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Color Image Segmentation Based on New Clustering Algorithm and Fuzzy Eigenspace

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Abstract: This study proposes a novel method to segment color images based on new clustering algorithm and a new feature space obtained by transformation of RGB space using Fuzzy Principal Component Analysis (FPCA) technique. The clustering algorithm is based on recursive one-dimensional histograms analysis, that separate multimodal 1D-histograms. We propose an intuitive idea for selecting the fuzzy principal components, simultaneously with clustering task, not necessary the first principal components. Quantitative and qualitative analysis of the performance of the proposed approach is examined on both real and medical images. Some experiments show that segmentation is better when using FPCA technique.

Key words: Fuzzy principal components, clustering, segmentation, 1D histogram, concavity

INTRODUCTION

Image segmentation is a low-level image processing task in variety of computer vision applications including robot vision, pattern recognition and biomedical image processing. Image segmentation is the technique of partitioning an image into disjoint and homogeneous regions. In recent years, research work has been focused on color image segmentation, since grey scale images can not satisfy the needs in many situations. Color is perceived by humans as a combination of tristimuli Red (R), Green (G), and Blue (B) which form RGB color space. Other kinds of color representation can be driven from RGB space by using either linear or non linear transformation. Hence, several color spaces such as RGB, HLS, YUY and CIEL L*a*b* are used in color image segmentation. Other spaces named hybrid color spaces, which have neither psycho-visual nor physical color significance, were defined in (Vandenbroucke *et al*., 2003). Their dimensions are not necessary equal to three. Previous studies, when comparing the influence of different color spaces on the segmentation results, found that no single color space is suitable for segmenting all types of images (Gauch and Hsia, 1992).

Most of the works in color image segmentation can be roughly classified into several categories: Histogram thresholding, clustering methods, region growing, edge based approaches and Fuzzy methods. A combination of these approaches is often used for color image segmentation (Chakraborty and Duncan, 1999; Kurugollu *et al*., 2001). The histogram thresholding based approaches are widely used for monochrome image segmentation (Sahoo *et al*., 1988). The statistic of pixels can be used to separate the image histogram into a number of peaks (modes), each corresponding to one region and there exist a threshold value corresponding to the valley between the two adjacent peaks. In the case of color images, 3D histogram segmentation is considered; and selecting threshold in this 3D histogram is not trivial job.

The edge based methods use gradient information to locate object boundaries. An edge detector basically applies directional derivative operators to an image, e.g., according to linear signal processing as a convolution by an appropriate filter kernel. Depending on this filter and further signal processing, there exist a large number of edge detectors which can be essentially divided into first order and second order derivative based (Canny, 1986; Nevatia, 1977).

Region-based methods, including region growing, region splitting, region merging and their combination (Tremeau and Bored, 1997), rely on the homogeneity of spatially localized features and other pixel statistics. They are less susceptible to noise; also, if the high frequency information in an image is either missing or unreliable, the segmented images remain relatively unaffected. However, all region based approaches are by nature sequential and another problem with these methods is their inherent dependence on the selection of seed regions and the order according to which the image pixels and regions are processed.

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Fuzzy set theory provides a mechanism to represent and manipulate uncertainty and ambiguity. Fuzzy operators, properties, mathematics have found considerable applications in image segmentation (Cheng and Li, 2000). The most important fuzzy approaches to image segmentation are fuzzy clustering. The regions are considered as fuzzy sets and each pixel belong to each region with an associated degree of membership.

The clustering based approaches (Celenk, 1990) assign pixels to clusters only on the basis of their color; each cluster is then characterized by a constant color value. A classical technique for image segmentation is the C-Means algorithm (McQueen, 1967) and its variant fuzzy C-means algorithm (Bezdek, 1981). Since the effectiveness of color image segmentation depends on the color reference system used, most algorithms designed are only suitable for use in specific color space. The authors in reference (Ohta *et al.*, 1980) use K-L transformation of RGB color features to segment eight kind of color image by recursive thresholding. To achieve a lower classification error, the authors of reference (Verikas *et al.*, 1997) chose the "IJK" color space where I, J and K are given by the eigen solutions of the covariance matrix of the variables R, G and B similar to those derived by Ohta *et al.* (1980).

FUZZY PRINCIPAL COMPONENT ANALYSIS

The Principal Component Analysis (PCA) (Jolliffe, 1986) is widely used as statistical technique for unsupervised dimension reduction of multivariate data, clustering and pattern recognition with many applications areas in image analysis, data compression and regression. However, it is well known that PCA as any other multivariate statistical method is sensitive to outliers, missing data and poor linear correlation between variables due to poorly distributed variables. One of the approaches to robustify PCA appears to be the fuzzification of the matrix data (Pop Horia, 2001).

Let $X = \{x_1, x_2,...,x_n\} \subset \mathbb{R}^p$ the finite set of feature vectors, where n is the number of objects, p the number of original variables and $x_{ij} \in \mathbb{R}$ is the value taken by the jth feature for the ith object. To fuzzify the first principal component the problem is, however, to be able to determine the one fuzzy set and its linear prototype that best describes the data set X. For this purpose, Horia (2001) considers that this fuzzy set must be characterized by linear prototype denoted byL (u, v); v is the weighting centre of the fuzzy set and u, with $\|u\| = 1$, is the direction of the first principal component considered for fuzzyfication. The fuzzy membership degrees A (x_i) to the prototype L (u, v) for each object x_i are calculated according to the distance from x_i to the first principal component (Pop Horia, 2001).

$$A(x_i) = \frac{\frac{\beta}{1-\beta}}{\frac{\beta}{1-\beta} + d^2(x_i, L)\frac{1}{m-1}} \quad (1)$$

Where $0 < \beta < 1$ is an input parameter and $m > 1$ is the fuzziness index. An algorithm to select the optimal value of β that maximizes the eigenvalue associated to the first principal component is proposed in Pop Horia (2001). Once the fuzzy membership degrees $A(x_i)$ are determined, the traditional covariance matrix is then replaced by fuzzy covariance matrix, given by (Pop Horia, 2001):

$$Cjk \ \frac{\sum_{i=1}^{n} A(x_i)^m.(x_{ij} - \bar{x}_j).(x_{ik} - \bar{x}_k)}{\sum_{i=1}^{n} A(x_i)^m} \quad j,k=1,...,p \quad (2)$$

Where $\bar{x}_j$ and $\bar{x}_k$ are simultaneously the arithmetic means of the jth and kth variables, $m > 1$ is the fuzziness index. The first fuzzy principal component is the direction of the unit eigenvector u associated with the largest eigenvalue λ of the fuzzy covariance matrix. The algorithm discussed above fuzzyfies only the first component, in order to get a most effective method; we have to deal with the problem of fuzzifing all the components. For this purpose, we use the algorithm, named Fuzzy PCA orthogonal, and described bellow:

- Determine β optimal by using the optimal the algorithm proposed in (Pop Horia, 2001).
- Determine the fuzzy membership degrees for the β determined above.
- Using these fuzzy membership degrees, compute the fuzzy covariance matrix *C*
- Compute eigenvectors and eigenvalues of *C*; the maximal eigenvalue λ and its eigenvector u are used.
- Compute the data scores and remove the values on the first positions.
- Recursively call Fuzzy PCA orthogonal on the reduced size set and determine the eigenvalues and the eigenvectors from this projected space.
- Return to the original space and rewrite these eigenvectors and eigenvalues in terms of the original set of coordinates.

In this study, RGB space is used as input space, and a fuzzy principal component analysis method is applied to compute the Fuzzy Principal Components (FPC_s) which determine the new feature space. As the colors in RGB are highly correlated, especially considering illumination effect such as highlight, the transformation of RGB space by using FPCA is a necessary step.

COLOR SEGMENTATION APPROACH

We consider the new feature space obtained by the transformation described in pervious section. Color segmentation is then performed by clustering the new feature space in a number c of clusters S_k where c is automatically determined by the proposed clustering approach. This approach separates the clustering process on two parts: Mode detection and classification.

Mode detection: The mode detection approach is based on the property called monotonicity which states that if a set S of observations is dense region in *p* multidimensional space, then S is also dense region in any lower dimensional subspace. Hence, dense regions in multidimensional space are detected via successive projections onto selected direction of (FPCs). For this purpose, the algorithm construct a hierarchy of dense regions starting with the set of all image pixels, and recursively splitting it into dense sub-regions until all sub-regions obtained are unimodal regions. The distribution of the projected pixels onto the direction of the selected (FPCs) is described by the 1D histogram. The splitting process is mainly based on the detection of dense regions by searching the peaks of this 1D histogram. A critical parameter of the 1D histogram is the bin width h. In fact, this parameter controls the trade-off between under-smoothing or over-smoothing the true distribution of pixels. If h is too large, the histogram will suffer from too little resolution. If h is too small, the histogram will suffer from too much statistical variability. Hence, h must approach zero, but at rate slower than 1/n, as n increases; this is assured by the following conditions:

$$\lim_{n\to\infty} h = 0 \tag{3}$$

$$\lim_{n\to\infty} nh = 0 \tag{4}$$

Equation 3 and 4 imply that the parameter h must be function of the pixel numbers considered to build the histogram. The formula in (5) provides an automatic determination of this parameter.

$$h = \frac{\max - \min}{\text{integer}(n^a)} \quad \text{with } 0 < a < 1 \tag{5}$$

Where min and max are respectively the lower and the higher values taken by the projected objects onto the direction of the (FPCs) considered to build the 1D histogram.

The modes of 1D histogram are detected by the local test of the convexity of this 1D histogram. The local convexity at a sampling point is determined by analysing the variation of the mean value of the histogram computed within a family of domains expanding around the current sampling point (Vasseur and Postaire, 1980). The mode detection part can be performed by the following steps:

Step 1: Start with the complete color space that can be regarded as one mode.

Step 2: Degenerate (splitting up) this mode

- Select the most discriminate fuzzy principal component (FPCs).
- Build the 1D histogram of projected pixels belonging to the mode onto the direction of the selected (FPCs)
- Find the distinct peaks (modes corresponding to sub-regions) of the 1D histogram

Step 3: Repeat step 2 for all obtained modes until each sub-region is a unimodal region of the feature space.

Selection of PCs: Principal component (PCs) and Fuzzy Principal Components (FPCs) are generally ordered such that the k^{th} PC has the k^{th} largest variance among all (PCs). The traditional approach is to use the first few (PCs) in data analysis since they capture most of the information in the original data. But previous studies (Yeung and Hart, 2001) showed that the first (PCs) may contain less a cluster structure information than other (PCs). Our approach, compute the Fuzzy Principal and Residual Components (FPCs) and use a heuristic idea for selecting automatically specific direction of these (FPCs) simultaneously with clustering. Indeed, for each mode detected, the algorithm builds p 1D histograms of the projected mode pixels onto the *p* directions of (FPCs). Then the fuzzy principal component that will be selected must have higher number of local maxima in the corresponding 1D histogram.

Classification: Once the different modal regions of the feature space are identified, the pixels falling into them are used as prototypes. The pixels, which do not fall in one of the detected modal regions, remain unlabelled. To complete the classification scheme, the knn classification procedure (Cover and Hart, 1967) is appealing approach to the problem. This decision rule assigns an unlabelled object, say x, to the class of the majority among its k nearest neighbours in the training set. The performance of the knn classification scheme depends on the number k of neighbours. Our experiments on different data sets, with different ranges of k values showed that $k = 7$ is the best choice.

RESULTS AND DISCUSSION

The algorithm proposed in this study has been tested on real and medical color images. Each image is originally described in the RGB space. The specifications of each image are summarized in Table 1.

The algorithm has one parameter α that needs to be specified by the user. To analyze the influence of this parameter, we compared the obtained segmentation by varying its values in the interval [0, 1]. For this, the color image segmentation results are evaluated quantitatively using the evaluation function proposed by Liu and Yang (Liu *et al*., 1994):

$$F(I)=\frac{1}{1000\,(n_1, n_c)}\sqrt{c}\sum_{k=1}^{c}\frac{e_k^2}{\sqrt{S_k}} \qquad (6)$$

Where, I is the segmented image, $n_1.n_c$ size of image, c the number of regions (number of clusters) in the segmented image, S_k the area of pixels of the k^{th} region and e_k the color error of kth region. For each region, the color error in RGB space is calculated as the sum of Euclidean distances between color of region pixels and the color attributed to this region in the segmented image. The smaller the value of F(I), the better is the segmentation results. Experimental investigations are performed using this function F. Figure 1 compares the segmentation results obtained using PCA and FPCA with the peppers image.

We can see that the proposed approach combined with (FPCs) gives better results for all values of $\propto \in$ [0.3,0.4]. For the other value of $\propto$ the algorithm produces over segmentation or under segmentation. Similar results are obtained for the other used images. As conclusion, a fuzzy principal component analysis combined with our clustering approach is more robust. Figure1 points out also that the optimal value of $\propto$ for peppers image is 0.36. The segmented image corresponding to this optimal value is represented in Fig. 3c. This figure shows that the algorithm discriminates perfectly all objects in the image comprising the highlight.

On the other hand, the figure shows that the optimal values of $\propto$ for renal and brain images are respectively, 0.39 and 0.35.

Table 1: Description of the tested images

Image	Size of image	Size of reduced image
Peppers	512×512	128×128
Brain	214×245	107×122
renal	150×153	75×76

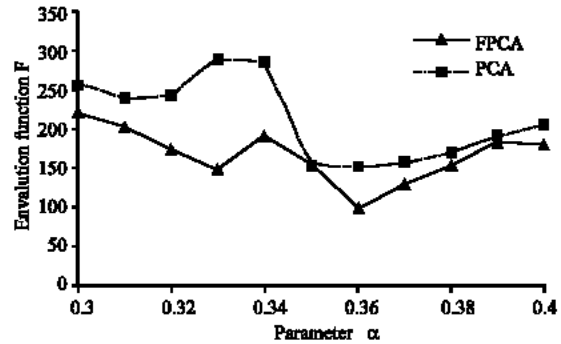

Fig. 1: The evaluation functions F according to the value of $\propto$ for the segmentation of the peppers image using the proposed approach combined with PCA and FPCA

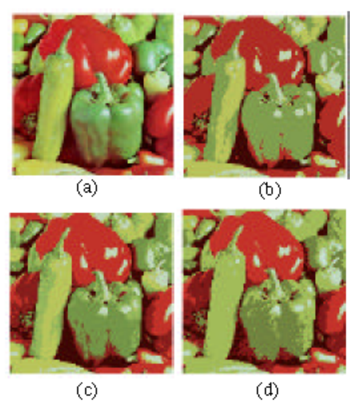

Fig. 2a: Original image of peppers. (b) Segmented image with $\propto = 0.31$. (c) Segmented image for $\alpha_{opt} = 0.36$. (d) Segmented image with $\propto = 0.4$

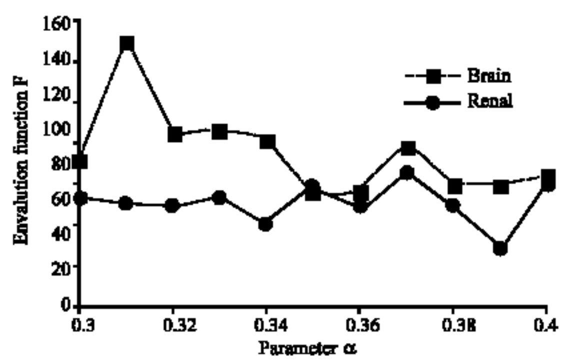

Fig. 3: The evaluation functions F according to the value of $\propto$ for the segmentation of the brain and renal images

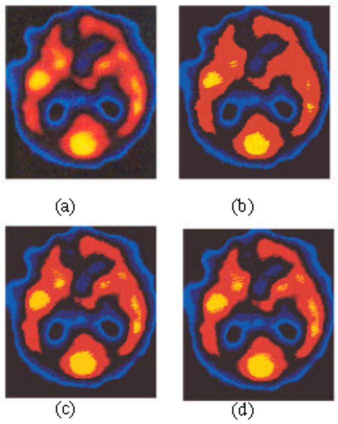

Fig. 4a: Original image of brain. (b) Segmented image with $\propto = 0.31$. (c) Segmented image for $\alpha_{opt} = 0.35$. (d) Segmented image with $\propto = 0.4$

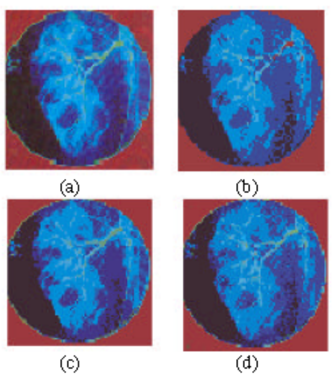

Fig. 5a: Original image of renal. (b) Segmented image with $\propto = 0.31$. (c) Segmented image for $\alpha_{opt} = 0.39$. (d) Segmented image with $\propto = 0.4$

Furthermore, Fig. 4 and 5 show some examples of brain and renal segmented images corresponding to some values of $\propto$. The segmented images corresponding to the optimal values of $\propto$ for both brain and renal images are plotted in Fig. 4c and 5c. We notice that good segmentation is correctly given by the optimal values of the parameter $\propto$.

CONCLUSION

A novel method for color segmentation which combines a new clustering approach and fuzzy principal component analysis technique is presented. The clustering approach is based on a detection of the spatial distribution modes of multidimensional observations (pixels). The main idea is to define a new fuzzy feature space from RGB space by computing the Fuzzy Principal Components (FPCs) and to search the modes hierarchically among different direction of the (FPCs) selected automatically by the algorithm. This selection is local to each mode considered and it is not necessary the first principal components. The proposed approach provides good results on both real and medical images used in this paper. Future works include a fuzzification of the clustering algorithm combined with fuzzy PCA technique with the possibility of fuzzifing only the components used by the algorithm.

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