EigenHistograms: Using Low Dimensional Models of Color Distribution for Real Time Object Recognition

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Abstract. Distribution of object colors has been used in computer vision for recognition and indexing. Most of the recent approaches to this problem have been focused on defining optimal spaces for representing pixel values that are related to physical models and that present some invariance. We propose a new approach to identify individual object color distributions by using statistical learning techniques and to allow their compact representation in low dimensional spaces. This approach outperforms generic "optimal" spaces when color illumination is constant, allowing changes in object pose and illumination direction. This approach has been tested for real time industrial inspection of multicolored objects.

1 Introduction

Object appearance in an image is caused by many factors, including object pose, illumination directions and illumination color. Traditional recognition methods [7],[6] have mainly used geometric cues as shape models and feature matching for detecting and identifying objects in images, but they have not demonstrated the level of performance that allow them to be systematically used in real time for a large number of applications (i.e. face recognition). Recently, some new approaches based on the direct representation of object appearance have been developed for object recognition and pose estimation. Turk and Pentland [3] used principal component analysis to describe face patterns in a low dimensional appearance space. Murase and Nayar in [4] have shown real time recognition of complex 3D objects based on Principal Component Analysis (PCA) of geometrical shape of the objects. The PCA approach is very appropriate for real time applications because of the low cost of the recognition algorithms, however it is limited to the analysis of the geometric shape and depends on the object's pose.

Color distributions can be efficiently used as signatures for object recognition in the appearance-based framework. The earliest approach [2] showed the usefulness of color histograms for indexing large object databases independently of object's pose. Most of the recent approaches focus on illumination color invariance [1],[5] known as color constancy, but although these methods perform

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better than histogram indexing when color illumination changes, they use color information only where surface color varies and are very sensitive to noise.

The above mentioned approaches do not consider color distribution changes due to illumination pose, which can induce significant changes in color histograms. In this work we consider the problem of non constant illumination and introduce statistical techniques to construct a low dimensional space for representing this effect. To achieve pose invariant object's recognition we consider the image (or a Region Of Interest (ROI)) histogram and perform the recognition process in the color distribution of the object applying the principal component analysis technique. In section 2 and 3 we discuss the color representation and the PCA approach as a statistical technique to recognize objects. In section 4 we define the EigenHistogram approach as a PCA applied to the object histograms in order to recognize multicolor objects. Finally, we discuss the experimental results obtained in an industrial (pharmaceutical) application, compare the eigenhistogram technique to other color inspection techniques and finish the article with conclusions.

2 Color Indexing

We describe the histogram intersection algorithm as developed by Swain and Ballard [2]. Colors in an image are mapped into a discrete color space containing n colors. A color histogram is a vector in an n-dimensional space where each element represents the number of pixels of color j in the image. Each object in the image database is represented by its histogram M which will be used to be compared to the histogram I of another image presented to the system.

To measure the distance d between a model M and an image I we can use the following expression:

$$l = \frac{1}{d} = \frac{\sum_{i=1}^{n} min(I_i, M_i)}{\sum_{i=1}^{n} M_i} \tag{1}$$

It is easy to see that when the image coincides with the model, the distance measure (1) is 1 and when their colors differ the measure tends to 0. Two histograms are called α-similar if l is greater than or equal to α. For a fixed threshold t, a model is going to be retrieved if its histogram is t-similar to the histogram of I.

Histogram representation is computationally simple and presents some interesting invariances (object's rotation and translation) but difficulties arise when there are variations in the object pose in space, illumination color and illumination intensity.

3 Principal Component Analysis as a Classification Technique

Principal Component Analysis is a dimension reduction method which its first goal is to minimize the dimension of n-dimensional vectors to m-dimensional vectors (where $m < n$). PCA can be seen as a linear transformation that extracts a lower dimensional space that preserves the major linear correlations in the data and discards the minor ones. Vector projections can be used as representatives of original vectors for recognition purposes. In computer vision, the eigenspace approach has led to a powerful alternative to standard techniques such as correlation or template matching for appearance-based object recognition [4],[3]. The reconstruction error of the eigenspace decomposition is an effective indicator of similarity. In [8] it has been shown that reconstruction error can be interpreted as an estimate of a marginal component of the probability density of the object.

Having a data vector x ($x \in R^n$), PCA projects it onto the m ($m < n$) dimensional linear subspace spanned by the leading eigenvectors of the data covariance matrix: $\Sigma = E[(x-\mu)(x-\mu)^T]$, where $\mu = E[x]$ and E denotes an expectation with respect to x. The leading m eigenvectors $\{e_i | i_1, \dots, i_m\}$ of a positive semidefinite matrix are the m eigenvectors which correspond to the m largest eigenvalues. The indices are assigned such that the corresponding eigenvalues in decreasing order are given by $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_m$.

Let be $f : R^n \rightarrow R^m$ an encoding function from a vector $x \in R^n$ to a vector $z = f(x) \in R^m$, where $m < n$. Let be $g : R^m \rightarrow R^n$ a decoding function from z to $x' = g(f(x)) \in R^n$, a reconstruction of x. PCA encodes x as: $z = f(x) = V(x-\mu) = (e_1^T(x-\mu), \dots, e_n^T(x-\mu))$ where V is an $m \times n$ matrix whose rows, e_i are the leading m orthonormal eigenvectors of Σ and z is the m dimensional encoding. The components of z are called the principal components. PCA reconstructs/decodes x' from z as follows: $x' = g(z) = V^T z + \mu$

The mean squared error in reconstructing the original data is: $\epsilon = E[||x - g(f(x))||^2]$

Using PCA we can obtain the least error in terms of reconstructing the original vector. PCA builds a global linear model of the data: an m dimensional hyperplane spanned by the leading eigenvectors of the data covariance matrix.

Using the retroprojection technique and having a vector to recognize, it is only necessary to project this vector into the m-dimensional space, retroproject to the original space and calculate the error with respect to a set of model vectors in order to decide which is the corresponding one.

4 Color Object Recognition by Principal Component Analysis of Color Histograms

Given p images of the same object k corresponding to different views taken under different illumination conditions, we compute the set of histograms that represents it as follows: $O_k = \{H_{1k}, \dots, H_{pk}\}$

This set of histograms represents all possible variations for the object color distribution. Considering that color change is derived from different illumination directions, we assume that these variations span a low dimensional linear subspace of R^n (being n the number of colors represented in the histogram) which can be computed using PCA. Principal Component Analysis of a histogram set defines an encoding function that projects each histogram from the set on a low dimensional subspace defined by the m principal eigenvectors e_i of the histogram covariance matrix. Given that e_i form an orthonormal base for object histograms, we call each e_i an *EigenHistogram*.

Given a set of objects we represent each one by its *EigenHistogram* set e_{ik}. When the system is presented with a new image, the recognition process performs as follows:

1. The color histogram I of the new image is computed.
2. For each object r in the database, compute $\epsilon_r = |I - g(f(I))|^2$ using the EigenHistogram set e_{ir}.
3. Classify I as O_{r*}, where $r* = argmin\{\epsilon_r\}$.

This technique has shown a great capacity to represent complex color distributions under illumination changes in pose and intensity.

5 Experimental Results

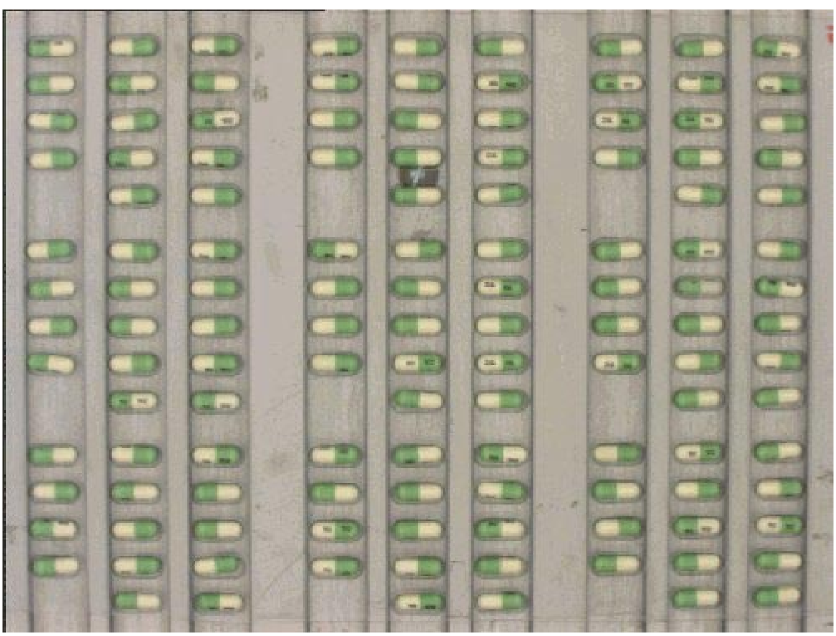

Fig. 1. Example of a blister used to learn the color distribution of a certain capsule

In order to test our approach, the method has been used in a large object database composed of thousands (20 520) of pharmaceutical tablets and capsules. Different blisters with up to 135 capsules are learned and inspected in real time (see Fig. 1 and Fig. 2). Capsules belong to 20 different types where each type can

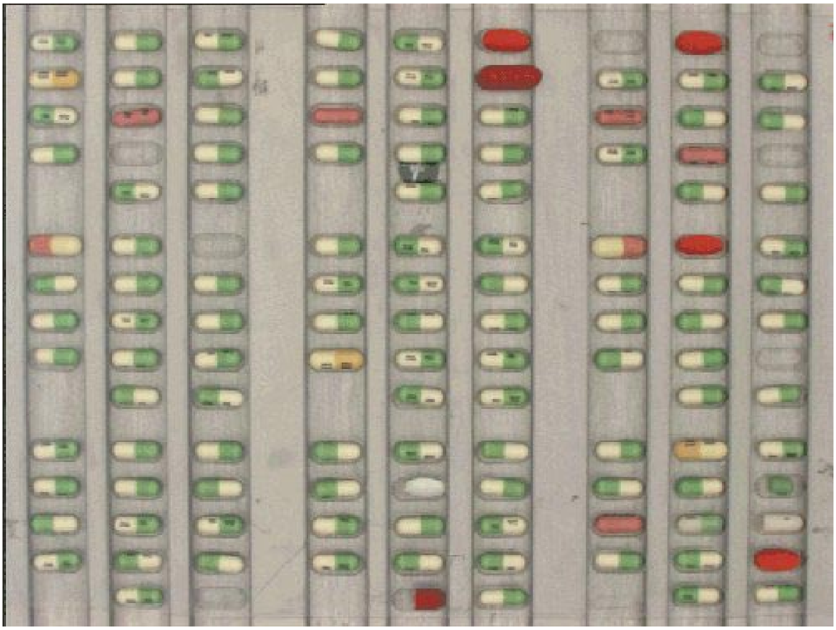

Fig. 2. Example of a blister used to inspect the capsules from Fig.1

be of 1 or two colors. Some of the capsules have black letters that can be completely or partly visible. The illumination spatially differs as well as due to the plastic material of the capsules, shines can appear. Therefore, the colors of each product should be represented by a color distribution instead of a constant color.

For each product we manually define the rois of the capsules and use their histogram to determine the color distribution by the PCA. We determine the EigenHistogram extracted from the covariance matrix of the rois histogram of each type of capsules and use them to project and retroproject the rois during the inspection process. Other blister faults can occur in case of broken capsules or open capsules. Rois are determined using the blister alveolus position. capsules are limited to the alveolus location, yet have freedom to move inside the alveolus.

Our work has focused on comparing EigenHistograms in RGB sensor color space to the classical color indexing in different color spaces. In particular, we have used the following color spaces:

1. $(\mathbf{R}, \mathbf{G}, \mathbf{B})$: sensor color space.
2. $(\mathbf{RG}, \mathbf{BY}, \mathbf{WB})$: three opponent color axes, where $RG = R - G$, $BY = 2B - R - G$, $WB = R + G + B$.
3. $(\mathbf{l_1}, \mathbf{l_2}, \mathbf{l_3})$: photometric invariant color features for both matte and shiny surfaces, as described in [5].
4. $(\mathbf{r}, \mathbf{g}, \mathbf{b})$: normalized colors $r(R, G, B) = R/(R + G + B)$, $g(R, G, B) = G/(R + G + B)$, $b(R, G, B) = B/(R + G + B)$.
5. $(\mathbf{c_1}, \mathbf{c_2}, \mathbf{c_3})$: photometric invariant color features for matte, dull surfaces, as described in [5].

Table 1. Error Probability (in %) as a function of the training capsules

Method	1 Capsule	5 Capsules	128 Capsules
(R,G,B) Indexing	0.022	0.006	0.004
(RG,BY,WB) Indexing	0.066	0.030	0.030
(l_1, l_2, l_3) Indexing	0.082	0.006	0.060
(r,g,b) Indexing	0.028	0.020	0.045
(c_1, c_2, c_3) Indexing	0.015	0.012	0.022
EigenHistograms	0.083	0.033	0.002

Tables 1 and 2 exhibit the performance of our method on the test objects. Table 1 shows the error rate as a function of the number of training capsules. In case of small number of training capsules it seems that the best approaches of color indexing use the (R, G, B) and (c_1, c_2, c_3) methods. When the number of training capsules is increased to improve the color object recognition, the best results are obtained using the EigenHistogram approach.

Table 2. Discrimination capacity of different color indexing techniques

Method	Time	m_1	s_1	m_2	s_2
(R,G,B) Indexing	16ms	0.243	0.006	0.796	0.002
(RG,BY,WB) Indexing	25ms	0.309	0.006	0.829	0.003
(l_1, l_2, l_3) Indexing	662ms	0.329	0.009	0.866	0.001
(r,g,b) Indexing	161ms	0.401	0.031	0.927	0.002
(c_1, c_2, c_3) Indexing	313ms	0.460	0.030	0.892	0.004
EigenHistograms	60ms	0.093	0.007	0.822	0.008

Table 2 shows the results obtained for each method of color object inspection considering 21 blisters of different rois where each blister contains correct and wrong objects. The purpose of this test is to observe the global probabilistic distributions of wrong and correct color objects. In the table 2 the third and fourth column show the mean and variance of the distance measure l for the classification of the wrong objects, the fifth and sixth columns show the mean and variance of the probability error in the classification of the correct products. One can note that the smallest mean of the probability error[1] for wrong products is achieved in case of EigenHistograms that shows the discrimination power of

[1] Remember that according to (1) the distance measure of similar objects tends to 1 and for different objects tends to 0.

our method. The small variance of the probability error for the class of wrong capsules obtained from the EigenHistogram approach shows that the wrong objects are identified even when the inspection rois do not exactly coincide with the training rois. The fifth column shows that the eigenhistogram tecnique is still good in recognizing the correct objects with the high distance rate of 0.822.

Figure 3 shows both mean distributions of the inspection values l obtained in different experiments with different rois obtained by small translations and scaling. The x axis denotes the means obtained for both classes where the distance mean for each experiment of the wrong objects was between 0 and 0.196 and of the correct objects was between 0.705 and 0.936. The y axis of Fig. 3 denotes the number of tests where the means corresponding to the different intervals have been obtained. From the graphics it can be appreciated that both distributions are well separated illustrating the discrimination "power" of the EigenHistogram classification technique. As a result, we can summarize from the tables that the EigenHistograms have the better recognition results and the better discrimination capacity.

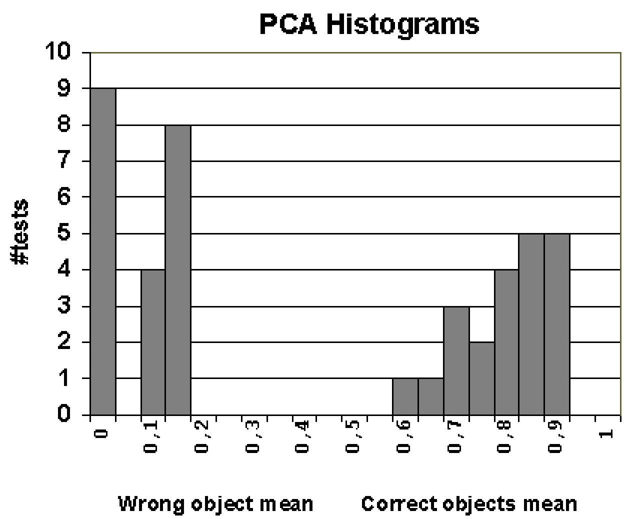

Fig. 3. Inspection values obtained on a blister with 200 correct and wrong objects

From the table it can be seen that the fastest inspection techniques are the (R,G,B), (RG, BY, WB) and the EigenHistogram methods where the time of inspection of up to 135 capsules is in less than 0.065s using an INTEL PENTIUM 200MMX with 32Mb of RAM. The fact that the EigenHistogram method consists of a projection and a retroprojection of a histogram to measure its distance to the original histogram determines the O(nm) complexity of the algorithm. In practice, we obtained that a number of EigenHistograms $m = 8$ and working with color histograms of $8 \times 8 \times 8$ $n = 512$ is sufficient to represent and recognize the color distribution of the pharmaceutical objects.

We should note that different color indexing methods are useful for color object recognition but can not cope with the problems of small defaults in the geometric shape (e.g. capsules of different shape and size like broken capsules or open capsules). It is due to the fact that these approaches analyze the color of the image. Another issue is that we model the color distribution of the roi (not only the product) using the fact that the background in the trained and inspected rois belongs to the same distribution. In many industrial applications the environment of inspection is constant, hence such an assumption is appliable.

6 Conclusions

This paper presents a new approach to color-based indexing and recognition that describes object colors using probabilistic models of their histograms. Histogram distributions of multicolored objects are represented and generated using eigenbasis vectors, that we call EigenHistograms. Object recognition is achieved by examining its proximity to database subspaces. As a result object multicolored recognition is achieved invariantly to object pose and changes in illumination directions. This approach has been tested and validated on a large object database consisting of multicolored pharmaceutical products and is applied for real-time inspection of capsules and other pharmaceutical objects. Our future plans involve extending the EigenHistogram approach to the problem of color object recognition in unknown environments as well as to the tracking problem.

Acknowledgments

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