Color image retrieval techniques for a global localization of an indoor mobile robot

A. CHAARI[1,2], S. LELANDAIS[1], C. MONTAGNE[1], M. BEN AHMED[2]
[1] IBISC Laboratory - CNRS FRE 2873 - Universityof Evry
40, rue du Pelvoux - 91020 Evry Cedex - FRANCE
[2] RIADI Laboratory - National School of Computer Science
University of Manouba - 2010 La Manouba - TUNISIA
Chaari.anis@laposte.net s.lelandais@iut.univ-evry.fr

Abstract

In this paper we propose a both spatial and colorimetric distance D for a two dimensional color pallet built from the baker's transformation. The baker's transformation provides a quantization of the image into a space where colors that are nearby in the original space are also nearby in the output space, thereby providing dimensionality reduction and invariance to minor changes in the image. Whereas, the distance D provides for partial invariance to translation, sight point small changes and scale factor. Our feature is used in an image retrieval process that has to help a missing robot in an indoor environment. We built a structured image database corresponding to the flat where the robot works. When the robot is lost, it takes an image of its environment that we call request image and the system looks for the closest image in the database witch indicates its position (room and orientation). A hierarchical approach is then conceived by describing in the off line phase each room with a color feature. In a first search phase, we eliminate rooms whose colors are far from those of the request image and then we achieve the search by our distance D. Results obtained with this approach are better than those of the classical color histograms.

1. Introduction

In this paper we propose a new approach for the robot localization problem by using image retrieval techniques to provide a qualitative estimate of the robot position. DeSouza and Kak propose in [1] a good outline of the various approaches of vision system localization, as well in interior structured as in external not structured environments. We work, through ARPH project [2], on the global localization of an indoor robot with a vision system using a color camera. This global localization which consists in finding the room and the orientation in this room is necessary after a long moving when the robot is lost and when the problem of the local localization is difficult to solve.

The chosen approach of the robot localization is described as follows: we build an image database with a lot of indoor images, which have been taken inside the environment where the base works. For each image, we know its room and orientation. When the robot is lost, it takes an image of its environment. This image, called request image, is used as query to the database which has to return the closest image. It is a classical problem of image retrieval but, in this case, this task is more difficult because some images of the database are very close: they have been taken in the same room, with a little difference of orientation and a small shift of the view point.

Content based image retrieval systems (CBIR), witch resolve our localization task, were essentially developed because of the quantities of digital images which are increasingly bulky. These images are, in general, compressed then filed in databases. Once these data stored, the problem is capacity to find them simply. The re-use of these bases passes by the joint development of methods of indexing and research.

Many academic and/or industrial content-based image retrieval systems were developed: Mosaic [3], Qbic [4], Surfimage [5], Netra [6], VisualSEEK [7], ... They allow an automatic search for images per visual similarity. The standard architecture of all this marketed systems comprises an off-line phase to generate image indexes and an on-line phase for the research problematic.

A content-based image retrieval system comprises generally four tasks. The two principal ones are obviously the indexation and research. The indexation consists in computing a signature summarizing contents of an image which will be then used for research. The attributes usually used within this framework are color, texture and shape. The research is generally based on a similarity measure between the signature of the request image and those in the corresponding database. The two other tasks are navigation and analyzes. Navigation is mainly related to the types of consultation of databases. This functionality is often static with a search for one or more answers to a given request. A new type of research more interactive results in a more incremental approach and especially more adaptive to the needs of users. From the images results found at the time of a first research, the user can refine his research according to an object or a selected zone. In addition, the analysis is a very particular functionality which consists in providing quantitative results and not of visual nature (for example, the number of images with a blue color bottom). This functionality is thus summarized to extract statistics from characteristics of images. Automatic robot localization problematic requires only the first two task: indexation and research.

In addition, systems are generally based on a request by the example: further to a request image taken by a robot in our case, the search engine returns the closest images of the database within the meaning of a given similarity measure. The ideal tool of research is then which gives the quickly and the simply access to the required relevant images to a request image taken instantaneously by the mobile robot. The similarity between two images is evaluated by using a specific criterion which can be based on color, shape, texture or a combination of these features. Many techniques were proposed with color based image retrieval [8, 9, 10], and it is impossible to define the best method without taking account of the application. Colorimetric information is very significant in a domestic environment. Indeed, such a medium includes elements of very varied origins which do not have colorimetric coherence between them. A discrimination of these elements, and thus of images of the database, can be more powerful by taking their colors into account.

The remainder of this paper is organized as follows. In the next section we present image databases we use for our retrieval task. Color histogram and some similarity measures are presented in section 3. The components and details of our system are described in sections 4, 5 and 6 respectively. Section 7 describes experimental results and section 8 summarizes the conclusions of this work.

2. Image databases

Two complete and well structured image databases are built for the global localization of the robot. The first database contains 240 images and the second 586 images. The size of images is 960x1280 pixels. These images have been taken in different rooms from two houses. For each room we find a lot of images, corresponding to different available position of the robot and different orientation with a rotation of 20° or 30° according to the room dimensions. Figure 1 shows two examples of images from the first database.

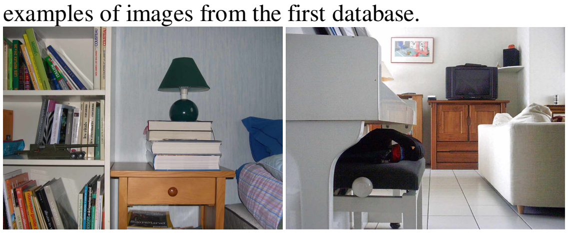

***Figure 1**. Examples of indoor images from our first database*

In the second database we take also the luminosity into account. For the same position, we have two or three images which have been taken at different day time. We took also a lot of request images which are different from the database images. For the first database we have 20 request images and 35 for the second database.

3. Color histograms

Color histograms remain the most used techniques as for the use of color information in retrieval systems. The robustness of this descriptor and its invariance to the position and orientation changes of objects make the strong points of it. Nevertheless, these performances are degraded quickly according to the size of the database. But in our application, the image database is not very bulky. Indeed, in an indoor medium, we don't exceed a few hundreds of images to describe structurally the environment of the robot. The use of the histograms for color images indexing is based primarily on the techniques of selection of the adapted color space, the quantification of the selected space and the comparison methods by similarity measures. We have tested the RGB and the Luv color spaces. To the RGB color space witch give best results, we developed several uniform quantizations with a goal of testing different size of pallets.

Most of the similarity measures used in image retrieval computes the similarity between two histograms. Two category of measures are presented : the bin-by-bin similarity measures witch compare contents of corresponding histogram bins (Minkowski distance, Histogram intersection and the χ^2 test) and the cross-bin measures witch compare non-corresponding bins (Mahalanobis distance and the Earth Mover Distance). Hereafter we present those similarity measures between a request image (I) and all the database images (H).

- **Minkowski distance :**

$$d(I,H) = \left(\sum_{k=0}^{M-1} \left|h_k^I - h_k^H\right|^r\right)^{1/r} \qquad r \geq 1 \qquad (1)$$

Euclidean distance L_2 is obtained for r = 2

- **Histogram intersection:**

$$Inters\,(I,H) = \frac{\sum_{k=1}^{N_I} \min(h_k^I, h_k^H)}{\sum_{k=1}^{N_I} h_k^H} \qquad (2)$$

This function deducts the number of pixels of the model having a direct correspondent in the request image [8]. Values close to 1 indicate a good resemblance.

- **The χ^2 test:** A color histogram can be considered as the realization of a random variable giving colors in an image. Thus, the histogram comparison can be brought back to a test of assumptions, on which it is necessary to determine if two achievements (i.e. two histograms) can come from the same distribution. The χ^2 test is based on the assumption that the present distribution is Gaussian [11]. The χ^2 test is given by:

$$\chi^2 = \sum_{j=1}^{N_I} \frac{(h_j^I - h_j^H)^2}{(h_j^I + h_j^H)^2} \qquad (3)$$

- **Mahalanobis distance** or generalized quadratic distance d_{QG} was used by Equitz and Niblack [12] to take the intercorrelation between color components into account. A weighting matrix W which include the resemblance between colors was proposed. The generalized quadratic distance resulting from the euclidean distance is defined by the following formula:

$$d_{QG}(I,H) = \sqrt{(H-I)W(H-I)^T} \qquad (4)$$

The components w_{ij} of the weighting matrix W can be interpreted like indices of similarity between the i and *the* j element of the pallet. Thus W is generally represented by the reverse of the colors classes intercorrelation matrix. Other proposals of weightings matrices attached to the representation of color spaces to define the colorimetric distances between colors were introduced recently [13].

- **EMD Distance** "Earth Mover Distance" proposed by Rubner [14] consists in extracting the minimal quantity of energy necessary to transform a signature into another. Having the distances d_{ij} between colors components of the two histograms H and I of m and n dimensions, it is a question of finding a whole of flow $F = [\, f_{ij} \,]$ which minimizes the cost of the following quantity:

$$\sum_{i=1}^{m} \sum_{j=1}^{n} d_{ij} f_{ij} \qquad (5)$$

To control the energy exchanges implied, the direction of transfer must be single ($f_{ij} \approx 0$) and a maximum quantity of transferable and admissible energy of each color component should be defined. From the whole of optimal displacements F, EMD distance is then defined like the following resulting work standardized:

$$d_{EMD}(H,I) = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} d_{ij} f_{ij}}{\sum_{i=1}^{m} \sum_{j=1}^{n} f_{ij}} \qquad (6)$$

The formalism suggested by Rubner meets all conditions to determine the optimal distance between two histograms but the complexity introduced by the algorithm of optimization makes it expensive in computing time [15].

4. A color feature to image retrieval

For this retrieval task, we propose to use color information. For each image we compute a color pallet by using the baker's transformation (BT for short). The BT is an ergodic process which mixes in a very homogeneous way all the elements of an involved space [16]. One iteration of the BT is based on two steps: first, an "affine" transformation is used which gives an image twice larger and half high (cf. fig 3) from an original image (cf. fig 2). Then, the resulting image is cut vertically in the middle and the right half is put on the left half (cf. fig 4). After a suitable number of iterations, we obtain a well mixed image (cf. fig 5). From this mixed image we extract a definite size window which gives after some iterations a reduced scale version of the original image (cf. fig 6). Several sizes of window were tested to summarize the colorimetric aspect of the original image. Windows with a number of colors between 200 and 300 give the best color description. Moreover, this small image is a good representation of the color, shape and texture information (see figure 6) and we can consider it as a representative pallet of colors. In [17], we show how it is possible to use this pallet for colors quantization.

Figure 2. *Original image*

Figure 3. *First step of BT initial iteration*

Figure 4. *Second step of BT initial iteration*

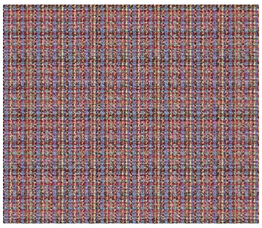

Figure 5. *Well mixed image*

Figure 6. 16x16 pallet deduced from a mixed window

5. Color & spatial distance

The idea is to use this color pallet as a feature and index for image retrieval. A first use of this pallet as an indirect descriptor is performed as follows: First we build a pallet database by computing the color feature for each image from the original database. Then, the request image is projected in the color space defined by each pallet from this pallet database. Progressively, we compute the color difference between the request image and the projected images and we select the pallet (i.e. the image) which leads to the minimum of this distance.

In [18], we associate to this new feature an Euclidean distance $L_2(P_{req} - P_{im})$ between the request image pallet P_{req} and image database pallets P_{im} that we call interpallet distance. Our feature proved its effectiveness and its robustness thereby providing dimensionality reduction and invariance to minor changes in the image sample like the move, the apparition and the occultation of small objects in the scene.

However, the space organization of colors of this two dimensional pallet is an additional information who can present invariance property to some other changes in the image. Thus, we emphasis this color feature aspect and try to model it by preserving the interpallet distance who give an interesting results. Indeed, as the figure 6 shows it, the pallet preserves the spatial distribution and the principal vicinity relations between colors present in the original image. This should give us a relative invariance as well for sight point small changes as for scale factor (i.e. distance between camera and objects).

5.1. Space distribution of colors

To describe the space aspect of the pallet, we built its colors statistical moments in order to coarsely describe colors distribution of the image. Stricker [13] establishes a balanced sum of average, variance and skewness (the third order moment) computed for each color channel, to provide a single number used in the indexing process. If p_{ij} is the value of the pixel j for channel i, these moments are defined by:

$$\mu_i = \frac{1}{N}\sum_{j=1}^{N} p_{ij} \quad \sigma_i=\frac{1}{N}\sqrt{\sum_{j=1}^{N}(p_{ij}-\mu_i)^2} \quad \text{and} \quad s_i=\frac{1}{N}\left(\sum_{j=1}^{N}(p_{ij}-\mu_i)^3\right)^{\frac{1}{3}} \tag{7}$$

The distance between two images is then defined like a weighted sum between these quantities for each channel:

$$d_{mom}(I,H)=\sum_{i=1}^{3} w_{i1}\left|\mu_i^I-\mu_i^H\right|+w_{i2}\left|\sigma_i^I-\sigma_i^H\right|+w_{i3}\left|s_i^I-s_i^H\right| \tag{8}$$

We notice that a space description of our two dimensional pallet by color moments as showed in [13], gives better results than a similar description of the entire original image. We deduce that this description of a pallet which represent on a reduced scale its original image, gives a more precise visual summary of it. In addition, the search time is much more faster while operating on pallets (0,7 second against 3 to 4 seconds for research by image moments with an image size of 1260x960 pixels).

Nevertheless, the success rate remains rather weak compared to our objectives (50% to find the right room). Thus, we studied the discriminating capacity of each of the first four moments (average, variance, skewness and kurtosis) to use them as a weighting factor to our interpallet distance. We compute the variation of these first four moments. The variance which has the greatest dynamics is used to build a weighting coefficient enough discriminating for strong variations and neutral for weak variations (lower than a threshold α). Then we discriminate through the coefficient λ, images having a variance of the first two moments lower than a threshold β. Following some experiments on our two image databases, we fixed α at 20 and β at 128.

$$w_1 = \lambda \frac{\Delta\sigma}{\sigma_{im} + \sigma_{req}} \tag{9}$$

with

$$\Delta\sigma = \begin{cases} \alpha & \text{if } |\sigma_{req} - \sigma_{im}| < \alpha \\ |\sigma_{req} - \sigma_{im}| & \text{else.} \end{cases} \quad (10)$$

and

$$\lambda = \begin{cases} 1 & \text{if } |\sigma_{req} - \sigma_{im}| < \beta \text{ and } |\mu_{req} - \mu_{im}| < \beta \\ \infty & \text{else} \end{cases} \quad (11)$$

thus

$$D_1 = w_1 \,.\, L_2(P_{req} - P_{im}) \quad (12)$$

5.2. Vicinity template of colors

To describe the textural aspect of colors distribution, we developed the co-occurence matrix *M(i,j)* and some relating features defined by Haralick [19] which are:

- Color Inertia: $$I = \sum_{i=0}^{M} \sum_{j=0}^{M} D_{ij}^2 . M(i,j) \quad (13)$$

with $D_{ij}^2 = (R_i - R_j)^2 + (G_i - G_j)^2 + (B_i - B_j)^2$

R, *G* and *B* are the three color channels of the RGB color space.

- Color correlation: $$C = \sum_{i=0}^{M} \sum_{j=0}^{M} \frac{D_i . D_j}{\sigma_i . \sigma_j} M(i,j) \quad (14)$$

with $D_i = ((R_i - R_{\mu_i})^2 + (G_i - G_{\mu_i})^2 + (B_i - B_{\mu_i})^2)^{1/2}$

and $D_j = ((R_j - R_{\mu_j})^2 + (G_j - G_{\mu_j})^2 + (B_j - B_{\mu_j})^2)^{1/2}$

with μ_i, σ_i (resp. μ_j, σ_j) who represent the color average and the color standard deviation for all the transitions for which the index color first pixel is i (resp. the index color second pixel is j).

thus $\mu_i = (R_{\mu_i}, G_{\mu_i}, B_{\mu_i})$

with

$$R_{\mu_i} = \frac{1}{\sum_{j=0}^{M} M(i,j)} . \sum_{j=0}^{M} M(i,j).R_j \quad (15)$$

and

$$\sigma_i = \sqrt{\frac{1}{\sum_{j=0}^{M} M(i,j)} . \sum_{j=0}^{M} M(i,j).D_j^2} \quad (16)$$

- Homogeneity : $$H = \sum_{i=0}^{M} \sum_{j=0}^{M} M(i,j)^2 \quad (17)$$

- Entropy : $$E = \sum_{i=0}^{M} \sum_{j=0}^{M} M(i,j) . \log M(i,j) \quad (18)$$

Moreover, we extract the maximum value of the co-occurence matrix and its two color components that we note (c_1, c_2).

Owing to the fact that a fine quantization of a color space gives a substantial signature, the construction of co-occurence matrices of pallets (low-size images) bring smooth and not enough discriminating distributions. To mitigate this problem with modelling the main colors vicinity, we developed the co-occurence matrices with a coarse uniform quantization of the RGB color space in 64 bins. We considered, in addition, an isotropic vicinity (8 connexities) of each pixel.

For the search phase, we developed the Euclidean distance $L_2(M_{req} - M_{im})$ between co-occurence matrices of pallets. We preceded this distance by a weighting factor w_2 especially built from the entropy variation which has the greatest dynamics and so the discriminating capacity among the other co-occurrence matrix features what gives the D_2 distance hereafter:

$$w_2 = \lambda \frac{\Delta E}{E_{im} + E_{req}} \quad (19)$$

with

$$\Delta E = \begin{cases} \gamma & \text{if } |E_{req} - E_{im}| < \gamma \\ |E_{req} - E_{im}| & \text{else.} \end{cases} \quad (20)$$

thus

$$D_2 = w_2 \, L_2(M_{req} - M_{im}) \quad (21)$$

We estimated the value λ according to the three dimensional connexity of color components of the co-occurence matrix maximum value between the request image and each database image. By assimilating uniform color bins to cubes (cf. fig 7), the three dimentional connexity is evaluated as follows:

Connex1: cubes adjacent by a surface e.g. cubes (1,2), (1,3)

Connex2: cubes adjacent by an edge e.g. cubes (2,3), (3,5)

Connex3: cubes adjacent by a point e.g. cubes (2,4).

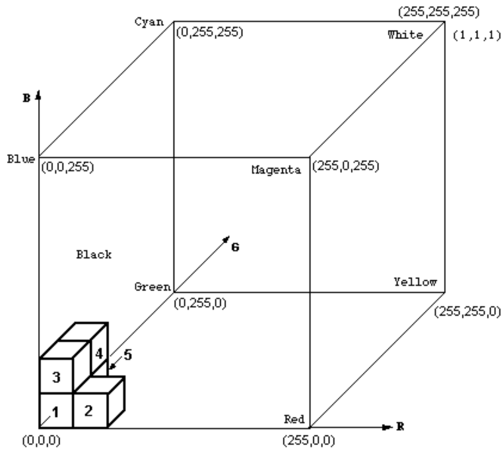

Figure 7. *RGB color cube*

We retained the best connexity of the request image pair of color $(c_1,c_2)_{req}$ with each database image pair of color $(c_1,c_2)_{im}$ through the following algorithm:

if $(c_1,c_2)_{req}$ = (c1,c2)im Then λ= 1
if $(c_1,c_2)_{req}$ Connex1 $(c_1,c_2)_{im}$ Then λ = 2
if $(c_1,c_2)_{req}$ Connex2 $(c_1,c_2)_{im}$ Then λ = 3
if $(c_1,c_2)_{req}$ Connex3 $(c_1,c_2)_{im}$ Then λ = 4
else λ = 8

5.3. The final distance *D*

The D_2 distance built by co-occurence matrices of the pallets gives lower results than the D_1 distance (only 55% of right room). But by finely analyzing answers of each request we note that there are some cases where the D_1 distance led to a false result whereas the distance D_2 leads to a right result (and *vice-versa*).

The final distance D we propose takes the normalized distances between pallets and between co-occurence matrices into account, each one balanced by a resulting term from color moments and co-occurence matrices attributes respectively. D is given by:

$$D = w_1 \, L_2(P_{req} - P_{im}) + w_2 \, L_2(M_{req} - M_{im}) \quad (22)$$

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6. Hierarchical approach

We conceive, in a preliminary stage, before applying our distance D, a hierarchical search using the classification of images according to rooms. We characterize each room by a discriminating color pallet. This room pallet is built by sampling color pallets of images taken in this room and by adding colors whose minimal distance to those retained is higher than a threshold fixed at 10.

In the search phase, we compute the difference between the request pallet and room pallets built previously through the Euclidean distance and we classify these distances by ascending order. We eliminate firstly rooms presenting non similar colors to those of the request image (see figure 8). Finally, we apply the *D* distance to images from the database taken in the rooms where the robot is most probably lost.

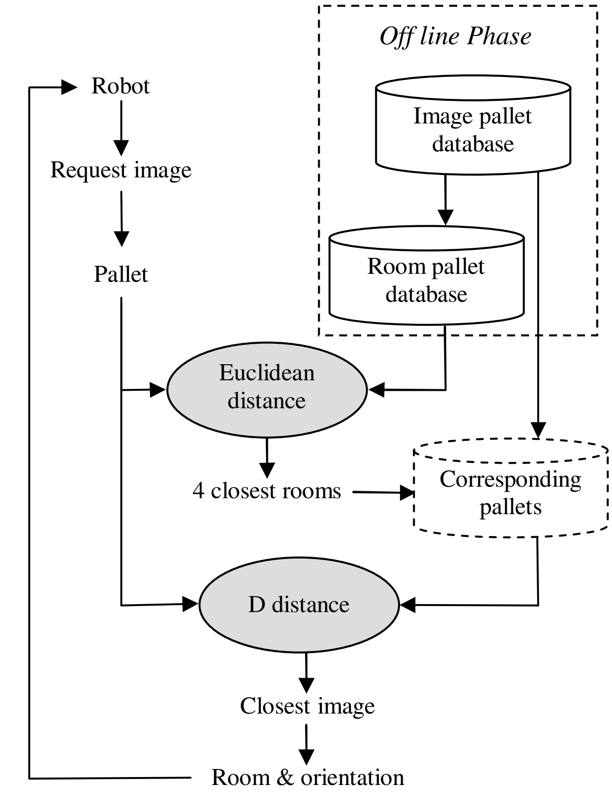

Figure 8. *Hierarchical search.*

To increase the speed of the system it is necessary to eliminate the maximum of rooms. However, we should not affect the system effectiveness by eliminating the room corresponding to the request image where the robot is lost. After some experiments on our two image databases, we kept in research the first four rooms given by the first hierarchical process. It should be noted that our aim is to eliminate rooms on witch certain images distort our results. This, being made, the performances of our system are improved.

7. Results

We present in table 1 results witch show the interest of our approach. We note better results with our distance D than the interpallet distance (about 70% of right rooms) owing to the fact that we consider as well the space organization and color vicinity as the colorimetric aspect of the pallet. For the request image (cf figure 9.a), we have false results by using the interpallet, D_1 and D_2 distance separately. The distance D combining these two last measures gives the right result. We have in this case the result image of the figure 9-b indicating the right room and the right orientation.

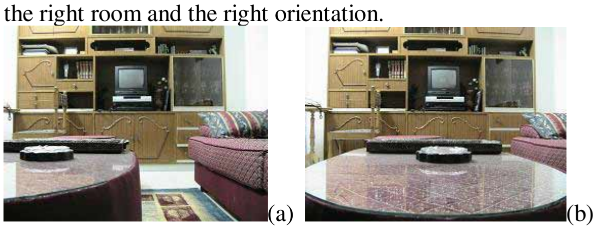

Figure 9. *a) Request Image from the database n°2; b) Response Image within D distance.*

In order to validate this work, we compare these results with a classical image retrieval technique which uses color histogram. We developed color histograms on RGB and Luv spaces. The RGB color space witch gives best results is performed to three uniform quantization into 64, 512 and 4096 color bins. The various bin-by-bin (histogram intersection, L_2 and χ^2) and cross-bin (Earth Mover Distance and Mahalanobis distance) similarity measures developed previously were implemented and tested to our image databases.

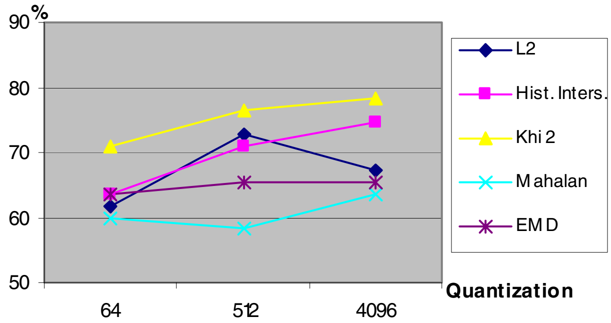

Figure 10. *Histogram* results

Table 1:Results of our methods

	Database 1				Database 2				Databases1 & 2
	Time	Results	%		Time	Results	%		%
Spatial and color distance : D									
Right room & orientation	2 sec	12	60%	65%	3 sec	18	51,5%	71,5%	69%
Right room		1	5%			7	20%		
False room		7	35%			10	28,5%		31%
Hierarchical approach with the distance D									
Right room & orientation	4 sec	12	60%	70%	5 sec	20	57%	88,5%	82%
Right room		2	10%			11	31,5%		
False room		6	30%			4	11,5%		18%

As showed in figure 10, the quantization to 64 colors proves very coarse for color histograms. Quantization to 512 bins improve considerably these results but the 4096 bins discretization gives the best results except the Euclidean distance witch give best results with 512 bin quantization. We explicit results of the 4096 color histograms in the table 2. We note the worst results with the cross-bin similarity measures witch tend to overestimate the mutual similarity of color distributions. Moreover, the computational complexity of the EMD and Mahalanobis distance are the highest among the evaluated measures. Indeed, computing the EMD between 4096 color histograms in our database take over than 30 minutes. The χ^2 test gives the best results among the five developed distance. This statistical measure gives an error rate of 22% to find the right room. In addition, computing time at around 4 seconds is acceptable for a global localization task.

Table 2: Histogram results

	Base 1 & 2			
	Time	Results		
	Histogram Intersection			
Right room & orientation	4 sec	31	56,4%	74,5%
Right room		10	18,1%	
False room		14	25,5%	
	Euclidean Distance L_2			
Right room & orientation	4 sec	27	49,1%	67,2%
Right room		10	18,1%	
False room		18	32,8%	
	χ^2 test			
Right room & orientation	4 sec	32	58,2%	78,2%
Right room		11	20%	
False room		12	21,8%	
	Mahalanobis Distance			
Right room & orientation	60 sec	20	36,4%	63,6%
Right room		15	27,2%	
False room		20	36,4%	
	Earth Mover Distance : EMD			
Right room & orientation	35 mn	23	41,8%	65,4%
Right room		13	23,6%	
False room		19	34,6%	

Our method gives better results than those of the color histograms. We have especially best results than the effective χ^2 test. For the second database which integrates different illumination conditions, we have a rate of 88% to find the right room giving a correct estimate of the robot position. This results provided only with a color based description of indoor images is an encouraging result. A final system obviously must integrate other type of signature like shape and texture. A more structured environment with a local search by detecting known and non removable objects can enhance the performance of our system.

IV. Conclusion

In this paper we present a new approach for image retrieval aim to localize an in-door robot. This approach uses a pallet extracted by using baker's transformation. This pallet gives a good representation of initial colors and preserves the spatial organization of the original image. We built an appropriate distance which integrates the space and the color aspects of this pallet to improve the image description and to find the closest one in a retrieval task. Results are better than results obtained from a classical color histogram method. Thus we have developed one retrieval technique which is fast and effective.

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Author Biography

Anis Chaari received his engineer diploma in computer science from the ENSI, Tunisia, in July 2004. From 2003, he worked on image processing in his engineering school. His Master was, in 2005, about global localization of an indoor robot per image retrieval techniques. Now he works on a thesis with the IBISC Laboratory at Evry and RIADI Laboratory at Tunis about multimodal biometric recognition.

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