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Texture features to index and retrieve Roman mosaic-images

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***Abstract*—In this work, we apply and compare three texture features on historical images domain: Local Binary Pattern (LBP), Sobel Local Binary Pattern (Sobel-LBP) and Gabor Binary Pattern (GBP). This Study is in the purpose to index and retrieve Roman mosaic-images. Similar images are extracted using normalized histogram intersection measure. The applied texture descriptors are tested on database containing 800 images of historical Roman mosaics from the 1st to 4th century. Tests demonstrate that the Local Binary Pattern gives interesting results compared to the others features when applied to Roman mosaic-images.**

***Keywords*— Local Binary Pattern, Gabor Binary Pattern, Sobel Local Binary Pattern, Roman mosaic-image indexing, Pattern recognition**

I. INTRODUCTION

Image processing is important in modern data storage and indexing and retrieval process, especially, with the development of multimedia techniques, digital libraries and image databases. There are many constraints which affect the images index such as images database, choise of image features and dimension of the feature vector. Many researchers have focused on extracting visual features from images, particularly, if those images have a great historical value, such as paintings or manuscripts. Recently, many initiatives were undertaken by libraries, museums and governmental institutes all over the world with the aim to preserve their cultural heritage and make it more accessible to public[1,2,3,4]. Some museums in the world, such as Bardo museum in Tunisia (http://www.bardomuseum.tn), house a huge and exceptional collection of mosaics from the 1st to 4th century of great historical value. Roman mosaics have very rich and complex content of different shapes, colors, sizes, and textures which document the daily life at that time.

Local binary pattern (LBP) operator was firstly proposed by Ojala et al. [5] as a texture feature. It is robust to illumination, simple to implement and achieved very competitive results. The LBP or its variants are highly successful in computer vision applications such as face analysis and recognition [6,7,8,9], texture classification [5,10,11,12], Background elimination[13] and image retrieval [14,15].

Many researchers have used the Sobel-LBP [6,7,16], they apply the LBP computation process on strong edges extracted by Sobel gradient operator. Huang el al. [6] proposed an approach in which gradient magnitude images is used to describe facial key points. Zhao et al. [7] uses the same idea for facial image representation. Yao and Chen [16] proposed local edge patterns (LEP) for color texture retrieval.

The LBP is robust to luminosity but it's sensitive to noise. So, some authors use the Gabor filter as pre-processing step to eliminate noise [9, 11] before applying LBP. Zhang and Zhao [11] use this technique in texture classification field. Whereas Zhang et al.[9] use it in the field of face recognition.

In this work we adopt these descriptors to test their ability in historical images database field. We proceed in this paper to carry on a comparative study between the LBP, Sobel-LBP and the Binary Gabor Pattern (BGP). The goal of this work is to build a system that indexes and retrieve images of an exceptional collection of historic roman mosaic-images.

The paper is organized as follows: in section II we present the LBP descriptor and its variants; in section III we detail the proposed approach; in section IV we present results and discussion followed by the conclusion section V.

I. LOCAL BINARY PATTERN (LBP) AND ITS VARIANTS

A. Local Binary Pattern (LBP)

LBP uses the grayscale difference to compute the binary pattern. LBP operator is a simple but very efficient texture operator. This operator labels the image pixels by thresholding neighborhood of each pixel with the center value [5]. Since correlation between pixels decreases strongly with distance and then texture information can be sufficiently obtained from local neighborhoods, LBP is usually applied on a 3x3 square neighborhoods and there is no need to consider neighbors of neighbors. The value of LBP code of a pixel (x_c,y_c) is defined as following:

$$LBP_m = \sum_{i=0}^{m-1} s(p_i - p_c)2^i \quad (1)$$

$$s(t) = \begin{cases} 1 & if \quad t \geq 0 \\ 0 & if \quad t < 0 \end{cases}$$

With *s(t)* is the thresholding function whereas p_c is the gray level of the central pixel, p_i is the value of gray level of its neighbors and *m* is the total number of involved neighbors.

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The LBP procedure applied to a given 3×3 pattern is illustrated in figure1.

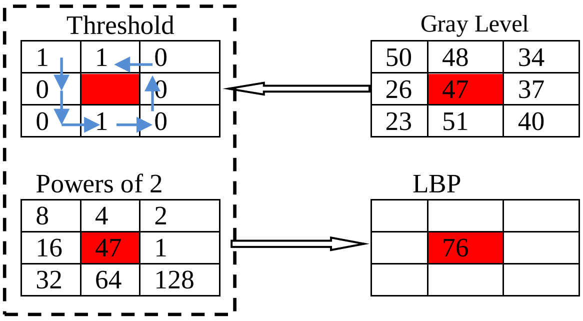


Fig. 1 Example of LBP feature of a pixel with 8 neighborhoods

After computing the LBP pattern of each pixel (i,j), the entire image is represented by making a histogram H to describe the texture feature and defined as follows:

$$H(x) = \sum_{i=1}^{I} \sum_{j=1}^{J} h(LBP_m(i,j), x), \ \ x \in [0, 2^m - 1] \qquad (2)$$

$$h(k,n) = \begin{cases} 1 \ \ if \ \ k = n \\ 0 \ \ otherwise \end{cases}$$

Where I and J are the image heigh and width respectivelly.

B. The Sobel Local Binary Pattern (Sobel-LBP)

Sobel edge operator is a discrete differentiation operator that computes an approximation of the gradient of the image intensity function. This operator uses a pair of 3x3 convolution masks, one estimate gradient in the x-direction and the other estimate gradient in y–direction. They are given by:

$$\Delta_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \qquad \Delta_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

The application of Sobel operators allows the detection of regions of high variations; they correspond to edges in the image. The convolution of Δ_x and Δ_y to the image at a pixel (i,j) for the gray level intensity I allows to the gradient component G_x and G_y and computed as:

$$\begin{aligned} G_x = {} & I(i+1, j-1) - I(i-1, j-1) \\ & + 2[I(i+1, j) - I(i-1, j)] \\ & + I(i+1, j+1) - I(i-1, j+1) \end{aligned} \qquad (3)$$

$$\begin{aligned} G_y = {} & I(i-1, j-1) - I(i-1, j+1) \\ & + 2[I(i, j-1) - I(i, j+1)] \\ & + I(i+1, j-1) - I(i+1, j+1) \end{aligned}$$

The edge strength in pixel (i,j) is given by the magnitude of the gradient vector expressed as:

$$G_{xy} = \sqrt{{G_x}^2 + {G_y}^2} \qquad (4)$$

The Sobel-LBP operator approach is taken as in Zhao et al. [7], a histogram for the whole image is built basing on the scalar field of G_{xy} using the equation 2.

C. The Local Binary Gabor Patterns

Gabor filters are band pass filters which are used in image processing for texture analysis. Two dimensional Gabor filter is expressed as a function G(x, y), where (x, y) is the position of the filter relative to the input signal, θ is the frequency of the filter, and ϕ is its orientation. Zhang et al.[9], expressed 2D Gabor filters as even-symmetric and odd-symmetric ones with following formulas:

$$G_e(x,y) = e^{-\frac{1}{2}\left(\frac{x'^2}{\sigma^2} + \frac{y'^2}{(\gamma\sigma)^2}\right)} \cos\left(\frac{2\pi}{\theta} x'\right)$$

$$G_o(x,y) = e^{-\frac{1}{2}\left(\frac{x'^2}{\sigma^2} + \frac{y'^2}{(\gamma\sigma)^2}\right)} \sin\left(\frac{2\pi}{\theta} x'\right)$$

Where $x' = x\cos\phi + y\sin\phi$, $y' = -x\sin\phi + y\cos\phi$, σ is the Gaussian envelope and γ is the spatial ratio.

Zhang et al.[11] propose to compute eight Gabor filters (even-symmetric and odd-symmetric) at different orientations $\{\phi_j / \ \phi_j = j\pi/8 | j=0..7\}$. The eight Gabor filters are applied to a circular image regions with a radius R centering at x and then summing to get a response vector $r_j = \{r_j / \ j=0..7\}$. Then, they compute the binary vector b using the equation 1 applied to the vector r_j by similar LBP strategy:

$$b = \sum_{j=0}^{m-1} s(r_j) 2^j \qquad (5)$$

Zhang et al.[11] define the rotation invariant binary Gabor pattern (BGP_{ri}) as:

$$BGP_{ri} = \max\{ROR\ (BGP, j) |\ j=0..7\} \qquad (6)$$

Where, ROR(x, j) denotes the circular bitwise right rotation of bit sequence x by j steps. For instance, 8-bit LBP codes 10000001, 11000000, and 00000011 all map to the maximum code 11000000.

II. ROMAN MOSAIC-IMAGES INDEXING AND RETRIEVAL

A. Roman Mosaic-Images Database

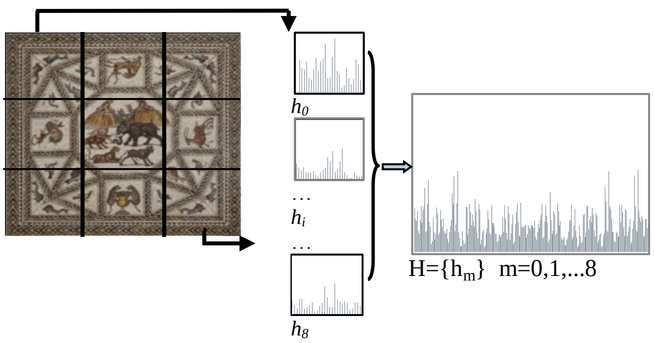
It is worth reminding that the Roman mosaic images constitute an exceptional collection in museums such as the well known Bardo museum of Tunisia. Mosaics are a harmonic stacking of small pieces of marble. One piece of marble is usually of few cm^2 size and called tesserae. Mosaics are of natural colors, complex content and they exhibit richness in terms of texture. Figure 2 shows two samples of Roman mosaic-images.

Fig. 2 Samples of Roman mosaic-images

B. Roman Mosaic-Images Indexing and Retrieval

In previous works, we have indexed Roman mosaic-images based on fuzzy color and shape [18,19]. In fact, these exceptional collections of images are very rich in texture. So, we propose in this paper to index our DB on texture features. For their efficiency and computation simplicity, we have used the LBP, Sobel-LBP and BGP.

In the proposed approach, we decompose the image into RxR regions, we compute for each region the normalized sub-histogram using the equation 2 and we concatenate the RxR sub-histogram to global one which characterizes the image texture features.
Figure 3 shows a mosaic image decomposition with R=3.



(a) (b) (c)

Fig. 3 An illustration of a mosaic image histogram for a given image a)Sample of mosaic-image of 3x3 regions decomposition b)Regions sub-histograms h_m c) The histogram H is concatenated by m sub-histograms {h_m with (m=0, 1, …, 8) }.

Our proposed approach is depicted in the diagram of figure 4. For each image from the DB, we extract the texture feature from predefined regions (RxR), and then we compute the normalized histogram to represent the feature vector.

The user can question the system and the histogram of query image is compared with pre-computed histogram data of all other images in the database using histogram intersection distance as similarity measure.

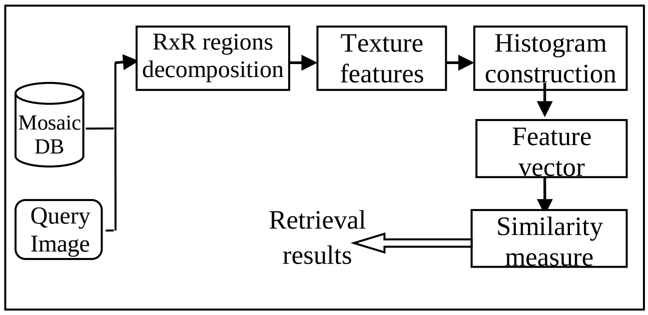


Fig. 4 The proposed Roman mosaic image retrieval system

Therefore, to match between the image query histogram h_q and histogram of images from the database h_t, we compute the histogram intersection measure presented as follows:

$$S(h_q, h_t) = \frac{\sum_{i=0}^{N-1} min(h_q(i), h_t(i))}{min(|h_q|, |h_t|)} \qquad (7)$$

Where N is the total number of bins, h_q and h_t are respectively the normalized query histogram and the normalized target histogram. $|h_q|$ and $|h_t|$ gives the magnitude of each histogram, which is equal to the number of samples. This similarity measure is used to reduce the contributions of the background texture, because, texture not present in the user's query do not contribute to the intersection distance. Furthermore, the intersection distance measure was judged as performing better than the quadratic distance for all histogram configurations [18]. Results are sorted based on their distances. A distance equal 1 represents a perfect match.

III. Experiments and Discussions

In our previous work [17,19], we provide a graphic user interface (GUI) whereby an object relevant boundary and/or color(s) can be drawn. In recent work [20], we propose a fusion between fuzzy color and texture information. In the present work, we suggest a comparison study between LBP [5], Sobel-LBP[7] and GBP_{ri} [11] applied on Roman mosaic-images. We tested our system using 800 mosaic-images collected mainly from the Bardo museum of Tunisia. Images from our database are in JPEG format with a resolution between 370x220 and 770x720.

In our experiments, we start by taking a decomposition of images into 2x2, 3x3, 4x4 and 5x5 overlapping regions. Our goal is to test which configuration gives the best results applied to our mosaic DB. A simple of decomposition of image into 3x3 regions is shown in figure3.

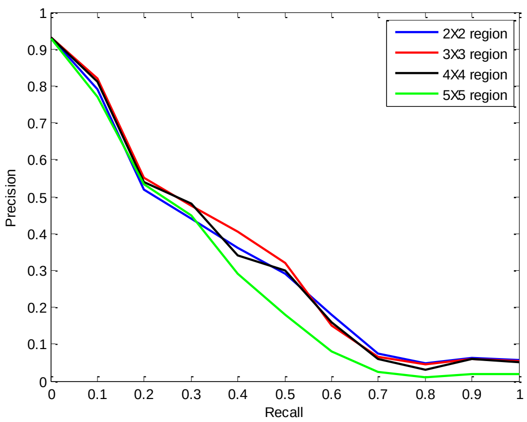


Fig. 5 Tests on Mosaic-image decomposition

As seen in figure 5, the decomposition of the mosaic-image into 3x3 blocks gives a satisfactory results compared with the decomposition of image into 2x2, 4x4 and 5x5 regions. In fact, in this kind of images principal objects are, mainly, placed at central area. Even, the objects are not in central position; they are at the left, right, top or bottom of the image. Our experimentations join the global architecture of Roman mosaics, in the following images are decomposed into 3x3 regions.

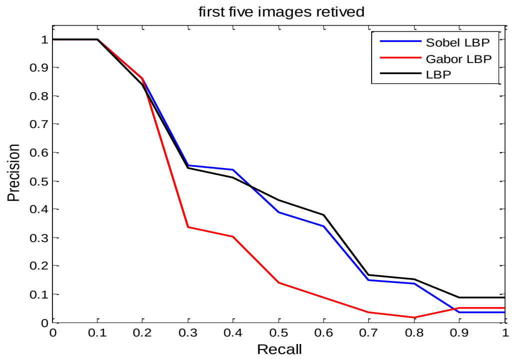
The texture feature is extracted from each region to construct the equivalent normalized histogram. We use the LBP features based on the image gray levels [5], GBP [11] and Sobel-LBP [7] as texture approaches. The vector feature stored is a combination of all regions histograms.

In order to evaluate our approach and to compare between presented texture-methods, we have used 60 queries with different textures and contents. Theses queries are chosen by members of research team in our laboratory. Our experiments are evaluated in term of recall and precision parameters. The recall measures the ability of the system to present all relevant images and defined as:

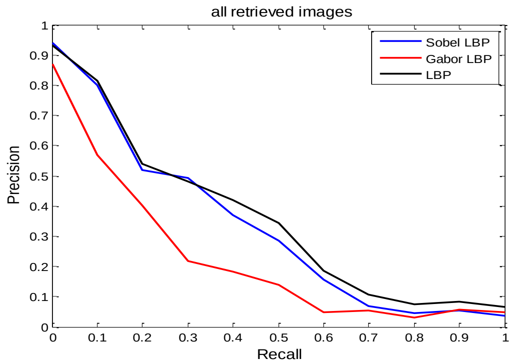
$$\text{Recall} = \frac{\text{number of relevant images retrieved}}{\text{number of relevant images in database}} \qquad (7)$$

We need also to evaluate the number of non-relevant images returned by the system. This can be accomplished by calculating the precision defined as:

$$\text{Precision} = \frac{\text{number of relevant images retrieved}}{\text{total number of images retrieved}} \qquad (8)$$



(a)



(b)

Fig. 6 Recall and precision curve using LBP, Sobel-LBP and BGPri descriptors: a)first five images retrieved, b)all retrieved images.

Figure 6 shows the precision as a function of the recall. The reached results indicate that LBP features contribute to enhancement of the system's precision rate more than the Sobel-LBP and the BGP_{ri}. In fact, the Sobel detector is sensitive to noise in pictures, it effectively highlight them as edges which reduce the accuracy of results returned by Sobel-LBP approach. However, filtering to reduce noise, leads to loss of edge strength, this is at the origin of non satisfactory results given by BGP_{ri} approach. Figure 7 confirms the point of vu detailed above by computing the average precision level as a function of number of images returned. LBP features gives best results compared to the two other features.

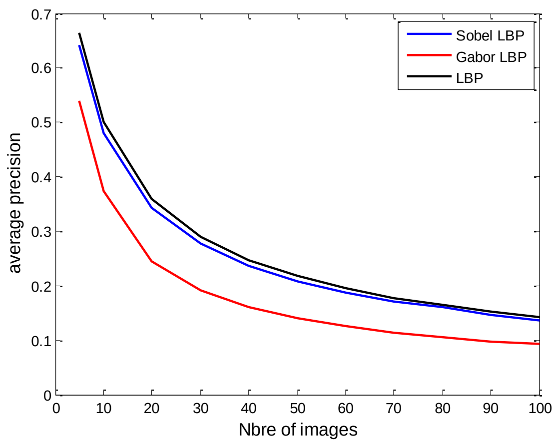


Fig.7 Average of precision rates with different returned image number

Figure 8 shows image query samples and their response, from mosaic-images databases, using the different proposed texture features. Similar images are displayed in decreasing global image similarity.

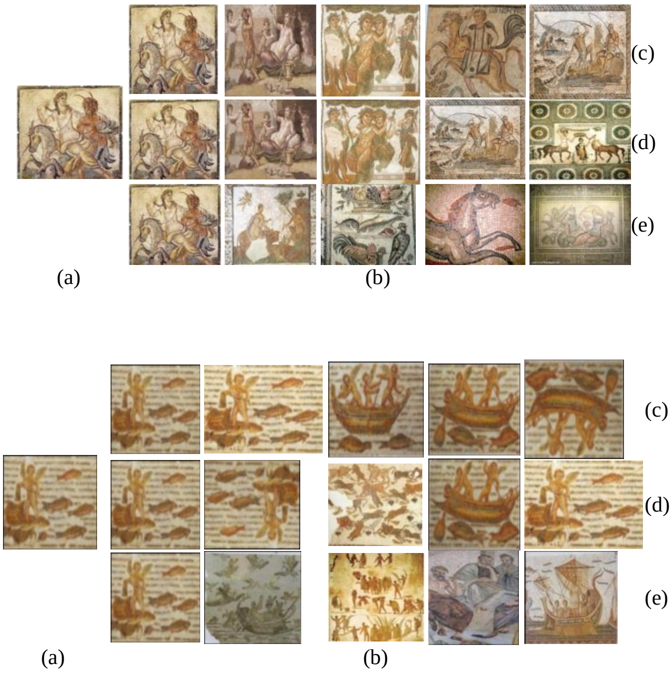


Fig. 8 Samples of (a) image query and (b) top five responses using approaches: (c) LBP (d) Sobel-LBP (e) GBP

In figure 8, we can remark the almost accord between the returned result of the LBP and Sobel-LBP approaches whereas the GBP approach is still in gap. We have tested also the image luminosity, rotation and scale. For example, the second query presents an angel and some fishes. The LBP approach gives a relevant images result, mainly the first and second ones which represent the image query with different scale and luminosity. While Sobel_LBP return as first and second responses the target image rotated in 0° and 90° and returns the image with different scale and luminosity in as the fifth response.

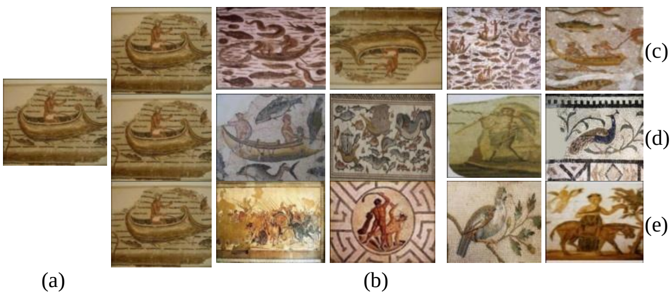


Fig. 9 Samples of (a) image query and (b) top five responses using approaches: (c) LBP (d) Sobel-LBP (e) GBP

IV. Conclusions

In this paper we presented a comparison study between standard LBP, Sobel-LBP and BGPri to extract texture features from Roman mosaic-images. To match the user query image, we use the normalized histogram intersection measures. The system was tested using 800 of exceptional collection of Roman mosaic-images. Results given by the standard LBP are more satisfactory compared to the Sobel-LBP descriptor, but the BGPri feature gives a less significant ones. We continue our study on other texture descriptors as future works to find the most satisfactory descriptor applied on Roman mosaic-images.

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