caused by these labels and algae stains, so it is very important to remove them from the pictures. We have develop an simple but fast and semi-automatic cleaning algorithm that redraws the labels with patterns of pixels statistically similar to the non-labelled areas (Figure 4).

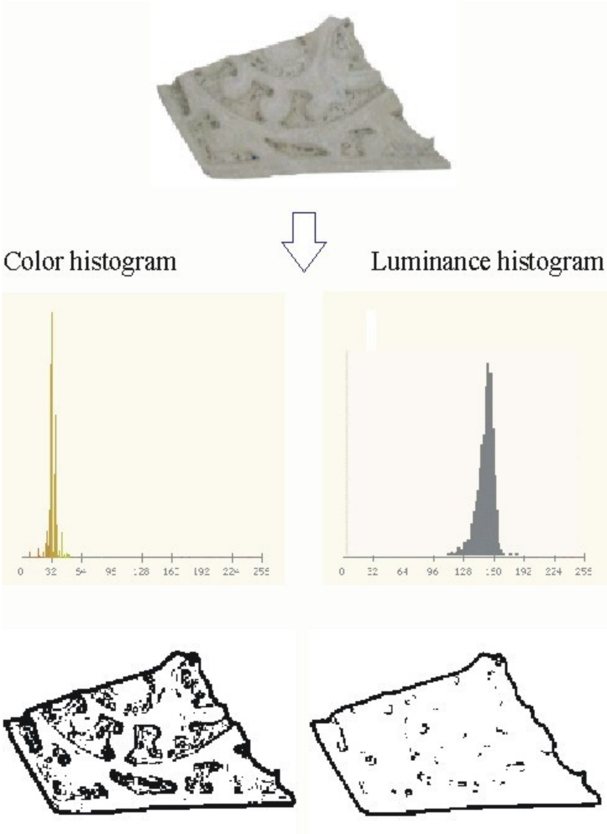

Figure 3: *Color and luminance histograms, and edge images of atauriques.*

4. CBIR features computing and matching algorithms

During acquisition, it is extremely important to control the scene dimensions in order to differentiate adequately the scale of the fragments. The relative size of these fragments must be present in the all the processing to avoid confusion in the marching process (a big leaf should not be matched to a small one, even if they are the same motif). Furthermore, the use of variable focal lens is not recommended.

The features computing algorithm consists of three phases: image pre-processing, texture synthesis and features extraction.

The main goal of pre-processing algorithms are to reduce the size and resolution of images, and extract the background. This processing increases efficiency and reduces the hardware requirements. Many processing algorithms are more efficient for low resolution images (i.e. edge and contour detectors).

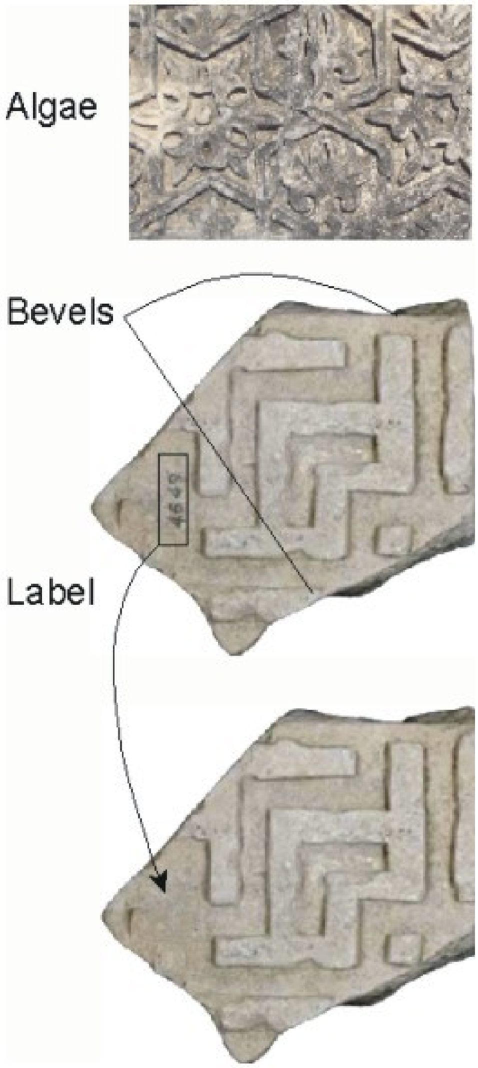

Figure 4: *State of conservation, and label removing.*

4.1. Texture synthesis algorithm

Texture synthesis is applied to reduce the fracture shape and bevels related information in the CBIR descriptors. Texturization translates the fragment's interior content into a global property.

The proposed algorithm is based on the Paul Francis Harrison's texturization technique (HARRISON, 2005). Pixels and textures are copied from the own image to the target areas. A comparison function decides if the references or keypoints are selected from their neighbours or from random locations.

In order to reduce the effects of contours, bevels and shadows at the edges, the area of keypoint candidates is reduced by scaling a constant factor. The removed points are labelled as background, so that; they will be filled out or re-drawn as new texture points. Figure 5 shows the results.

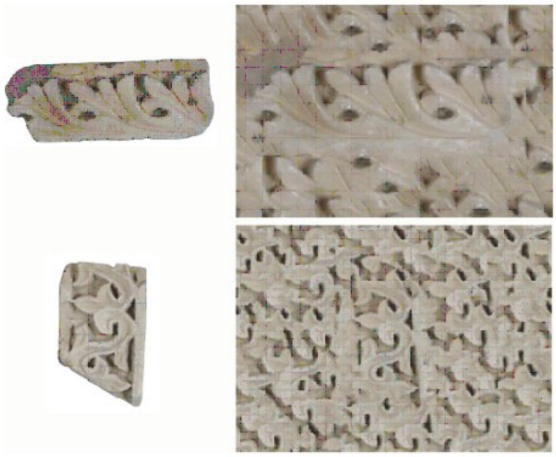

Figure 5: *Results of the texturization algorithm.*

4.2. Fourier and Haar features computation

Fourier and Haar are classic and easily computing transforms that operates directly on the original images, although in our case we transform the textured image.

The Fourier transform reveals texture properties like periodicity and coarsity, both directly related to the size and repetition of the texture seed element. To represent these properties, the energy is integrated in different areas of the complex Fourier transform. The result is a hash numerical vector used to compare to other images.

The Haar transform is a multiresolution technique able to represent non periodic patterns in different scales. Most significant coefficients are selected to encode these patterns. The previous texturization algorithm reduces the values of the coefficients in the areas that contain the fracture contour, increasing the relevance of the ornamental drawings. Again, these coefficients create a hash vector to compare with.

4.3. Matching algorithms

We have defined a different comparison metric for both, Fourier and Haar features. Fourier coefficients are compared using a euclidean distance. The coefficients of the reference image are compared with each and every image in the database. The numerical results allow creating a list sorted by similarity.

Significant Haar coefficients are used to compare similarities. Again, the result is an ordered list. The position in the list is the metric to fusion both as proposed Borda's Count algorithm (VAN ERP, 2000).

4.4. Optimization and scale dependencies

The scale of the pictures is a critical point in the matching process because it is involved in the computing time as well as in the success of the results. Two images taken with different focal distances will be considered as similar. The scene to picture size ratio

Scene dimensions	Image size (pixels)
120 x 90 cm	256 x 256
60 x45 cm	128 x 128
30 x 22,5 cm	64 x 64

Table 1: *Scene and image assignment.*

(hereinafter the scale) should be constant or, at least, preserved. The easiest way to achieve it is to always use the same scene dimensions. Although, a common scene for either small and big fragments will decrease the matching performances and increase the processing time.

Small fragment images contain bigger empty areas that should be filled with texture. In the best case, the texturized image just hides the fragment shape information, but the more textured the area the more probability of degrading the resulting image. Furthermore, the time to compute the texture increases exponentially.

To avoid both, classic Fourier features computation has been modified to include scene dependencies and multiple but fixed scales. The camera position and focal distance should be adjusted to take the pictures from a fixed scene area. These pictures will be spatially quantized to a fixed image size preserving the 4:3 or 3:2

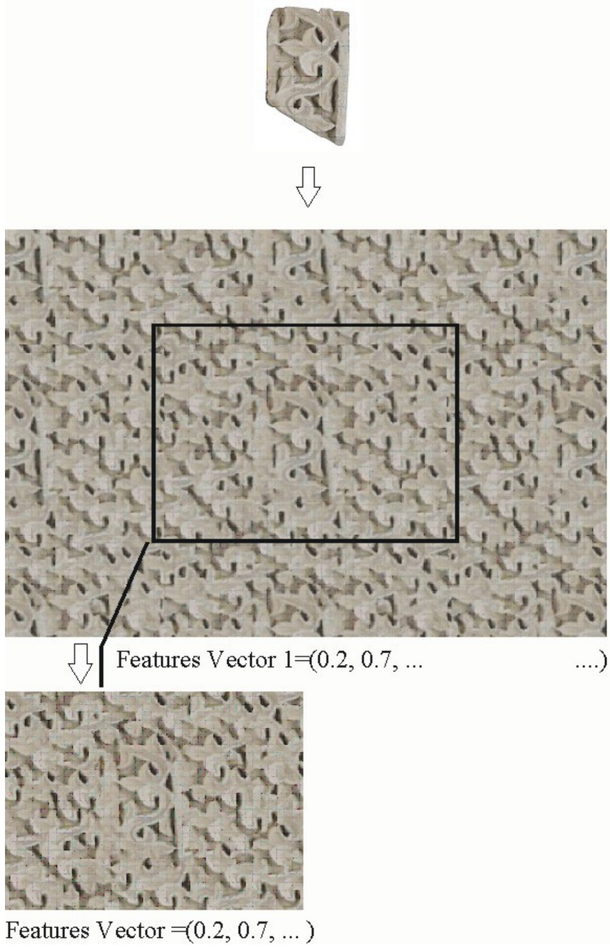

Figure 6: *Fourier features computation.*

aspect ratio of the image camera sensors. Table 1 shows the selected areas and image sizes.

Texturized image is computed on a doubled-size image that includes the original at the center. The goal is to *amplify* the information of the fragment content in the Fourier feature vector. A second texture image with the original image size is clipped from the first one. Figure 6 shows this operation.

Two Fourier feature vectors are generated. The matching algorithm allows comparing fragments of different sizes if one or both vectors have the same dimension, this is, if they have similar size.

Figure 7: *Examples of categories.*

5. Results

Two experiments have been designed to measure the performances of the algorithm. The first one is designed to reveal the aggregation ability. This is, the capacity of the algorithm to recognize similar fragments with the same content. The test database consists of 70 pictures clustered into 7 groups. Each group includes 10 pictures of fragments with same content. Figure 6 shows a small sample of this idea: 4 categories (rows) with 4 elements each (cols).

Figure 8 represents successful classification percentage, and shows that first two results can reach up to 90% of success.

6. Future works

To increase the system performances, we are testing a categorizing technique that consists in comparing the fragment to a set of reference images. These images are previously classified into categories. Each category contains different fragments but with similar ornamental drawings. In this way, a first comparison to the categorized images can provide usefull information to correct the matching algorithm (i.e correcting the results using the category matching frequencies).

Other local matching techniques will be tested. For example, the Scale-invariant feature transform (SIFT), or curve-matching.

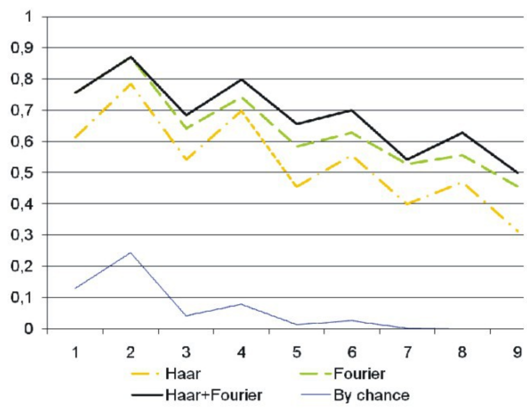

Figure 8: *Success vs number of resulting fragments.*

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