Using Principal Component Analysis in the Detection of Road Sign

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ABSTRACT: *In this paper, we present a method of segmentation of the images colors by leaning on the statistical nature of the image. This method is designed to answer the problem of detection road signs in an image taken by means of a sensor embarked on a vehicle on natural conditions. The presented method exploits only the information of color type, whose new presentation of color we give by means of a statistical entitled technique "Principal Component Analysis" to have a strong uncorrelatedness between the components establishing the space of color.*

Keywords: Segmentation, Principal Component Analysis, Color Image, Correlation, Space of color

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1. Introduction

The detection and the recognition of road signs make the objective of numerous subjects of research during several years [1].

Therefore, for to detect road signs, it is necessary to be able to distinguish their standardized signs. They are mainly two orders: la shape and the color.

Generally, road signs have on one hand, colors determined: red, blue, and the other. On the other hand, normalized forms: Circle, triangle...

The notion of the color plays, thus a relevant role in the detection of road signs. We limit our study on the detection of road signs while basing on the color.

In the literature, we often find techniques and methods which serve to solve the problem of the detection of road signs while basing on the color. In [2] a technique consists in fixing borders of the components: rouge, green, and blue, to determine the class of the pixel asked in the image. Françoise Dibos [3] proposes a combination of a classic method of growth of region and the model of minimization of energy proposed by Mumford and Shah. In [4] Ludovic Macaine present a new color image segmentation scheme which constructs regions by unsupervised pixel classification, even when there is not a one-to-one correspondence between the clusters of color points in the color space and the regions in the image.

In this paper, a novel technique using a method "Principal Component Analysis" is presented.It has for objective to uncorrelated the various spectral components on each pixel by means of a linear projection.

The paper is organized as it follows. Section 2 introduces a brief review of the image and systems of representation of color. Discusses the correlation and color images in Section3.The proposed technique of analysis of the main components is discussed in Section 4. Experimental results are presented in Section 5 and the conclusions are outlined in Section 6.

2. Image and systems of representation of color

The color is a very complex notion because it brings in phenomena of physical, physiological and psychological order [5]. Various theories were thus proposed and several studies were and are still led to try to model this so rich information that complex.

They discovered numerous systems of representation in which any color can be represented by a point have coordinates identify it numerically and respect specific properties.

These representations are realized for the greater part in spaces in three dimensions and the units of the components colors are purely conventional because they serve only to locate a color inside a solid in which it is registered.

There are several systems of representation of colors[6]. We chose the system according to whom is the most based on the sensations that the others much more physical as the famous system RGB

2.1 RGB color space

The colors RGB space remains the most wide-spread. Indeed, it is implemented in most of the material tools of display (screen, video projection). In this space, a pixel is coded by three components red, green and blue, in values inside a cube unit. This space was developed according to the knowledge connected to the human vision, the cones being more perceptible to these three colors. This model is additive, what means that all the colors are deducted from the black (R = G = B = 0) by adding more or less some components. In this space, every component is thus defined by a value between 0 and 1(Or between 0 and 255 according to the standard). The main inconvenience of this model lies in the manipulation of colors [7]. Indeed, if we want to increase the luminosity of a color, it is necessary to increment proportionally every component being given the correlation between the plans R, G and B .These constraints make of the additive model of colors (RGB).

Generally, the three data components natural images are always more or less correlated.

It confirms thus preferable to look for a representation of the same information in another configuration, for the most possible complete uncorrelatedness between the three components.

3. Correlation of the images in color

We take place in the context of the segmentation of color images. We are going to privilege the systems of colors: RGB. The image is considered in each system as a three-dimensional statistical distribution. Generally, the three data components natural images are always more or less correlated and therefore it is thus important to think of the new noted space (R'G'B) for the most possible complete uncorrelatedness between the three components.

The figures below show clearly the correlation for natural images (Figure 1.a) of the road either to the RGB system (Figure 1.b).

The first idea that came to us is to change the color space, we chose systems independent axes which there is a complete uncorrelatedness between the color components.

We go need thus methods of reduction and analysis of data allowing recapitulating reduced set values while keeping the maximum of present information in the original data. In the bibliography we find several methods [8] (Analysis of the main components, Analysis of the independent components, discriminating factorial analysis). In this paper we will adopt the method called the principal components analysis.

Figure 1. (a) natural image

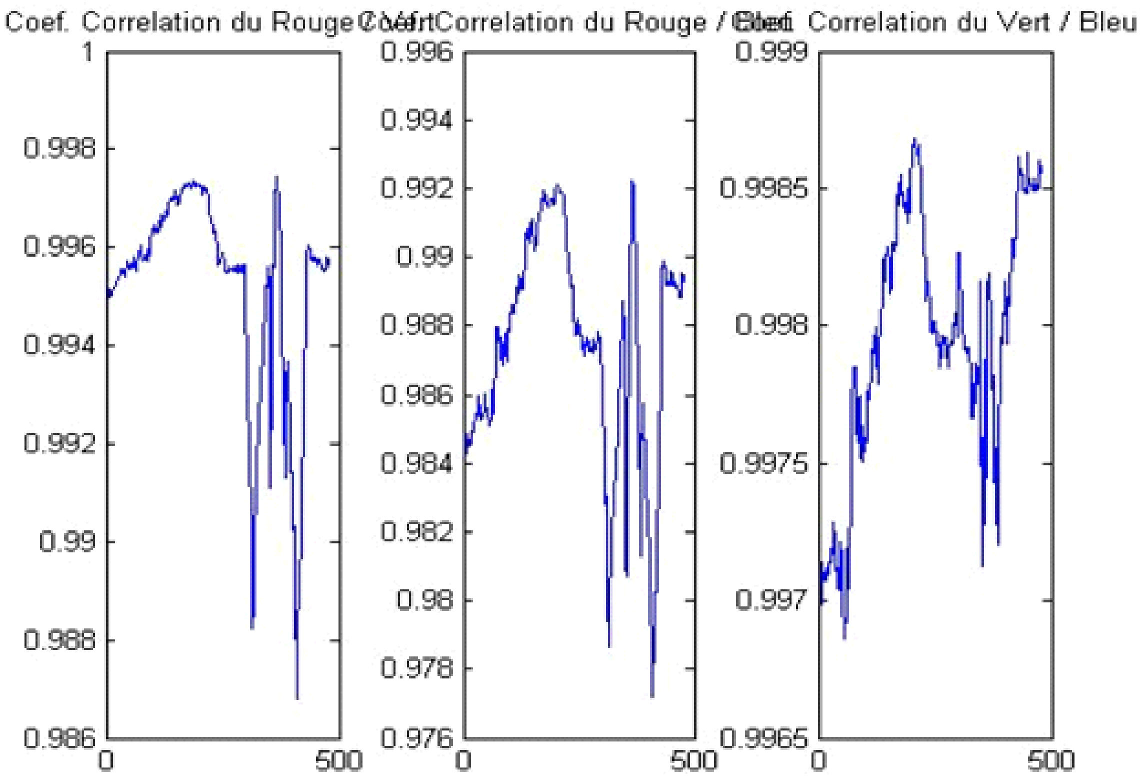

Figure 1. (b) correlation coefficient for an RGB image

4. Technique of analysis of the main components

We thus appeal to a purely statistical method which serves to analyze the statistics of the data by condensing the maximum of original information there of new components, so that they have an independence between them, these new variables are called principal components so it does the name of the method "*Principal Component Analysis*". It consists in transforming variables connected between them (correlated) in new independent variables some of the other (uncorrelated).

The Principal Component Analysis (ACP) is a classic technique used in image. It has for objective to uncorrelated the various spectral components on each pixel by means of a linear projection.

Images of the same scene recorded according to the different spectral bands of the sensor are highly correlated. Indeed a simple statistical study on the images colors, has led us to conclude that either the components (RGB) are highly correlated.

It is thus indispensable to study the statistics of these images to characterize the main elements before approaching the methods of analysis of the data.

Generally an image is composed of three components arranged one behind the other, each pixel of coordinates x (i, j) of the image is made up of three sub-pixels of the same coordinates (i, j), that pixel is presented as a vector [8, 9].

Is an image of size M * N, we obtain MN vectors of three components, these vectors represent the intensity levels of all pixels of the image.

The ACP is initially applied to the statistical terms used are not borrowed to imaging terms. This is why the pixels are named individuals and the three colored beams (Red, green, blue for an image in color) are called components or variables.

The ACP aims to uncorrelated the different spectral components of each pixel using a linear projection. To make this projection, the procedure consists in calculating a variance-covariance matrix on all the data and the diagonalized. We thus obtain by this process of diagonalization, a basis of eigenvectors Ej with $j \in [1; N]$ (associated with their eigenvalues¸ λj) which will establish the main components. The n first eigenvectors constitute a base of which one planned the original images to have a perfect uncorrelatedness.

4.1 Application

X is the matrix associated with the image, of resolution N * M of n components. The procedure of calculation of the main components of the image requires the calculation of the simple average of every component image and the matrix of covariance as follows [11]:

• Calculation of the average

We calculate the average m_x of each component by this expression of the simple average:

$$m_x = \frac{1}{MN} \sum_{k=1}^{MN} X_k \qquad (1)$$

In our case of color images, we shall have three averages (m_r, m_v, m_b).

• Calculate of the matrix of covariance:

We also calculate the matrix of covariance C_x of size n * n of the original image by means of the following formula:

$$C_x = \frac{1}{MN-1} \sum_{k=1}^{MN} (x_k - m_k)(x_k - m_k)^t \qquad (2)$$

Concerning the color images, the size of the matrix of covariance is 3 * 3.Let us note that the matrix of covariance is real and symmetric.

• Calculation of the main components:

We define A the matrix of maximal size n * n eigenvectors normalized by the matrix of covariance C_x. After the reorganization of the matrix A, of eigenvectors line ordered in decreasing order (of the most mattering in the least the importing) We end in the main component there y by means of the following expression:

$$y = (x - m_x) \qquad (3)$$

We succeed well a matrix of maximal size M * N * n with uncorrelated elements, consequently the matrix of covariance C_y of the matrix of the main components will there be diagonal and the values of this diagonal represent the eigenvalues corresponding corresponding to the eigenvectors contained in the matrix A. Other elements represent the partial correlations which are useless. (Figure 2)

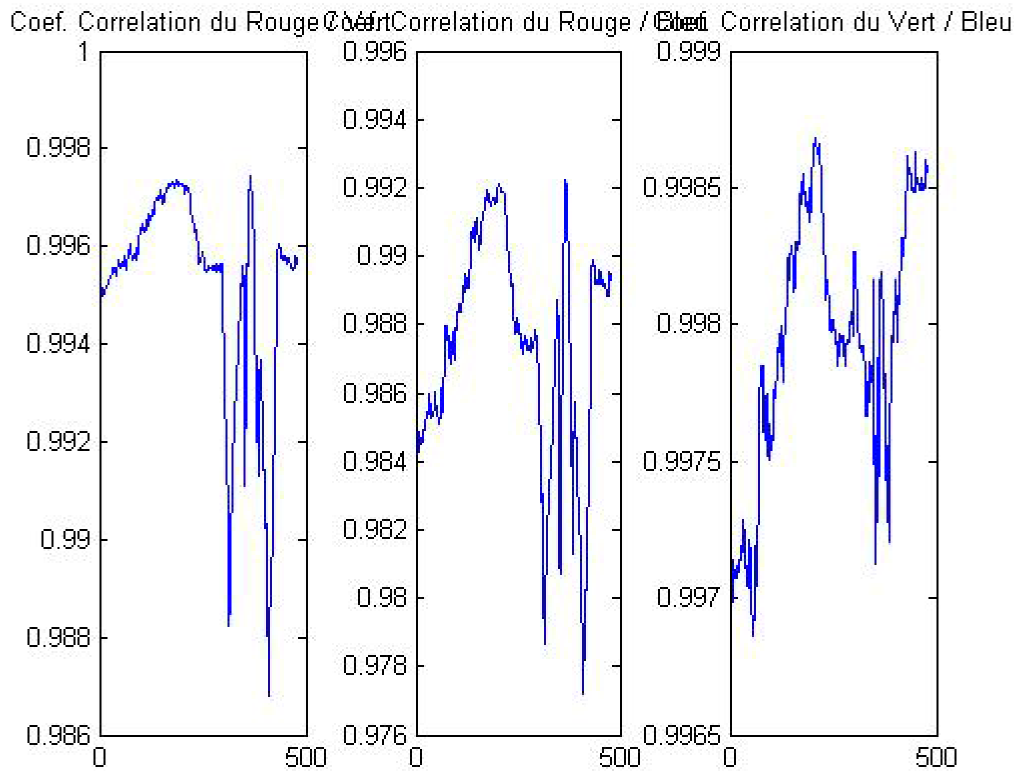

Figure 2. Correlation coefficient for image R’ G’ B‘

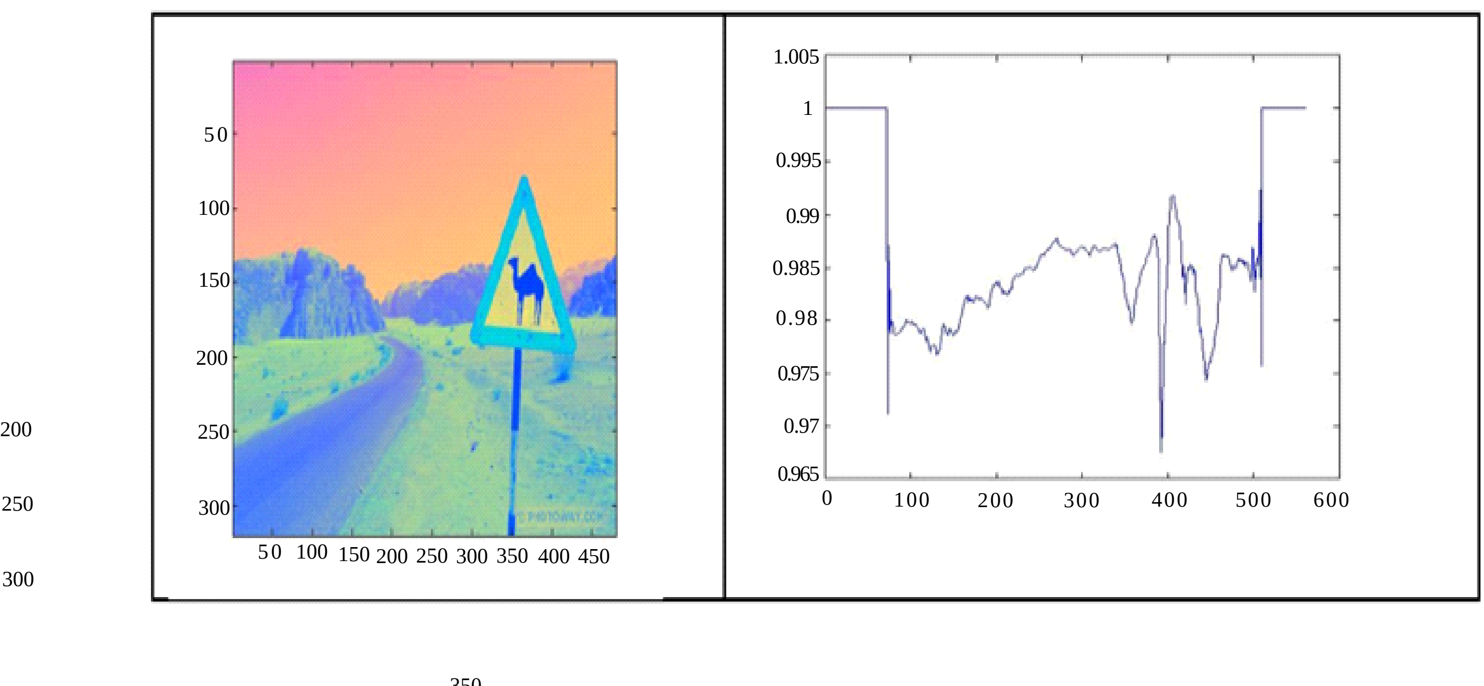

Figure 3. The representation of the image in the new space

4. Experimental Results

Now, we present experimental results demonstrating the appropriateness of the use of the technique of Principal Component Analysis for the uncorrelatedness of the components of the color image, these results (Figure 3) show the ability of theuncorrelatedness.

According to these results, it can be seen that this technique seems to meet our expectations. It is able to uncorrelated the components and hopefully eventually segment the images strongly correlated.

Finally, we were able to extract signs by means of technique of thresholding.

The figure (Figure 4) below shows the final result:

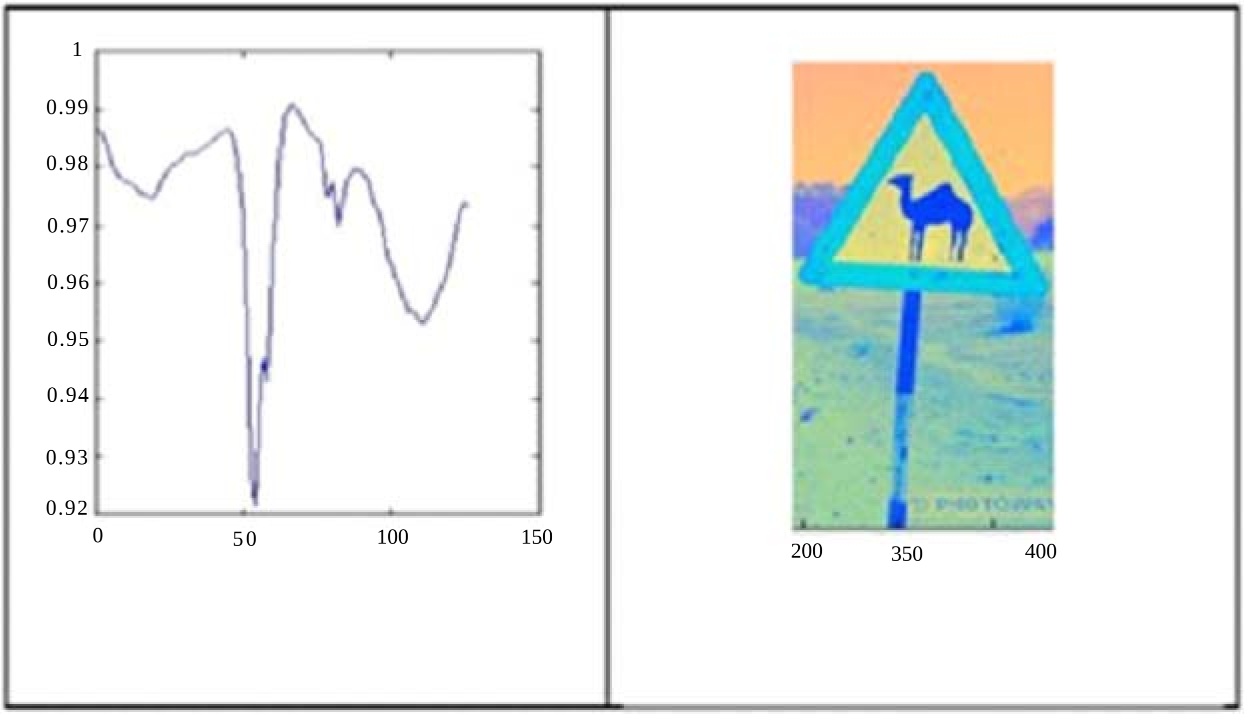

Figure 4. Image segmented through thresholding technique based on the correlation

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