International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878, Volume-8 Issue-3, September 2019

Performant Retrieval Image using Rectangular Mask and Combination of Color, Texture and Shape Descriptors

Nawal Chifa, Abdelmajid Badri, Yassine Ruichek

Abstract*: *The evolution of computer technologies has led to the growth of digital images, which has made the search for similar images in this volume of data a very important research component. Since several works have proposed image search systems entitled CBIR (Content-Based Image Retrieval). This paper presents a new and powerful method for creating CBIR in order to improve the accuracy of search through visual content. The originality of our method lies in its invariance to the rotation of images queries. She consists of applying rectangular masks of different size on the image, and extracting the color descriptor from the visible region on the mask, and then combining the result descriptor to the Uniform Local Binary Pattern (ULBP) texture features and add canny edge features. We compare the query features to the extract ones, using metric distance. We evaluate our techniques using Corel1K and Ukbench dataset. The average precision measured gives good results comparing to the others existing retrieval systems.

Index Terms*: *Rotation-invariant, HSV Color descriptor, Uniform Local Binary Pattern ULBP, Canny edge, rectangular mask, CBIR Content-based Image Retrieval.

I. INTRODUCTION

In the last decades, with the use of digital technology, the volume of multimedia data and digital images has experienced a great revolution. Therefore, with this large amount of visual information, searching for similar visual content from large image databases has become a crucial area of research. We need to classify and index these images database, in order to better explore it.

The visual image search systems called CBIR systems is new method to overcome the unreliability of the text search h. The principle of search by visual content consists of extracting features that describe the visual content of each image in the dataset, and stokes these descriptors a new indexed database. Those vectors will be compared thereafter with the descriptor of the query image using similarity measure, in order to find the most similar images to the query image [1].

Manuscript published on 30 September 2019

* Correspondence Author

Nawal Chifa*, Electronics Electrothecnic Automatic and information Processing laboratory, Faculty of Sciences Mohammedia, Morocco.

Abdelmajid Badri Electronics Electrothecnic Automatic and information Processing laboratory, Faculty of Sciences Mohammedia, Morocco..

Yasine Ruichek, CIAD Lab, UBFC, University of technology of Belfort-Montbeliard; 90010, France.

Several models have been developed for image retrieval [2]. We find systems that use low-level features, such as color, shape, and texture. For the color descriptor, we have several tools such as color histograms, dominant color [3]. The texture descriptor includes matrices of co-occurrence, Wavelet moment [4]-[6] and Local Binary Pattern [7], or shape features [8] [9]. To get good results with good accuracy, many works has combined two or three kind of global features [10] [11].

In recent years, and in order to get good results with good accuracy, many works combined two or three kind of the low-level features. The proposed framework represents a powerful technique for retrieval images in large databases using fusion of different descriptor from low-level.

The main contributions of this work in this active research area in CBIR are as follows: 1) we introduce a new method to extract locally the features from different parts using mask. 2) We decompose the image into block going from the inside to the outside allowed us to obtain invariant descriptors for rotation. 3) We combine color texture and shape resulting features, and test this technique over the standard database.

In the next section, we expose our method of extraction and combination of features, in the section 3 we present our simulation in Corel bases, and in section 4 we evaluate and compare our result.

II. RELATED WORK

This section presents a brief description of some recent work in the CBIR field that has used a combination of several features. R.Ashraf [12] extracted the edge of the image from the Y components after converting the color image to Y. In addition, he combine the result matrices from the three channels: Y-luminance Cb and Cr; and combine them to obtain RGB image. Next, the histograms information is extracted on each individual RGB image channel. Then, to obtain a descriptor vector, the discrete wavelet transformation is applied to the histograms obtained above. Artificial Neural Networks (ANN) is used and applied on dataset. Walia et al. [13] propose also a technique fusion color, texture and shape feature of an image. The first color moments (mean, standard deviation and skewness of colors) calculated from each channel color H-S-V, and then we compare the result vector to with the query one and return the first thirty similaires images. In second stage, for each sorted image Edge Histogram Descriptor (EHD) and Angular Radial Transform are combined along to obtain the relevant images

N.Shrivastava [14] developed a system of research by phase, in beginning stage he extracts a histogram color HSV of 81 bin. The output of stage, he ranks the N first relevant image based on their metric distance with the image of the query. Next, the N result image is compare to the query image using Gabor texture feature and keeps the first P relevant image. At last, the shape features is extracted using Fourier descriptors.

The works mentioned above have shown that combinations of color descriptors shape and textures; provides very efficient results for image registration systems, but sometimes a bad technique of this fusion can give unsatisfactory results. That is why it is important to use a suitable combination of descriptor that which allows creating performing systems. This paper aims at selecting an efficient fused feature who satisfies the Invariance to image rotation, translation and noise, and give and gives a better precision in comparison with the previous works.

III. PROPOSED WORK

As explained above color, shape and texture represent global descriptors and examples of low-level image features. The combination of these descriptors has often given good results. First thing is to study our dataset and our request. In this paper, we have used Corel Image Library, with 1000 color, images of 10 objects, fig.1 and the Ukbench dataset with 10200 images of 2550 objects, for every object, we have four image with different orientation of the object fig.2. As we can see ours databases are rich in color, and the color features are widely used in CBIR, so we have used histogram color as first descriptor, because it gives a pretty rich information with a simple and fast extracting algorithm, as well as for its property of invariance rotation and translation. However, do not consider any spatial distribution of the color in the image. Even if images have dramatically different contents, they will still be considered similar if their color distributions are similar as well [7]. To overcome this problem we extracted the histogram color from local region of image and concatenated the results vectors, using rectangular mask. For more precision, we combined to the color feature, local texture descriptor the LBP, And Hu moment [15] for shape information; at the next paragraph, we explore our method with more details.

A. *Local Color Feature Extraction:*

Our image descriptor will be a 3D color histogram [16] this histogram represents the overall distribution of colors in the image. His calculation consists of a quantification of the chosen color space, for our system we used the space HSV; whose components H and S are close to human vision, followed by the calculation of the histogram of the pixels thus transformed [17].

To convert our image from the RGB to HSV, we start out by retrieving the red (R), green (G), blue (B) values, in a scale from 0 to 1, inclusively, as well as the largest and smallest of the R,G,B, values, and the difference between the two.

Fig.1: Example of COREL1000 dataset

Fig2: Example of object subset of Ukbench dataset

$$V=\max(R,G,B) \tag{1}$$

$$S = \begin{cases} \frac{V-\min(R,G,B)}{V} & if\ V <> 0 \\ otherwise \end{cases} \tag{2}$$

$$H = \begin{cases} 60(G-B)/(V-\min(R,G,B)) & if\ V = R \\ 120+60(B-R)/(V-\min(R,G,B)) & if\ V = G \\ 240+60(R-G)/(V-\min(R,G,B)) & if\ V = R \end{cases} \tag{3}$$

As explained earlier, extracting the color histogram does not support semantic color distribution, to solve this problem several works proposed methods of extracting color histograms from several regions of the image, same with dividing image into block [10] or using segment method [18]. These approaches have proved their effectiveness with very satisfactory results, but they do not care about the invariance rotation of image. Therefore, in our work we propose a new method of extraction features, from rectangular regions features fig.3:

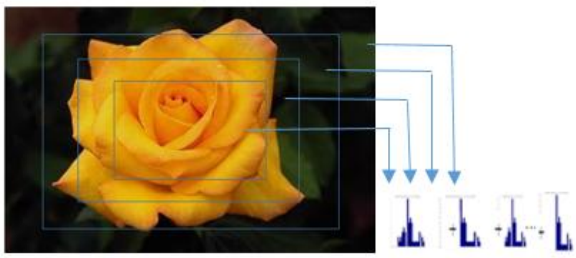

Fig3: extract HSV histogram from each block of image

Fig.4: rectangular masking image different sizes for different region of two examples

and in order to access each block we masque the other block using rectangular mask and extracting features from each masked images Fig.4, for our system we use just 3 masked regions.

The steps of extracting the color features using color-masked histogram are as follows:

Convert a RGB image into HSV

(1) Applied the tree rectangular mask as shown in figure2

(2) From every masked image the color histogram will be calculated for each channel; Hue with eight bins, saturation twelve, and the value three bins for the tree image, which forms a size vector: 8 * 12 * 3 = 288.

(3) Convert the histogram to vector and concatenate the tree vector to obtain one who describe the local distribution of the colors

Vhsvi = Vhsvi1+Vhsvi2+Vhsvi3

i= {1,……., N}

N the number of images in the database used

N the number of images in the database used

B. *Texture Feature Extraction:*

For the texture information, we use the local binary pattern LBP, who is an efficient local descriptor and invariant to scaling and rotation. It is applied to a grayscale image; his principal is to find for each pixel a new gray code depending on the surrounding pixels. Fig.5 gives an example and (5) represents the calculation equation of the new value of the central pixel

$$LBP_{P,R} = \sum_{p=0}^{p-1} s(g_p - g_c)2^p \,, s(x) = \begin{cases} 1\,, x \geq 0 \\ 0\,, x < 0 \end{cases} \qquad (5)$$

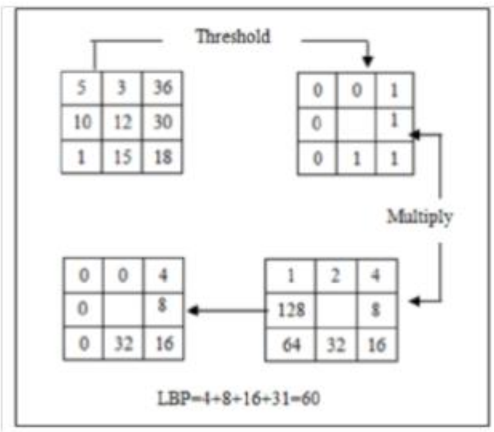

Fig.5: Example for calculation the LBP operator

After the application of the equation on all pixels of the image, we end up with a new digital image, which will calculate the histogram to obtain our LBP descriptor. The latter contains redundant information. To minimize the size of this descriptor, we used the LBP uniform, which takes into account relevant information, so that it only takes into account when calculating the values having two transitions: 1-0 or 1-0, for example, the code 00100000 contains two transitions and the model 0000001 contains one. On the other hand, Model 1001000, it has four transitions 0-1 or 1-0, so is not considered uniform

In total, using this principle we have 58 possible uniform patterns in neighborhood of 8 sampling points are shown in fig.3. Using only 58/256 of the local information may appear as a loss of information, but the uniform LBP detects microstructures (e.g. edges, lines, spots, flat areas).This Uniform LBP operator is an excellent measure of the texture structure of local image texture, and gives satisfactory results concerning rotation invariance. Therefore, we combined the result histogram to the HSV one.

C. *Edge Feature Extraction*

Many descriptor of shape information have been cited above, in our system we use the Hu Moments, who is performant descriptor to describe, characterize, and quantify the shape of an object in an image we opted for this descriptor because of its invariance to image scale and rotation transformation. Hu Moments are extracted from the silhouette of an object in an image. Therefore, to obtain this shape we have to apply some sort of segmentation, thresholding or edge detectors. Canny operator [19] has been used in our system, given these characteristics of edge information preservation, while eliminating false edges and noises in the image. Fig.6 illustrate an example of edge detecting by canny operator.

Fig.6: Example of image (a) and edge detected by canny operator (b)

The general two dimensional $(p+r)^{th}$ order moment of the function f(x,y) (for out case $f(x,y)=I_{canny}(x,y)$) are defined for implementation in digital as:

$$m_{pq} = \sum_{m=1}^{M} \sum_{n=1}^{N} x^p y^r f(x,y) \qquad (6)$$

The invariant features can be achieved using central moments; we obtain translation invariant moment by redefining it into a central moment:

$$\mu_{pq} = \sum_{m=1}^{M} \sum_{n=1}^{N} (x-\overline{x})^p (y-\overline{y})^r f(x,y)dxdy$$
$$where \;\; \overline{x} = \frac{m_{10}}{m_{00}} \,, \overline{y} = \frac{m_{01}}{m_{00}} \qquad (7)$$

Scale invariance is calculated by dividing it by 00-th moment.

The normalized central moments are defined as follows:

$$\alpha_{pq} = \frac{\mu_{pr}}{\mu_{00}^{\gamma}}, \gamma = (p + r + 2)/2 \quad (8)$$

Hu [20] set up the seven moments, based on the central moments calculated above, the resulting moments proved to be invariant to rotation, scale and translation.

$$\emptyset_1 = \alpha_{20} + \alpha_{02} \quad (9)$$

$$\emptyset_2 = (\alpha_{20} - \alpha_{02})^2 + 4\alpha_{11}^2 \quad (10)$$

$$\emptyset_3 = (\alpha_{30} - 3\alpha_{12})^2 + (3\alpha_{21} - \alpha_{03})^2 \quad (11)$$

$$\emptyset_4 = (\alpha_{30} + \alpha_{12})^2 + (\alpha_{21} + \alpha_{03})^2$$

$$\emptyset_5 = (\alpha_{30} - 3\alpha_{12})(\alpha_{30} + \alpha_{12})[(\alpha_{30} + \alpha_{12})^2 - 3(\alpha_{21} + \alpha_{03})^2] + (3\alpha_{21} - \alpha_{03})(\alpha_{21} + \alpha_{03})[3(\alpha_{30} + \alpha_{12})^2 - (\alpha_{21} + \alpha_{03})^2 \quad (12)$$

$$\emptyset_6 = (\alpha_{20} - \alpha_{02})[(\alpha_{30} + \alpha_{12})^2 - (\alpha_{21} + \alpha_{03})^2] + 4\alpha_{11}(\alpha_{30} + \alpha_{12})(\alpha_{21} + \alpha_{03} \quad (13)$$

$$\emptyset_7 = (3\alpha_{21} - \alpha_{03})(\alpha_{30} + \alpha_{12})[(\alpha_{30} + \alpha_{12})^2 - 3(\alpha_{21} + \alpha_{03})^2] - (\alpha_{30} - 3\alpha_{12})(\alpha_{21} + \alpha_{03})[(3(\alpha_{30} + \alpha_{12})^2 - (\alpha_{21} + \alpha_{03})^2] \quad (14)$$

The seven moment using the α_{pr} make the moment invariant to the scaling, translation and rotation. We put them in one vector and concatenate to the previous one.

D. *System architecture and algorithms:*

The first step is preparing our images in databases to extract the features. By converting every image to HSV color, and applying the rectangular mask as showed in Fig.4, then convert the same image to gray in order to extract the uniform LBP features, and at last detect the edge using the canny descriptor, and extract the invariant moment, and combined the tree vectors to have one vector who describe the image. Fig.6. illustrates our approach:

Algorithm:

For every image (i) in the dataset do:

***Step 1**: Extract the color descriptor:*

Convert image to HSV color, apply the three rectangular masks, extract the histogram color from every region, and obtain local color descriptor:

Vhsv= Vhsv1 +Vhsv2+Vhsv3

Step 2: Extract the LBP descriptor:

Convert the image to gray, extract the invariant uniform LBP vector Vlbpun

Step 3: extract the shape vectors:

From the gray image, apply the canny descriptor, to have the edge of objects, and then apply the Hu moment and put the result in vector: VHu

Step 4: Combine all vectors:

At last, we concatenate the all of the vector after multiplied the vector by weighting factor to have one who describe our image and store it in a base indexed by the names of the images, and to be compared thereaf-ter with the vector descriptor of the image request

*Vimgi= {α*Vhsv; β*VLBP; γ*VHu}*

Step 5: Apply the same method to the Query image and obtain the VQ

Step 6: Calculate the Euclidean distance between the requested vector and the other vectors previously calculated

$$Di\sqrt{\sum_{i=1}^{n}\left|V_{imgi} - V_Q\right|^2} \quad (15)$$

(i=1,2,3......n) , n= number of image in dataset, next we sort the distance in ascending order; and take the first sixty, and display their corresponding image.

IV. EXPERIMENTED METHOD:

To test our approach, We used the two bases presented in section 3; the first Corel which contains 1000 images, of standard size (256 * 384 or 384 * 256), and which are distributed over 10 different classes fig.1; the second Ukbench with 10200 images of 2550 objects, for each object we have four images with different orientation of the object fig.2

First, we used the first image database. And to test the efficiency of our descriptors, we realized a search engine that extracts from each image of the base the combined descriptors by adopting our method described in the preceding paragraph, the resulting vectors are then stored in an indexed database. In the second phase, we randomly select twenty-five images from each category, these images represent the images requests, which will be treated with the same method presented in this work to obtain their visual signature, and the latter is compared to those of the indexed database, using the Euclidean distance. At the end, we return the size images whose distance with the image request is the smallest.

To measure the performance of our system, we use the universal measurement value: precision and recall [21].

In order to obtain these measurements, we define Ai the number of image returned and which are similar to the request image, and Ri the total number of images returned by the system, (for our system 16), the calculation formula of accuracy is given as follows:

Pi = (Ai ∩ Ri)/Ri

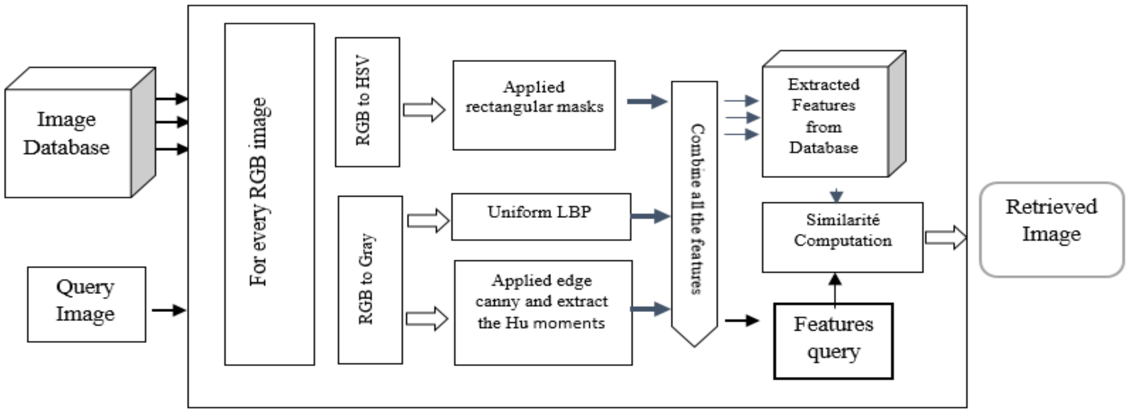

Fig.7: illustrative diagram of our proposed image retrieval approach

Fig.8: example of search result: (a) normal orientation of image request, (b) (c) and (d) using image query rotated

Fig.8 illustrates same example of our result and we compare our average with other work in the table1. Fig.9 reports the performance comparison, the system in terms of precision rates with the same systems.

The comparison reveals a good average compared to other methods already used. Remains that the originality of our method is its invariance to the rotation; that is, if our requested image is rotated in another direction, we can obtain the same good results. This is due to the types of descriptors used, which are invariant to the rotation and to our rectangular mask approach used to extract the color histograms locally. In the second dataset, we have experimented our method to same rotated object in the dataset using at first simple extraction of color histogram and then using the rectangular mask, we obtained very successful result as showing in fig.9.

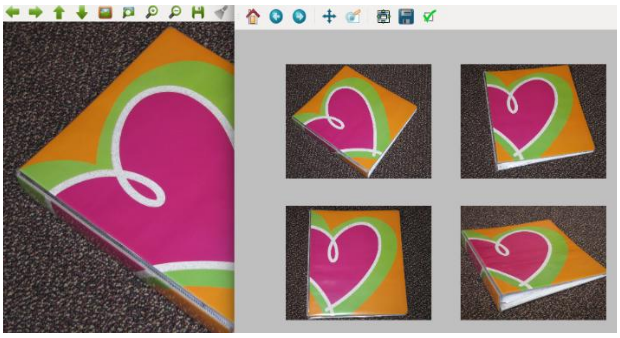

Fig.9: example of search result for an object in different orientation

Table1. Precision value comparison of our methods with other existing ones on Corel-1000

CLASS	WAL [12]	ASHRAF[12]	SHRIVASTAVA [14]	ELALAMI [22]	OUR METHOD
AFRICA	69.57	75	74.8	72.60	88.75
BEACH	54.25	60	58.2	59.30	58.5
BUILDING	63.95	50	62.1	58.7	61.7
BUS	89.65	90	80.20	89.10	89.5
DINOSAUR	98.7	100	100	99.30	100
ELEPHANT	48.8	85	75.00	70.2	63.02
FLOWER	92.3	80	92.30	92.8	94.3
HORSES	89.45	55	89.6	85.6	88.6
MOUNTAIN	4.30	70	56.10	56.20	56.2
FOOD	70.90	70	80.3	77.20	79.65
MEAN	**72.51**	**73.5**	**76.90**	**76.00**	**78,02**
INVARIANCE TO THE ROTATION	No	No	No	No	**Yes**

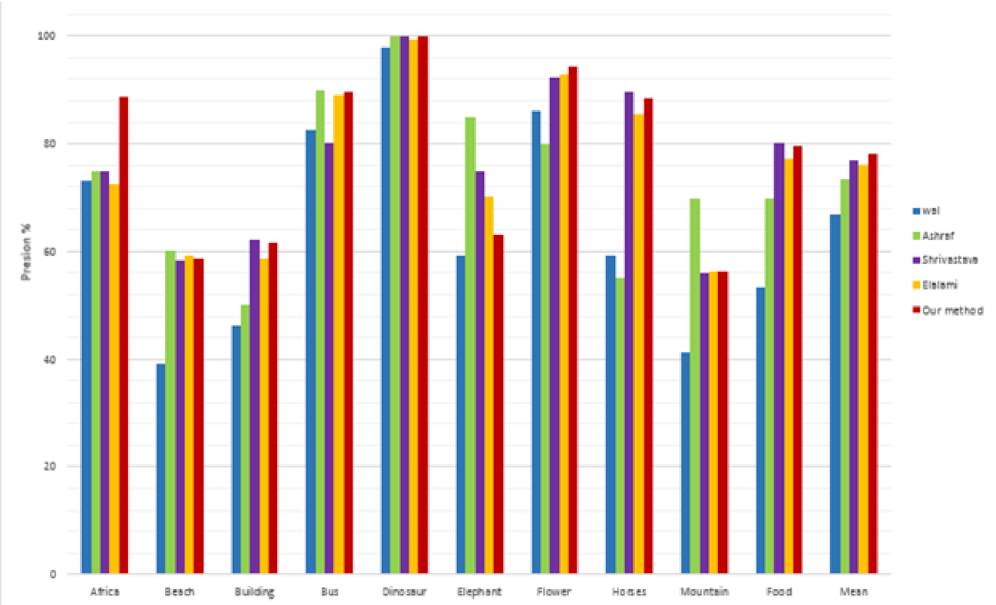

Fig.10: Graph of precision between proposed approach and others techniques

V. CONCLUSION

In this work, we proposed a Content-Based Image Retrieval with new approach of extraction histogram features, which takes into consideration the rotation of the images, the results was very performant. The histogram color (HSV) descriptor is extract from locals regions of Image using the rectangular masks, which allows us to obtain a color descriptor invariant to the rotation. The result vector is concatenate to the LBP uniform vector and Hu moment descriptor; both of them are invariant to the rotation. At next, using the Euclidian distance, the query feature is compared to the other in dataset. We test this method to rotated images, and we found the same good results. The originality of our approach lies in its invariance to rotation and in its robustness compared to existing methods.

This method was checked on the Corel base, which is often used in this type of work, and we extended it to the Ukbench database and for both she has shown efficient in rotation and precision.

REFERENCES

1. N.Chifa, A.Badri, Y.Ruichek, A.Sahel, "Image engine based on color histogram and Zernike moment"; Computer Communication Networks and Telecommunications, Springer International Publishing, 1st Edition, Vol. 659 ,pp. 632–640, 2017.
2. JC. Carson, M. Thomas, S. Belongie, J. M. Hellerstein, and J. Malik. Blobworld: "A system for region-based image indexing and retrieval", In Third International Conference on Visual Information Systems. Springer, 1999.
3. M. J. Swain and D. H. Ballard. "Color indexing", Int. J. Comput. Vision, 7(1):pp11–32, 1991.
4. M. Do and M. Vetterli "Wavelet-based texture retrieval using generalized gaussian density and kullback-leibler distance" IEEE Trans.on Image Proc., pp146-158 2002.

5. S. Liapis and G. Tziritas. "Image retrieval by colour and texture using chromaticity histograms and wavelet frames". In Visual Information and Information Systems, pp.397–406, 2000.
6. R.M. Haralick , K. Shangmugam ,Textural feature for image classification, IEEE Trans. Syst. Man Cybern. (6) (1973) 610–621 SMC-3 W.-K. Chen, Linear Networks and Systems (Book style). Belmont, CA: Wadsworth, 1993, pp. 123–135.
7. OJALA T., PIETIKÂINEN M., MÂENPÂÂ T. "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. Pattern Recognition". Vol. 24, N.7,pp. 971–987,2002
8. Belongie, J. Malik, and J. Puzicha. "Shape context: A new descriptor for shape matching and object recognition". In NIPS, pp. 831–837, 2000.
9. M. K. Hu. "Visual pattern recognition by moment's invariants", IRE Transactions on Information Theory, Vol.8, pp. 179–187, 1962.
10. N.chifa, A.Badri, Y.ruichek, A.sahel "Powerful Combination of Color Descriptor and LBP Descriptor for Image Retrieval", International Journal of Computer Applications Technology and Research Vol.5–N0.4, pp. 210 - 214, 2016.
11. A. K. Jain and A. Vailaya." Image retrieval using color and shape". Pattern Recognition, 29(8):1233–1244, August 1996
12. Rehan Ashraf, Mudassar Ahmed, "Content Based Image Retrieval by Using Color Descriptor and DiscreteWavelet Transform" Journal of Medical Systems, Image & Signal Processing, springer, 42:44,March 2018.
13. Walia E, Vesal S, Pal A. "An effective and fast hybrid framework for color image retrieval". Sens Imaging 2014;15(93):1–23.
14. Nishant Shrivastava, Vipin Tyagi." An efficient technique for retrieval of color images in large databases" Computers and Electrical Engineering, Elseiver Volume 46, August 2015, Pages 314-327
15. F. Xiang, H. Yong, S. Dandan, Z. Jiexian, "An Image Retrieval Method Based on Hu Invariant Moment and Improved Annular Histogram", ELEKTRONIKA IR ELEKTROTECHNIKA, Vol.20, No.4, ISSN 1392–1215, 2014
16. M. E. Elalami, "A novel image retrieval model based on the most relevant features", Knowledge-Based Syst., vol. 24, no. 1, pp. 23-32, 2011.
17. M. Singha and K. Hemachandran, Performance analysis of color spacesin image retrieval, Assam Univ. J., vol. 7, No. 2, 2011.
18. N.chifa, A.Badri, Y.ruichek, A.Sahel "Efficient Combination of Color, Texture and Shape Descriptor, Using SLIC Segmentation for Image Retrieval, " Chapter Artificial Intelligence and Computer Vision, Vol, 672 of the series Studies in Computational Intelligence, pp. 69-80, November 2016.
19. L Ding, A Goshtasby, "On the Canny edge detector", Pattern Recognition, Vol.34, No.3, pp. 721-725, March 2001.
20. Hu, M.-K. "Visual pattern recognition by moment invariants". Information Theory, IRE Transactions on, 8, 179–187.
21. Hersh, W.R., J. Pentecost, and D.H. Hickam, "A task-oriented approach to information retrieval evaluation". Journal of the American Society for Information Science. Vol 47: p. 50-56, 1996.
22. M.E. ElAlami, "A new matching strategy for content based image retrieval" system, Appl. Soft Comput. Vol.14, pp.407–418, 2014.

AUTHORS PROFILE

Chifa Nawal, received the mastery degree in data processing electronics electrotechnics and automatic, , from Hassan II University Casablanca, Faculty of Sciences and Technology of Mohammedia, Morocco, in 2004, and M.Sc. degree in Scientific Computing in High Energy and Experimental Physics from Hassan II University Casablanca, Faculty of Sciences Aïn Chock - Casablanca, Morocco, in 2014. Currently pursuing her PhD in image processing and information engineering at the EEA&TI Laboratory (Electronics, Electrotechnics, Automatic and information Processing), Hassan II University Casablanca, Faculty of Sciences and Technology of Mohammedia. Her main research areas are computer vision and image understanding, pattern recognition, machine learning

Abdelmajid Badri is a holder of a doctorate in Electronics and Image Processing in 1992 at the University of Poitiers–France. In 1996, he obtained the diploma of the authorization to Manage Researches (Habilitation à Diriger des Recherches : HDR) to the University of Poitiers–France, on the image processing. Qualified by the CNU-France in 61th section (informatics Engineering, Automatic and Signal processing. He is an University Professor (PES-C) at the University Hassan II of Casablanca - Morocco (FSTM) where he teaches the electronics, the signal processing, image processing and telecommunication (Department of Electric Engineering). He is a member of the laboratory EEA&TI (Electronics, Electrotechnics, Automatic and information Processing) which he managed since 1996.
The research works of A. Badri concerns the communication and Information Technology (Electronics Systems, Signal/Image Processing and Telecommunication). He managed several doctoral theses. He is a co-author of several national and international publications. He is responsible for several research projects financed by the ministry or by the CNRST or by the industrialists. He was member of several committees of programs of international conferences, reviewer of several revues and chairman of several international congresses in the same domain. He is a member and co-responsible in several scientific associations in touch with his domain of research. He is an expert CNRST and Ministry. He was responsible for several academic structures (Director of ESTC, Director of ENSAMC an interim, Vice Dean FSTM, Head of the Electric Engineering Department).

Yassine Ruichek received his PhD degree in control and computer engineering and Habilitation à Diriger des Recherches (HDR) degree in physic science from the University of Lille (France) in 1997 and 2005, respectively. From 2001 to 2007 he was associate professor at the University of Technology of Belfort-Montbéliard (UTBM), France. Since 2007, he is full professor at UTBM. He headed the computer science department from 2006 to 2008 and the Systems and Transportation Laboratory from 2012 to 2015. He was/is involved and responsible in many projects (ANR, PREDIT, H2020, FC, BFC, …). His research interests include computer vision, image processing and analysis, pattern recognition, data fusion, and localization, with applications in intelligent transportation systems and video surveillance.