Advanced Algorithm Partitioning of Markov and Color Image Segmentation

Mohamed Lamine Toure ,Zou Beiji, Felix Musau
School of Information Science and Engineering
Central South University
Changsha, 410083, Hunan, China
mohamedelcsu@hotmail.com, bjzou@vip.163.com, musaunf@gmail.com

***Abstract*—The color vision systems require a first step of classifying pixels in a given image into a discrete set of color classes. In this paper we introduce a new method of algorithm partitioning, and color image segmentation based on similarities or dissimilarities of the pixels. We consider fuzzy segmentation with markov, and normalized cut method. Experiments show these different processes used an effective solution on natural images, and computational efficiency. Finally, the algorithm has proven our process of experiments on gray scale, color, and texture images show promising segmentation results successful.**

Keywords-FuzzyImage,Markov,Normalizedcut, Segmentation, Similarities.

I. INTRODUCTION

Color image segmentation is useful in many applications, from the segmentation results, it is possible to identify regions of interest, and objects in the scene, which is very beneficial to the subsequent image analysis or annotation. Recent work includes a variety of techniques: for example, stochastic model based approaches [1][2][3],[4],[5],morphological watershed based region growing [6], energy diffusion [7] and graph partitioning [8].Quantitative evaluation methods have also been suggested [9].However, due to the difficult nature of the problem, there are few automatic algorithms that can work well on a large variety of data.

The problem of segmentation is difficult because of image texture. If an image contains only homogeneous color regions, clustering methods in color space such as [10] are sufficient to handle the problem. In reality, natural scenes are rich in color, and texture. It is difficult to identify image regions containing color-texture patterns.

The classical broadly-accepted formal definition of image segmentation is as [10].

Today color image segmentation is a rapidly developing area of digital image processing [12] .Color image segmentation attracts more attention due to the increasing computational potentialities of personal computers, and possibility of their usage for color image processing. Nevertheless, this problem remains less investigated than segmentation of grayscale images. There are many application areas for color image segmentation, one of them is Optical Character Recognition systems. Segmentation is the first stage in operation of optical character recognition systems. OCR systems usually apply binarization methods for segmentation of grayscale images. However, application of these methods for color images is impossible in general. For this reason, development of segmentation methods for color images is a very typical problem.

Several authors are applying different techniques for color in order to improve the final result of the segmentation, for example, (Park, 1998) presents a new algorithm based in mathematical morphology that performs a clustering in 3D color space; fuzzy techniques are applied by Yang et al. (Yang, 2002). Markov Random Fields are applied for clustering in (Jayanta, 2002).

As in Shi and [16] Malik proposed a new measure o disassociation, the normalized cut (Ncut):
Markov random fields are frequently used to model stochastic interactions among classes and to allow a global Bayesian optimization of the classification result[17,18].

II. RELATED WORK

The figure 1 below try an algorithm of segmentation in areas different for a function from partition P(x)=(x,y) of which the coordinates in point of the image is I(x,y).

If $P(o)$ is a homogeneity predicate which is defined on groups of connected pixels, then the segmentation is a partition of the set (I) into connected components or regions $\{C_1,...,C_n\}$ such that :

$$\bigcup_{i=1}^{n} C_i \text{ with } C_i \cap C_j = \varnothing \text{ , } \forall_i \neq j \qquad (1)$$

The uniformity predicate $P(C_i)$ is true for all regions C_i and $P(C_i \cup C_j)$ is false when $i \neq j$ and sets C_i and C_j are neighbors.

The figure below shows an example partition of a simulated image consisting of three classes.

Where:

$S_1, S_2, S_3.......S_i$ Represent the number partition of (S).

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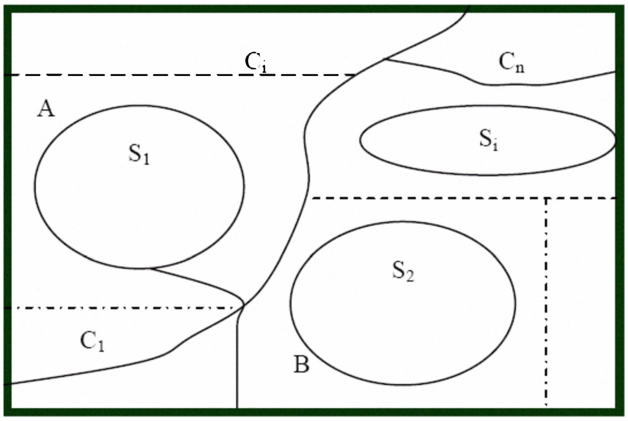


Figure 1. a partition of S .

To achieve the classification of the image, we impose three conditions that the solution must satisfy. The first is a condition of partition in the sense that each pixel must be tagged once and only once. Moreover, the classification process must take into account the observed image, and the Gaussian distribution of intensity of each class, to provide a solution close to observations. Finally, the model must provide a regular solution for which the lengths of the interfaces between regions are minimal.

Let us consider a model which has two classes (A and B) noted "0", and "1". This assumption is realistic in the context of image processing, if is a question of detecting an object start from a homogeneous bottom. Each site can be defined on the interval [0, 1]. To consider S .the set of whole of indices is S^1 ... S^n which is a partition of S . Let us pose $N = Card(S)$ and, for $1 \le i \le n$, $N^i = Card(S^i)$.

Suppose $N^1 = 1 \le N^2 \le ... \le N^n$, and for $1 \le i \le n-1$ associate has each .

$s \in S^i$, a subset s^+ of S^{i+1} which call an inferior part of S and $(s)_{s \in S^i}$ can also become a partition of S^{i+1} . The single element of S^1 is to call root. In addition s^{++} the whole of the form a set will indicate of superior par and we can calling s^- .

Consider $X = (X_s)_{s \in S}$ a random process has value in $[0,1]^N$. The law of X_s is defined by a density h_s according to measurement $v = \delta_0 + \delta_1 + \mu$. the mass of Dirac δ_0, δ_1 and the measure of Lebesque μ on $]0,1[$ respectively represent hard information, and fuzzy information [11]. The condition of standardization implies:

$$h_s(0) + h_s(1) + \int_0^i h_s(t)\,dt = 1 \quad (2)$$

The law of X is defined by the initial law $h(x)$, and the density of transition : $f(x_s / x_{s-})$.

$$\pi(x) = hs(x_1) \prod_{i=2}^{n} \prod_{s \in S^i} f(x_s / x_{s-}) \quad (3)$$

III. PROBLEM SOLVING

In this part we seek to analyze the hidden process and estimate the parameter. The reason for introducing such a term is to analyze the shadow areas for a pixel, and deduct an effect similar to that of term contained in the equation.

A. *Estimate of the hidden process*

Being gives an observation $Y = \left(Y_s^{(2)}, Y_s^{(2)}, ..., Y_s^{(D)}\right)_{s \in S}$ of random vector of multispectral observation and for $Y = y$, we wish to estimate a realization $x \in [0,1]^N$ the process of final decision, founded on a strategy Bayesian uses criterion to maximize the posterior marginal [10].Being given a function of loss: $L^* : [0,1]^s \text{ x } [0,1]^s \to \mathbf{R}^+$

And a whole of observation $Y = y$, the decision $d^\wedge(Y)$ minimize the expression : $E[L^*(X, d^\wedge(Y))]$ .Criterion MPM returns has to minimize $E[L^*(X_s, d^\wedge(Y))]$ in each site of the expression of s .

We choose the cost, distance in absolute value: $L(x_s, x_s^\wedge) = \left| x_s - x_s^\wedge \right|$, who presents in term of robustness (noise, hyperparameter), and compatibility with the function of loss `0-1' of the hard segmentation.

For a realization $Y = y$, we minimize the conditional hope:

$$E[L(X_S, d^\wedge(Y))] \left| Y = y \right| \quad (4)$$

The calculation of (4) required distribution of a posteriori

$$E[L(X_S, d^\wedge(Y))] \left| Y - y \right| = h_s^Y(0).\text{L}(0, d^\wedge(y))$$

$$+ h_s^Y(1).\text{L}(1, d^\wedge(y)) + \int_{t \in]0,1[} h_s^Y(t).\text{L}(t, d^\wedge(y))\text{dt} \quad (5)$$

The decision in each site is that which minimize (5):

We must calculate the densities $h_s^y(x_s)$ as a preliminary:

For that, transitions $f^y(x_s / x_{s-})$ are initially calculated before the tree in function of the probabilities backward. $\beta = (x_s) = f(y_{s++} / x_s)$.

$$f^y(x_s / x_-) = \frac{f(x_s / x_{s-}) f x_s(y_s) \beta_s(x_s)}{\int_0^1 f(\omega_s / x_{s-}) f \varpi_s(y_s) \beta_s(\varpi_s d\nu(\varpi_s)} \quad (6)$$

These last being calculated recursively while posing:

$\beta_s(x_s) = 1$, for $s \in S^n$

$$\beta_s(x_s) = \prod_{t \in s^+} \left(\int_0^1 \beta_t(x_t) f(x_s / x_{s-}) f x_s(y_s) dv(x_s) \right) \quad (7)$$

For: $s \in S - S^n$

For $s = S^1$ (root of tree), the probability $h_1^y(x_1)$ is calculated from $\beta_1(x_1)$:

$$h_1^y(x_1) = \frac{h_1(x_1) f x_1(y_1) \beta_1(x_1)}{\int_0^1 h_1(\omega_1) f \omega_1(y_1) \beta_1(\varpi_1) dv(\varpi_1)} \quad (8)$$

The density $f^y(x_s, x_{s-})$ are then calculates before:

$$f^y(x_s, x_{s-}) = h_s - (x_{s-}) f^y(x_s / x_{s-}) \quad (9)$$

We deduce the value from marginal posteriori $h_s^y(x_s)$ [12].

$$h_s^y(x_s) = \int_0^1 f^y(x_s, x_{s-}) dv(x_{s-}) \quad (10)$$

Thereafter, the integrals above are calculated from the discretization of the interval in M value equivalents:

B. *Estimate of the parameter*

We propose the following estimate of the parameters:

We suppose X is stationary, and its law given by: $c_{ij} = f(x_s = j, x_{s-} = i)$ does not depend on: s.

The estimate of the parameters is to carry out by an algorithm EM [12, 13] in the following way.

1-initialization $\theta = (c_{ij}^0, \mu_k^0, \Gamma_k^0) 0 \prec i, j \leq 1, 0 \leq k \leq 1$

2. For all of the $q \in \square N^+, \theta^{q+1}$ we calculate from y and θ^q by:

$$c_{ij}^{q+1} = \frac{1}{\sum_{i=2}^n N^i} \sum_{i=2}^n \sum_{s \in S^i} f(x_s, x_{s-}) \quad (11)$$

For $k \in \{0,1\}$ (class hard): with $A = \sum_{i=1}^n N^i$

$$\mu_k^{\wedge q+1} = \frac{1}{A} \sum_{i=1}^n \sum_{S \in S^i} h_s^y(k) y_s \quad (12)$$

$$\Gamma_k^{\wedge q+1} = \frac{1}{A} \sum_{i=1}^n \sum_{S \in S^i} h_s^y(k) (y_s - \mu_k^{\wedge q+1})(y_s - \mu_k^{\wedge q+1})^T \quad (13)$$

For $k \in]0,1[$ (class hard):

$$\mu_k^{\wedge q+1} = (1-k) \mu_0^{\wedge q+1} + \mu_1^{\wedge q+1}$$

$$\Gamma_k^{\wedge q+1} = (1-k)^2 \Gamma_0^{\wedge q+1} + k^2 \Gamma_1^{\wedge q+1}$$

IV. Results of Experiments

We have presented a new system of algorithm segmentation of color image.

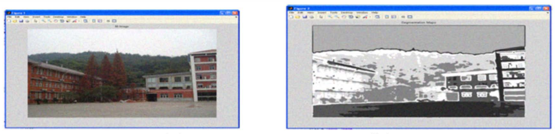
The first segmentation attempts to segment coarsely using the thresholding technique, while the second segmentation allows to reduce the classification errors concerning each pixel of the image based on the evidence theory.The paradigm for deriving mass distributions associated with the images to be fused has been successful.

The process is explained with the image in figure 2, followed by many images, in all cases the results obtained with the fusion of information from the different order of segmentation have been better than the ones obtained only with information from the first.

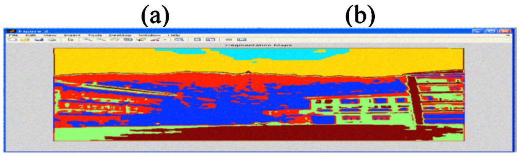
However, when information from the first source is mixed with the information from the other layers using the theory of evidence the problem is partially solved.. This is the principal advantage of our system.

Figure(2), the following parameters have allowed us to observe the distribution of pixels.

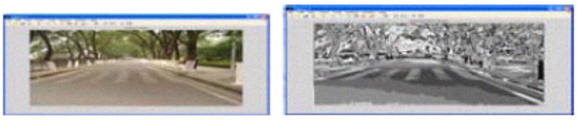
- Parameters for the Segmentation:
- a)-Part I
- nBins=15; >> winSize=7; >> nClass=6; >> %Read InputImage;inImg=imread('Input.jpg');>> imshow(inImg);title('Input Image'); %Segmentation
- outImg=colImgSeg(inImg, nBins, winSize, nClass); %Displaying Output.
- figure;imshow(outImg);title('Segmentation,Maps');> colormap('default');
- Fig2-(a) represent original image.(b)- Image segmentation and (c)- Color Image Segmentation with nClass=6.



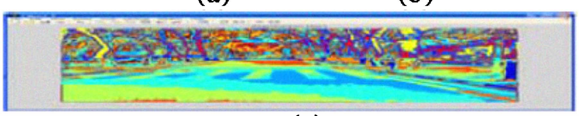
(a) (b)



(c)



(a) (b)



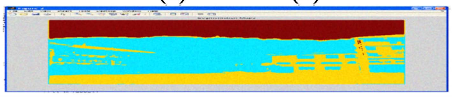
(c)

We changed the parameters to evaluate the distribution of pixels in different areas depending on the number of classes. Figure (3) shows the results observed by the pixels reducing the number of classes.

- b)-Part II
- nBins=15; >> winSize=7; >> nClass=3;

Figure 3. (a)originalimage.(b)Imgsegmentation(c)-nClass=3.

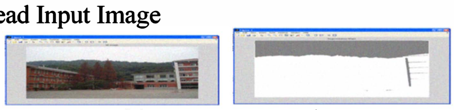
(a) (b)



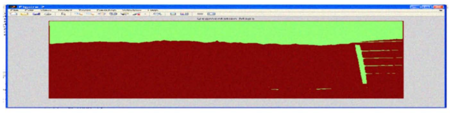
(c)

- Figure (3), shows the result for the number of parameters equal to two classes
- C)-Part III
- nBins=15; >> winSize=7; >> nClass=2;

%Read Input Image



(a) (b)

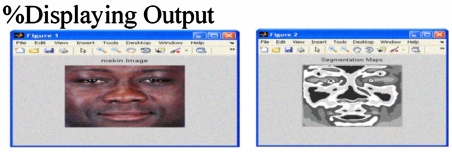


(c)

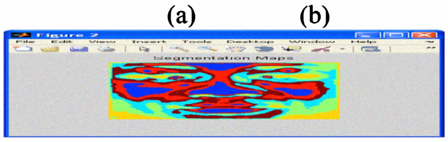
(a)-orginal image.(b)Imag Segmented;c)nclass2

Figure 4. , shows the experiment performed on the test face with the same conditions as in Figure 2

- a)- Part IV
- nBins=15; >> winSize=7; >> nClass=6; >> %Read Input Image;inImg=imread('Input.jpg');>> imshow(inImg);title('Input Image');%Segmentation; outImg = colImgSeg(inImg, nBins, winSize, nClass);
- %Displaying Output



(a) (b)

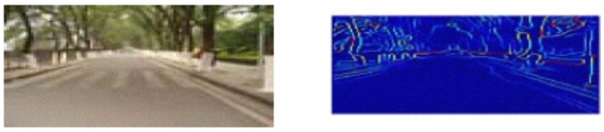


(c)

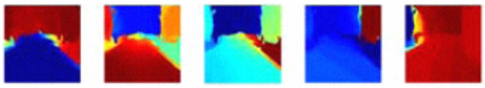
In this part, we have analyzed the Normalized Cuts for image segmentation problem, which is based on Graph Theory. This algorithm treats an image pixel as a node of graph, and considers segmentation as a graph partitioning problem. The Normalized Cuts algorithm measures both the total dissimilarity between the different groups as well as the total similarity within the groups. Amazingly, the optimal solution of splitting points is easily computed by solving a generalized eigenvalue problem. The figure(5-c) show he result of simulation.

Figure 5. shows the experiment carried out with the segmentation Ncut. Fig5(a) -represent original image. (b)- Image spectral and (c)-

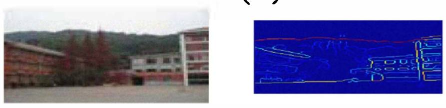
Image normalized with the different region dominate by same color.



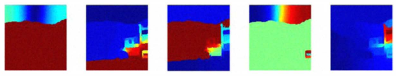
(a) (b)



(c)

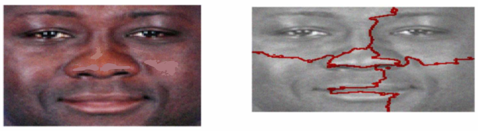


(a) (b)

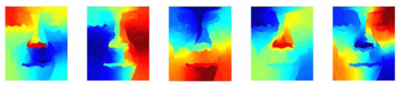


(c)

Figure 6. shows the experiment carried out with the segmentation Ncut.



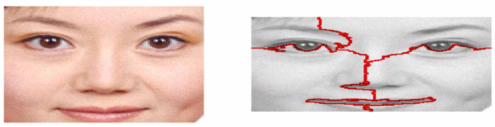
(a) (b)



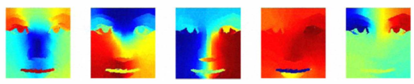
(c)

(a)-represent original image.(b)-Image partitioning by region and (c)- Show Image spectral normalized with the different region dominate by same color.

Figure 7. shows the experiment carried out with the segmentation Ncut.



(a) (b)



(c)

(a)-represent original image. (b)- Image partitioning by region and (c)- illustrate Image spectral normalized with the different region dominate by same color.

Figure 8. shows the experiment carried out with the segmentation Ncut.

V. CONCLUSIONS AND FUTURE WORK

This paper analyze an algorithm to partition color images with a base of multiple theories information markov. The first segmentation attempts to segment coarsely using the thresholding technique, while the second allows to reduce the classification errors concerning each pixel of the image.

The thresholding, and the data fusion techniques allows us to analyse the repartition of pixel following the different region. The result emonstrate that the selection of the most relevant color space at each iteration step allows to provide relevant segmentation results.Figure5represent the segmentation by normalized cut with the variation of parameter for the number of class. We have to test the result of the face recognition by the different region, and the partition of pixel which is successful.

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