Histogram of fuzzy ranks for object recognition across illumination changes

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Abstract

In this paper, we propose an original color image analysis scheme to retrieve among all the target images of a database, those which contain the same object as that represented by the query image, these images being acquired under different illumination conditions. Rather than considering the color vectors of the pixels to characterize the images, we propose to exploit the concept of ranks of CCD sensor responses which are assumed to be preserved in case of illumination changes. Since these ranks are not directly available from a color image, we propose to estimate their probabilities of occurrence thanks to fuzzy functions. These probabilities are used by our object recognition scheme whose effectiveness is assessed with a public database that contains images of objects acquired under different illuminations.

Introduction

Object recognition across illumination changes

In this paper, we propose an original scheme to retrieve among all the target images of a database, those which contain the same object as that represented by the query image, these images being acquired under different illumination conditions (see figure 1).

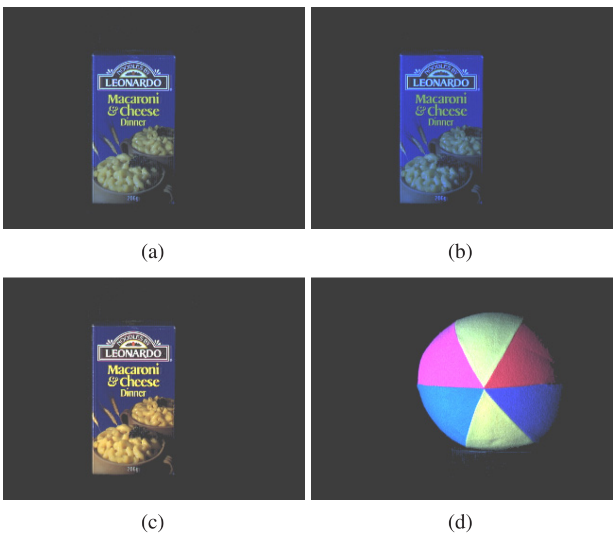

Figure 1. As the images (a), (b) and (c) contain the same object observed under different illuminations, they are similar. As the image (d) contains another object, the pairs of images ((a), (d)), ((b), (d)) and ((c),(d)) constitute pairs of different images.

In this context, the image indexing scheme consists in extracting robust and efficient characteristic indices from the target and query images. These indices are typically derived from the shape, the texture or the color properties of the objects. Object recognition is performed by means of a matching scheme which compares the indices of the query image with those of the target images. The matching scheme is based on a similarity measure between these indices. The target images are ranked with respect to their similarity measures with the query image, in order to determine those which contain the same object as that represented by the query image.

One of the most widely used image indices based on the color distribution is the color histogram [1]. The color histogram $\mathbf{H}[\mathbf{I}]$ of an image $\mathbf{I}$ is composed of bins $\mathbf{H}[\mathbf{I}](\mathbf{c})$ associated with color vectors $\mathbf{c}$ whose coordinates are the levels of the three color components, namely the red (c^R), the green (c^G) and the blue (c^B). Each bin indicates the number of pixels which represent the object in the image and which are characterized by this particular color.

Since the color vector of a pixel P, denoted $\mathbf{c}(P) = [c^R(P), c^G(P), c^B(P)]^T$, is not only a measure of the reflectance properties of the elementary surface of the object projected onto the pixel P but also a function of both the camera and the illumination [2], the color histogram of an image is very sensitive to these parameters. Therefore, many authors propose to characterize the images by histograms which are invariant to illumination changes [3, 4]. The determination of these invariant color histograms is based on illumination change models which describe the variations of colors caused by any illumination change. Most of these models try to represent these variations by linear transformations [5] and are consequently constraint to use very restrictive assumptions about the camera and the illumination. That's the reason why object recognition based on the intersection between these invariant color histograms generally performs poorly [3, 4].

Rather than considering the color vectors to define complex illumination change models, we exploit the concept of ranks of color component levels which respect interesting properties in case of illumination changes.

Ranks of color component levels

A color image $\mathbf{I}$ can be separated into three color component images I^k, $k \in \{R, G, B\}$, where each pixel P is characterized by one color component level $c^k(P)$. Within each color component image, the pixels are sorted in the increasing order of their levels and are associated to a rank, so that the rank is close to 0 for the first ordered pixels, and equal to 1 for the last ordered pixels. Finlayson [6] introduces the rank $\mathscr{R}^k[\mathbf{I}](l)$ of the color component level l which is the rank of the pixels characterized by this level within the color component image I^k and is expressed as :

$$\mathscr{R}^k[\mathbf{I}](l) = \frac{\sum_{i=0}^{l} H^k[\mathbf{I}](i)}{\sum_{i=0}^{L-1} H^k[\mathbf{I}](i)},\ k \in \{R,G,B\}, \quad (1)$$

where L is the number of levels used to quantize the color components (L is generally set to 256), and $H^k[\mathbf{I}](l)$ is the number of pixels characterized by the level l in I^k. Note that this rank can be interpreted as the normalized cumulative histogram of I^k.

The rank of the level l can also be expressed as :

$$\mathscr{R}^k[\mathbf{I}](l) = \frac{Card\{P \in \mathbf{I}/c^k(P) \leq l\}}{Card\{P \in \mathbf{I}\}}. \quad (2)$$

Finlayson assumes that the ranks of the levels within a color component image are not modified by illumination changes [6]. Thus, he proposes to characterize each pixel P by its three ranks $\mathscr{R}^k[\mathbf{I}](c^k(P))$, $k \in \{R,G,B\}$, and to compute for each image $\mathbf{I}$, the histogram $\mathscr{H}[\mathbf{I}]$ of ranks. Each of its cells $\mathscr{H}[\mathbf{I}](\mathscr{R}^R,\mathscr{R}^G,\mathscr{R}^B)$ contains the number of pixels whose ranks are equal to $\mathscr{R}^R$, $\mathscr{R}^G$ and $\mathscr{R}^B$ in the color component images I^R, I^G and I^B, respectively. Then, Finlayson proposes to compare two images by means of the intersection between their histograms of ranks.

Nevertheless, we have shown experiments which reveal that the ranks of color component levels are not strictly preserved in case of illumination changes [7].

Paper overview

In the second section, we define the concept of ranks of camera sensor response which respect interesting properties in case of illumination changes.

In the third section, we present the relationship between the ranks of the camera sensor responses and the ranks of the color component levels. Furthermore, we show that the ranks of sensor responses can not be precisely evaluated from a color image.

Consequently, we propose to estimate their probabilities of occurrence thanks to fuzzy functions. In the fourth section, we describe how to characterize each image by the histogram of fuzzy ranks.

In order to show the improvement brought by our scheme, we compare, in the fifth section, the object recognition results obtained by the intersection between histograms of ranks and those obtained by the intersection between the histograms of fuzzy ranks.

Ranks of camera sensor responses

Definition

Within a color image $\mathbf{I}$, we associate with each pixel P, a vector denoted $\mathbf{x}(P) = [x^R(P), x^G(P), x^B(P)]^T$ whose coordinates $x^k(P)$, $k \in \{R,G,B\}$, are the responses of the acquisition CCD camera sensors to the color stimulus reflected by an elementary surface and projected onto the pixel P.

For each CCD sensor, the pixels are sorted in the increasing order of these responses and are associated with a rank, so that the rank is close to 0 for the first ordered pixels, and equal to 1 for the last ordered pixels. The rank $R^k[\mathbf{I}](x)$ of the CCD sensor response x is the rank of the pixels associated with this response for the k^{th} CCD sensor and is expressed as :

$$R^k[\mathbf{I}](x) = \frac{Card\{P \in \mathbf{I}/x^k(P) \leq x\}}{Card\{P \in \mathbf{I}\}},\ k \in \{R,G,B\}, \quad (3)$$

where P are the pixels which represent the object in the image $\mathbf{I}$.

Ranks of camera sensor responses and illumination changes

Finlayson presents experiments which consist in analyzing the sensor responses of different acquisition devices to 462 Munsell chips lit by 16 different lights [6]. This study reveals that the preservation of ranks $R^k[\mathbf{I}](x^k(P))$ of sensor responses holds across a wide range of illuminants.

This property is very interesting in the context of object recognition across illumination changes. Then, for each pixel, he proposes to estimate the ranks of the three CCD sensor responses from the three color component levels of this pixel and to characterize it by these estimated ranks.

Therefore, he assumes that the ranks $R^k[\mathbf{I}](x^k(P))$ of the sensor responses are identical to the ranks $\mathscr{R}^k[\mathbf{I}](c^k(P))$ of the color component levels. Consequently, he deduces that the ranks of color component levels are preserved in case of illumination changes. That leads him to characterize the images by their histograms of ranks.

Nevertheless, we have shown that the ranks of the color component levels are not strictly invariant to the illumination condition changes [7]. Hence, the ranks $R^k[\mathbf{I}](x^k(P))$ of the sensor responses $x^k(P)$, $k = R,G,B$, at each pixel P can not be assumed to be identical to the ranks $\mathscr{R}^k[\mathbf{I}](c^k(P))$ of the color component levels $c^k(P)$.

Ranks of color component levels and ranks of sensor responses

In this part, we present the relationship between the ranks of the color component and the ranks of the sensor responses.

Color component levels and sensor responses

Under Lambertian assumptions, the sensor response $x^k(P)$, $k \in \{R,G,B\}$, to a color stimulus reflected by the elementary surface observed by the camera and projected onto the pixel P depends on the spectral power distribution $E(\lambda)$ of the incident illuminant, on the spectral reflectance $\beta(P,\lambda)$ of the elementary surface projected onto P and on the three spectral sensitivity functions $\mathscr{C}^k(\lambda)$, $k \in \{R,G,B\}$, of the camera sensors, so that :

$$x^k(P) = \int_\lambda \mathscr{C}^k(\lambda)\beta(P,\lambda)E(\lambda)d\lambda,\ k \in \{R,G,B\}. \quad (4)$$

Then, the sensor response $x^k(P)$ is quantized by the electronic device of the camera into L levels to provide $c^k(P)$, the k^{th} color component level of P, thanks to the analog-digital converter f :

$$c^k(P) = f(x^k(P)). \quad (5)$$

Assumptions about the quantization function

In order to consider that the ranks of the color component levels are identical to the ranks of the sensor responses, Finlayson assumes that the function f is strictly increasing (see figure 2(a)). This assumption is very restrictive.

Our work is based on a less restrictive assumption. Indeed, since the function f represents the analog-digital converter, it would be more realistic to consider that this is only an increasing function (see figure 2(b)) so that :

$$if\ \ x^k(P') > x^k(P)\ \ then\ \ c^k(P') \geq c^k(P). \quad (6)$$

When f is a monotonic increasing function, the color component levels and sensor responses respect this property (see figure 2(b)) :

$$if\ \ c^k(P') > c^k(P)\ \ then\ \ x^k(P') > x^k(P). \quad (7)$$

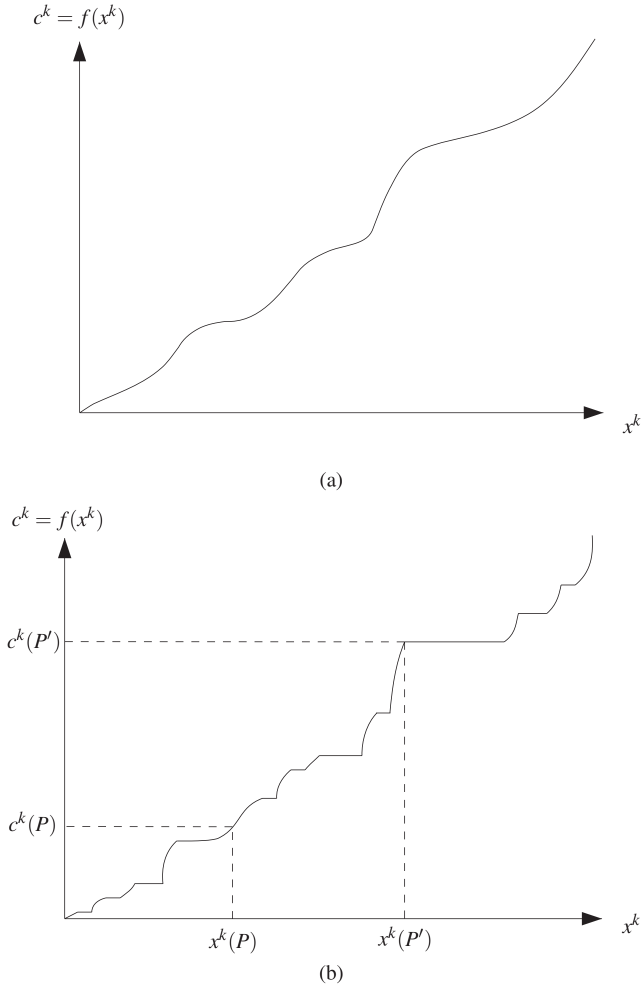

Figure 2. Assumptions about the analog-digital converter f. In the figure (a) f is strictly increasing, while in the figure (b) f is only increasing.

We propose now to analyze the consequences of such an assumption on the relationship between the ranks of the color component levels and the ranks of the sensor responses.

Relationship between the ranks

We consider a color image $\mathbf{I}$. We denote N^k the number of levels which are present in the color component image I^k and $\{\mathscr{R}_1^k, \mathscr{R}_2^k, ..., \mathscr{R}_{N^k}^k\}$ the subset of successive ranks of these levels sorted by the increasing order so that $\mathscr{R}_{i-1}^k < \mathscr{R}_i^k$.

Let us consider one of the pixels P_i characterized by the rank $\mathscr{R}^k[\mathbf{I}](c^k(P_i)) = \mathscr{R}_i^k$ in the color component image I^k.

From equations (6) and (7), we deduce that the number of pixels Q so that $x^k(Q) > x^k(P_i)$ is higher or equal than the number of pixels Q' so that $c^k(Q') > c^k(P_i)$:

$$Card\{Q \in \mathbf{I}/x^k(Q) > x^k(P_i)\} \geq Card\{Q' \in \mathbf{I}/c^k(Q') > c^k(P_i)\}. \quad (8)$$

By dividing each member of equation (8) by the number of pixels within the image $\mathbf{I}$, we obtain :

$$\frac{Card\{Q \in \mathbf{I}/x^k(Q) > x^k(P_i)\}}{Card\{P \in \mathbf{I}\}} \geq \frac{Card\{Q' \in \mathbf{I}/c^k(Q') > c^k(P_i)\}}{Card\{P \in \mathbf{I}\}.} \quad (9)$$

The left member of this equation can be simplified as :

$$\begin{aligned} &\frac{Card\{Q \in \mathbf{I}/x^k(Q) > x^k(P_i)\}}{Card\{P \in \mathbf{I}\}} \\ &= \frac{Card\{P \in \mathbf{I}\}}{Card\{P \in \mathbf{I}\}} - \frac{Card\{Q'' \in \mathbf{I}/x^k(Q'') \leq x^k(P_i)\}}{Card\{P \in \mathbf{I}\}} \end{aligned} \quad (10)$$

$$= 1 - R^k[\mathbf{I}](x^k(P_i)). \quad (11)$$

Equation (11) is deduced from equation (3).

From equation (2), the right term of equation (9) is expressed as :

$$\begin{aligned} &\frac{Card\{Q' \in \mathbf{I}/c^k(Q') > c^k(P_i)\}}{Card\{P \in \mathbf{I}\}} \\ &= \frac{\sum_{m=c^k(P_i)+1}^{L-1} H^k[\mathbf{I}](m)}{\sum_{j=0}^{L-1} H^k[\mathbf{I}](j)} \\ &= \frac{\sum_{m=0}^{L-1} H^k[\mathbf{I}](m)}{\sum_{j=0}^{L-1} H^k[\mathbf{I}](j)} - \frac{\sum_{m=0}^{c^k(P_i)} H^k[\mathbf{I}](m)}{\sum_{j=0}^{L-1} H^k[\mathbf{I}](j)} \\ &= 1 - \mathscr{R}^k[\mathbf{I}](c^k(P_i)) \\ &= 1 - \mathscr{R}_i^k. \end{aligned} \quad (12)$$

Thus, equation (9) becomes :

$$\begin{aligned} 1 - R^k[\mathbf{I}](x^k(P_i)) &\geq 1 - \mathscr{R}_i^k \\ R^k[\mathbf{I}](x^k(P_i)) &\leq \mathscr{R}_i^k. \end{aligned} \quad (13)$$

In the same way, since f is a monotonic increasing function, each pixel Q so that $c^k(Q) < c^k(P_i)$ respects the property : $x^k(Q) < x^k(P_i)$. That is to say that the number of pixels Q so that $x^k(Q) < x^k(P_i)$ is higher or equal than the number of pixels Q' so that $c^k(Q') < c^k(P_i)$:

$$Card\{Q \in \mathbf{I}/x^k(Q) < x^k(P_i)\} \geq Card\{Q' \in \mathbf{I}/c^k(Q') < c^k(P_i)\}. \quad (14)$$

By dividing each member of equation (14) by the number of pixels within the images, we obtain :

$$\frac{Card\{Q \in \mathbf{I}/x^k(Q) < x^k(P_i)\}}{Card\{P \in \mathbf{I}\}} \geq \frac{Card\{Q' \in \mathbf{I}/c^k(Q') < c^k(P_i)\}}{Card\{P \in \mathbf{I}\}}. \quad (15)$$

The first member of equation (15) can be expressed as :

$$\begin{aligned} &\frac{Card\{Q \in \mathbf{I}/x^k(Q) < x^k(P_i)\}}{Card\{P \in \mathbf{I}\}} \\ &= \frac{Card\{Q \in \mathbf{I}/x^k(Q) \leq x^k(P_i)\}}{Card\{P \in \mathbf{I}\}} - \frac{Card\{Q'' \in \mathbf{I}/x^k(Q'') = x^k(P_i)\}}{Card\{P \in \mathbf{I}\}} \\ &= R^k[\mathbf{I}](x^k(P_i)) - \frac{Card\{Q'' \in \mathbf{I}/x^k(Q'') = x^k(P_i)\}}{Card\{P \in \mathbf{I}\}}. \end{aligned} \quad (16)$$

Secondly, let us consider P_{i-1}, one of the pixels in the image $\mathbf{I}$, characterized by the rank $\mathscr{R}^k[\mathbf{I}](c^k(P_{i-1})) = \mathscr{R}_{i-1}^k$. Since we sort the ranks $\mathscr{R}_i^k$ of levels in the color component image I^k so that $\mathscr{R}_{i-1}^k < \mathscr{R}_i^k$, and since $\mathscr{R}^k[\mathbf{I}](c^k(P_i)) = \mathscr{R}_i^k$, there is no pixel in the color component image I^k which is characterized by a level between $c^k(P_{i-1})$ and $c^k(P_i)$. Hence, the second member of equation (15) can be expressed as :

$$\begin{aligned}
&\frac{Card\{Q' \in \mathbf{I}/c^k(Q') < c^k(P_i)\}}{Card\{P \in \mathbf{I}\}} \\
&= \frac{\sum_{m=0}^{c^k(P_i)-1} H^k[\mathbf{I}](m)}{\sum_{j=0}^{L-1} H^k[\mathbf{I}](j)} \\
&= \frac{\sum_{m=0}^{c^k(P_{i-1})} H^k[\mathbf{I}](m)}{\sum_{j=0}^{L-1} H^k[\mathbf{I}](j)} + \frac{\sum_{m=c^k(P_{i-1})+1}^{c^k(P_i)-1} H^k[\mathbf{I}](m)}{\sum_{j=0}^{L-1} H^k[\mathbf{I}](j)} \\
&= \frac{\sum_{m=0}^{c^k(P_{i-1})} H^k[\mathbf{I}](m)}{\sum_{j=0}^{L-1} H^k[\mathbf{I}](j)} + 0 \\
&= \frac{\sum_{m=0}^{c^k(P_{i-1})} H^k[\mathbf{I}](m)}{\sum_{j=0}^{L-1} H^k[\mathbf{I}](j)} \\
&= \mathscr{R}^k_{i-1}.
\end{aligned} \quad (17)$$

So, equation (15) becomes :

$$R^k[\mathbf{I}](x^k(P_i)) - \frac{Card\{Q'' \in \mathbf{I}/x^k(Q'') = x^k(P_i)\}}{Card\{P \in \mathbf{I}\}} \geq \mathscr{R}^k_{i-1}. \quad (18)$$

Since there exists at least one pixel which is characterized by the sensor response $x^k(P_i)$, we have :

$$\frac{Card\{Q'' \in \mathbf{I}/x^k(Q'') = x^k(P_i)\}}{Card\{P \in \mathbf{I}\}} > 0. \quad (19)$$

So, equation (18) becomes :

$$R^k[\mathbf{I}](x^k(P_i)) > \mathscr{R}^k_{i-1}. \quad (20)$$

Based on equations (13) and (20), we conclude :

$$\mathscr{R}^k_{i-1} < R^k[\mathbf{I}](x^k(P_i)) \leq \mathscr{R}^k_i. \quad (21)$$

We have shown that, when the analog-digital converter of the camera is assumed to be a monotonic increasing function, the rank $R^k[\mathbf{I}](x^k(P_i))$ of the sensor response corresponding to the pixel P_i in the color component image I^k ranges between $\mathscr{R}^k_{i-1}$ and $\mathscr{R}^k_i$.

Equation (21) shows that the ranks of the sensor responses are not associated with crisp values, but rather within intervals of consecutive values. That leads us to introduce the concept of fuzzy ranks and to characterize the color images by their histograms of fuzzy ranks.

Histogram of fuzzy ranks

Fuzzy ranks

In the previous part, we have shown that the ranks of sensor responses range within intervals of color component ranks. So the ranks of the sensor responses can not be exactly evaluated from the ranks of the color component. Hence, we propose to estimate their probabilities of occurrence thanks to fuzzy functions.

Since no prior knowledge is available about the distribution of ranks of sensor responses inside their associated color component rank intervals, we assume that they are equiprobably distributed.

Hence, we associate with each color component rank $\mathscr{R}^k_i$ a fuzzy subset constituted of all the possible sensor response ranks ranging between 0 and 1. We define the membership degree $\mu^k_{\mathscr{R}^k_i}$ of the rank r of a sensor response to this subset as :

$$\begin{cases} \mu^k_{\mathscr{R}^k_1}(r) = \frac{1}{\mathscr{R}^k_1} \;\; if \;\; r \in]0; \mathscr{R}^k_1] \\ \mu^k_{\mathscr{R}^k_i}(r) = 0 \;\; else, \end{cases} \quad (22)$$

and, for $i = \{2, ..., N^k\}$:

$$\begin{cases} \mu^k_{\mathscr{R}^k_i}(r) = \frac{1}{\mathscr{R}^k_i - \mathscr{R}^k_{i-1}} \;\; if \;\; r \in]\mathscr{R}^k_{i-1}; \mathscr{R}^k_i] \\ \mu^k_{\mathscr{R}^k_i}(r) = 0 \;\; else. \end{cases} \quad (23)$$

The membership degrees of the ranks which belong to the same intervals are equal.

Histogram of fuzzy ranks

In order to characterize the images by the ranks of the sensor responses which are not very sensitive to illumination changes, we propose to characterize each image by its histogram of fuzzy ranks, these fuzzy ranks being the membership degrees of the sensor ranks to the fuzzy subsets corresponding to color ranks.

From the histogram of ranks, we compute the histogram η of the fuzzy ranks in the image $\mathbf{I}$ as :

$$\begin{aligned} \eta[\mathbf{I}](r^R, r^G, r^B) = \\ \sum_{u=1}^{N^R} \sum_{v=1}^{N^G} \sum_{w=1}^{N^B} \mu^R_{\mathscr{R}^R_u}(r^R) \; \mu^G_{\mathscr{R}^G_v}(r^G) \; \mu^B_{\mathscr{R}^B_w}(r^B) \\ \times \mathscr{H}[\mathbf{I}](\mathscr{R}^R_u, \mathscr{R}^G_v, \mathscr{R}^B_w). \end{aligned} \quad (24)$$

For the implementation purpose, the rank r is quantified with $(M+1)$ levels, M being adjusted by the analyst, so that $r = 0, \frac{1}{M}, \frac{2}{M}, ..., \frac{M}{M}$. So, the histogram of fuzzy ranks contain M^3 cells.

Experimental results

Object recognition across illumination changes with the SFU database

We propose to demonstrate the improvement of the intersection between the pairs of histograms of fuzzy ranks for object recognition purpose across illumination changes. We use the Simon Fraser University (SFU) database [4] available at http://www.cs.sfu.ca/~colour/data. Its 187 images contain 17 objects lit by one of 11 available illumination sources and acquired with the same viewing conditions by one camera (see figure 3).

For object searching, the images acquired under one illumination, called the target illumination, are considered as being the target images and one of those acquired under one of the 10 other illumination sources, called the query illumination, is considered as being the query image. So, there are 11×10 different pairs of query-target illumination. The image retrieval is repeated for each of the 17 objects. Finally, 1870 retrievals are achieved (17 objects $\times$ 11 $\times$ 10 pairs of different illumination).

For each image retrieval, the 17 target images are ordered with respect to the intersections between their invariant color histograms and the invariant color histogram of the considered query image. When the first ordered target image is similar to the query image, the research result is considered as perfect.

Figure 3. The 17 objects of the SFU database.

We propose to compare the results obtained by the intersection between the histograms of the ranks [8] with those obtained by the intersection between the histograms of the fuzzy ranks.

Each column of table 1 indicates the percentage of successful image retrievals.

Intersection between	$(M = 16)$	$(M = 64)$	$(M = 256)$
histograms of ranks	89.89	75.08	48.72
histograms of fuzzy ranks	97.27	91.07	87.06

Object recognition results obtained by the intersections between different histograms with the SFU database.

Table 1 shows that, for object recognition across illumination changes, the intersection between the histograms of fuzzy ranks provides better results than those obtained by the intersection between histograms of ranks, for significantly different values of M. Furthermore, Table 1 shows that the quality of object recognition by the intersection between the histograms of ranks is very sensitive to M. On the other hand, the results obtained by the intersection between the histograms of fuzzy ranks remain stable when M varies.

Discussion

The improvements provided by our scheme with this database can be explained by three main points.

First, the processing of the histograms of fuzzy ranks is derived from two assumptions which are less restrictive than the classical assumptions. First, the analog-digital converter f is assumed to be only a monotonic increasing function. Secondly, the ranks of the sensor responses are assumed to be equiprobably spread inside the different intervals, whereas the histogram of ranks is based on the assumption that the ranks of the sensor responses are strictly identical to the ranks of the color component levels. As the object recognition results obtained by the histograms of fuzzy ranks are better than those obtained by the histograms of ranks, we deduce that the ranks of the sensor responses are really different from the ranks of the color component levels.

Secondly, the estimation of the ranks of the sensor responses is based on an original fuzzy approach. Indeed, since we can not estimate the ranks of the sensor responses by crisp values, we introduce the concept of fuzzy rank to represent the different intervals which are associated with the different ranks of sensor responses. This fuzzy approach contributes to improve the results of object recognition.

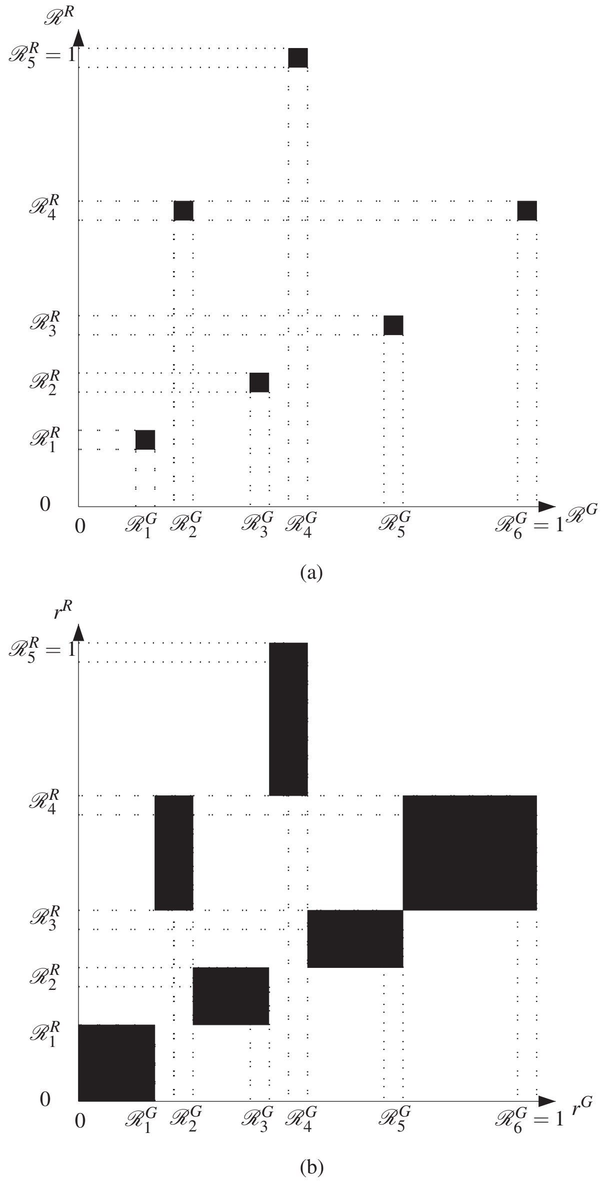

Figure 4. Projections of examples of histograms of ranks and fuzzy ranks onto the red-green color space. Figure (b) is the histogram of fuzzy ranks derived from the histogram of ranks represented in figure (a). The cells labeled as black contain a number of pixels strictly higher than 0, while cells labeled as white represent empty ones.

Finally, the performance reached by object recognition schemes depends on the number $(M)^3$ of bins of the histograms. For processing the histograms of ranks (fuzzy ranks, respectively), the number of bins is reduced from $(L)^3$ to $(M)^3$ by means of an uniform quantization of the ranks (fuzzy ranks, respectively). When the number of different ranks within an image is low, the resulting histogram of ranks is constituted by a high number of empty cells (see figure 4(a)). In this case, the intersection between two histograms of ranks may be low. On the other hand, whatever the number of ranks, the fuzzy ranks range within intervals which are spread on M bins for each color component, with respect to the content of the image (see figure 4(b)). Consequently, the number of empty cells in the histogram of fuzzy ranks depends on the content of the image and is lower than the number of empty cells in the histogram of ranks. This explains why the results obtained by the intersection of histograms of ranks are so sensitive to the values of M and why the results obtained by the histograms of fuzzy ranks remain stable when M varies.

Conclusion

In this paper, we have proposed a new approach to cope with the problem of object recognition across illumination changes. Rather than considering the color vectors of the pixels to characterize the images, we exploit the concept of ranks of CCD sensor responses which are assumed to be preserved in case of illumination changes. Since we can not determine these ranks from a color image, we estimate their probabilities of occurrence thanks to fuzzy functions. These probabilities are used by our object recognition scheme whose effectiveness is assessed with a public database that contains images of objects acquired under different illuminations.

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Author Biography

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Ludovic Macaire received the M.S (Engineer) degree in Computer Science from the UTC Engineering school of Compiegne, France, in 1988; the PhD in Computer Science and Control from the University of Lille in 1993, and the Habilitation à Diriger des Recherches from the University of Lille in 2004. Since 1993, he is an associate professor in the LAGIS Laboratory (Laboratoire d'Automatique, Génie Informatique & Signal) at the University of Lille. His research interests include color representation, color image analysis applied to segmentation and image retrieval.