A new CBIR technology to help reassembling moorish ornamental carvings

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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. Mostly 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 Contend-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 goal of this work, this is, to obtain a reduced and likely subset of candidates based in content similarities. But, to achieve successful results, many aspects of these algorithms must be adapted to our specific reconstruction problem.

In the 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 characteristic or descriptors like hue histograms, fourier transform, fourier descriptors, haar coeficients, etc (DESELAERS,2004).

CBIR algorithms must be computationally efficient in order to obtain results to a query shortly. 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).

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 can be considered by CBIRs as very different, and conversely, two different scenes can be appreciated as similar.

A B C

Figure 1: *Picture B is a brightened version of the picture A, but CBIR classifies A closer to the picture C.*

Many error sources can be removed by controlling picture illumination and background. Other errors require algorithm modifications that depend on the object 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.

3. Atauriques : image-related properties

Atauriques are plasterworks or stuccos wall facings decorated with vegetal an 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.

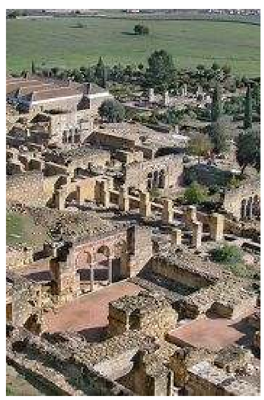

Figure 2: ***Madinat al-Zahra. (C) Junta de Andalucía***

Lumuminance and color histograms 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 dificult problem. The figure 3 shows these ideas. The modified CBIR algorithm proposed in this paper works with either local and global features, so the probability of a success match increases.

The state of conservation of the fragments influences critically in the results. The fragments are very deteriored. Algae change the color in several areas, creating shadows, edges and false textures. To reduce matching errors, algae should be physically removed. Altough, after cleaning, it is very common to label the fragments with an identification number. Mosty of image processing algorithms can find false contours caused by these labels, 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-labeled areas. Figure 4 shows this.

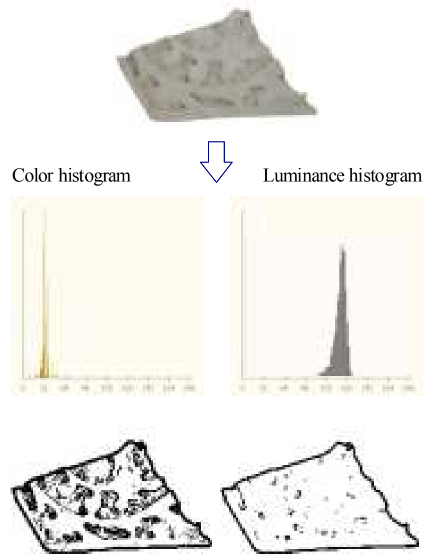

Figure 3: Color and luminance histograms, and edge images.

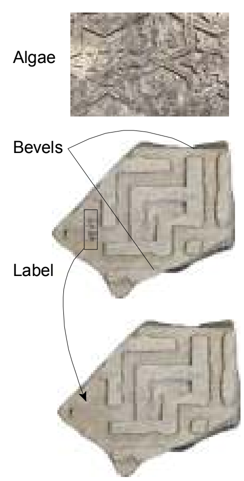

Figure 4: State of conservation

The fragments shows multiple and eroded fractures and bevels, so that, fracture shape matching becomes almost imposible. The proposed CBIR algorithm ignores the shape by the texture synthesis. The resulting image fill all the picture eliminating the shape of the fragment. Figure 5 shows this idea. Bevels are also reduce by image eroding algorithms.

4. CBIR features computing and matching algorithms.

During adquisition, it is extremely important to control the scene dimensions in order to differentiate adecuately 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, no matter they can be the same motif). Foremore, variable focal lens are not recommended.

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

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

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 interior content into a global property.

The proposed algorithm is based in the Paul Francis Harrison's texturization technique (HARRISON, 2005). Pixels and textures are copied from the own image to the target areas. A comparation function decides if the references or keypoints are selected from theirs neighboors 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 it by scaling a constant factor. The removed points are labeled as background, so that, they will be filled out or re-drawn as new texture points. The figure 5 shows the results.

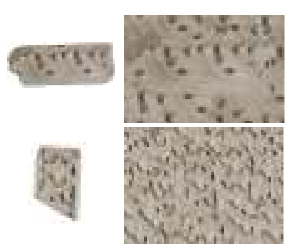

Figure 5: ***Results of the texturization algorithm***

4.2 Fourier and Haar features computation

Fourier and Haar are clasic and easily computing transforms that operates directly to the original images normaly, although, 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 on 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 coeficients are selected to encode these patterns. The previous texturization algorithm reduces the values of the coeficients in the areas that contain the fracture contour, increasing the relevance of the ornamental drawings. Again, these coeficients create a hash vector to compare with.

4.3 Matching algorithms

We have defined a different comparation metric for each, Fourier and Haar features. Fourier coeficients are compared using an euclidean distance. The coeficients of the reference image are compared with each and every image in the database. The numerical results allow creating a list, ordered 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).

5. Results.

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

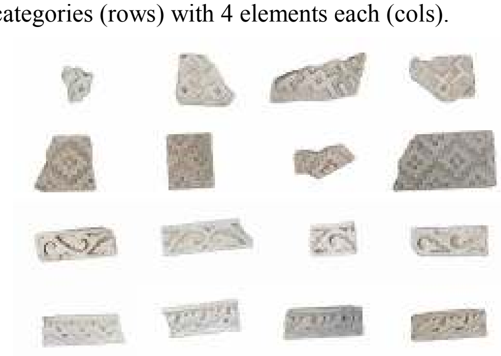

Figure 6: *Sample of Categories*

Figure 7 represents sucess classification percentage, and shows that first two results can reach up to 90% of success.

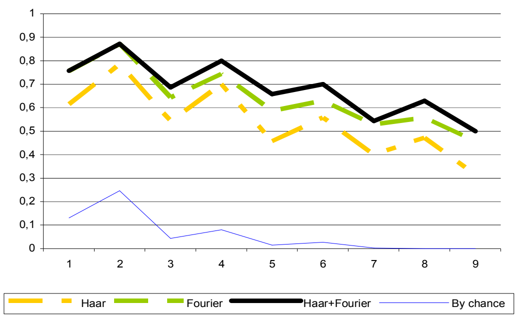

Figure 7: Success % vs number of resulting fragments.

6. Future works.

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

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

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