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An iterative algorithm for color space optimization on image segmentation

Mourad Moussa
Department of Applied informatics, Networked Objects, Control and Communication Systems (NOCCS) Laboratory
National Engineering School of Sousse, University of Sousse, Tunisia

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ABSTRACT

This paper proposes, a novel hybrid color component (HCC) issued from amounts number of color space with iterative manner, in fact traditional images obtained by RGB sensor weren't the effective way in image processing applications, for this purpose we have propose a supervised algorithm to substitute RGB level by hybrid and suitable color space at the aim to make well representation of the handled amounts of data, this step is extremely important because the obtained results it will be injected in many future studies like tracking, classification, steganography and cryptography. The second part of this paper consists to segment image coded in hybrid color space already selected, the used algorithm is inspired from kernel function where statistical distribution was used to model background and Bayes rule to make decision of the membership of each pixel, in this research topics we have extended this algorithm in the aim to improve compactness of these distribution. Cauchy background modeling and subtraction is used, and shows the high accuracy of automatic player detection.

Corresponding Author:

Mourad Moussa
Department of Applied Informatics
Networked Objects, Control and Communication Systems (NOCCS) Laboratory
National Engineering School of Sousse, University of Sousse
Pôle technologique de Sousse, Route de Ceinture Sahloul 4054, Tunisia
Email: Mourad.enim@yahoo.fr

1. INTRODUCTION

Object detection and tracking [1, 2], segmentation [3-5], edge detection [6], classification [7-9] and face recognition [10, 11] are the main steps of a computer vision system for image analysis. The purpose of segmentation is to simplify and or change the representation of an image into something that is more meaningful and easier to analyze. Color information is a crucial way to increase separability power of many distributions and objects in framework. G. H. Liu *et al.* [12] present image retrieval technique based on color difference histogram (CDH) to extract color features coded in $L*a*b*$. Color information is also used in steganography field [13, 14] and Biometric Authentication [15, 16], for instance S. Hemalatha *et al.* [17] propose a new image steganography technique to conceal secret information in color image, given the unsatisfactory results with the grey scale images, in fact color image can hold a big amount of secret information for this reason they have used two color spaces RGB and YCbCr, experimental results show that YCbCr doesn't requires enough computing time than the RGB one, and is easy for extracting secret images. S. Chitra *et al.* [18] propose a technique in biometric field that consists to face recognition based on skin color detection, the first step of this algorithm convert original image in HSV and YCbCr color space then collect the value of H, S, Cb, Crand finally check whether these values are satisfied with the specified threshold values.

The proposed paper is subdivided into two parts the first one is specified for (HCS) selection with supervised and iterative algorithm among a wide set of color levels issued from many color system commonly used in image processing, when we have introduce many tools allowing to select suitable hybrid chromatic level and we have propose many ways to make decision about color components like, firstly the use of partial and full data and secondly the use of data fusion theory. The second part is dedicated to image segmentation we have used a statistical method based on Cauchy distribution for modeling [19, 20] and probability theory based on Bayes rules for making decision about belonging of pixel to suitable clusters. At the first-time building background model and in the second time we detect and allocate each pixel to its class. Finally, we conclude this paper by experimental and discussion results.

2. ITERATIVE ALGORITHM FOR COLOR SPACE SELECTION

2.1. Introduction

We propose to analyze a measure of similarity of objects in a training image for each color component to build an optimal (HCS) where we want realize the segmentation step. It is assumed that an object or region can be a subset of highly color-connected pixels, which is represented by the color points in the color space around. To analyze such property of a subset-color, we propose to measure the degree of connection that quantifies the spatial arrangement of its pixels in the image level.

Let S and $\mathrm{N_s(p)}$ are respectively a color object and the set of neighbours pixels of a pixel P belonging to subset pixels of S. The connectivity degree between P and S denoted $\gamma_S(p)$ depends on the number of neighbor pixels S belonging to $\mathrm{N_s(p)}$. The degree of connection $\mathrm{DC(S)}$ criterion is expressed by (1):

$$DC(S) = \frac{\sum_{p \in S} \gamma_S(p)}{card(P \in S)} \tag{1}$$

The connectivity degree $\mathrm{DC(S)}$ is the average number of neighbor pixels of S which also belong to the same object. The connectivity degree is between 0 and 1, when DC is about 0 that means the pixel of considered cluster are dispersed in treated image, in the contrary case the set of pixel are considered as strongly connected.

2.2. Evaluation of connectivity degree of each component

To improve the quality of color image segmentation we should select the optimal color space [21, 22] to reach effective results. We compare a number of color components from conventional color spaces based on the connectivity criterion defined in previous section, and we select the most discriminant components to build the hybrid discriminating color space in which segmentation will be bring out. We select two images containing respectively class 1 and class 2, these images are used for supervised learning. We evaluate for each color component the connectivity degree of the two images representing the two existing classes. For each color component, we calculate the sum of two degrees of connectivity for class1 and class 2. Some components do not detect all class levels of colors, their degrees of connectedness do not therefore reflect the degree of class connectivity, these components are rejected like $u(Luv)$. On the other hand, the component $\mathrm{H(HSL)}$ lost the shape of the object, there is a certain over-detection, this component can't also have a real degree of connectivity of the detected class. The best degree of connectivity found is 0.9271, this value is provided by the components following colors: X(XYZ), L(Lab), a(Lab), b(Lab), I(YIQ). We build the (HCS) dimension consists of five components above where segmentation will be made. In our approach we will use the iterative algorithm based on discriminant analysis policy, which determines the three components most relevant colors constituting a (HCS).

2.3. Training sample construction

The proposed approach consists to search the efficient (HCS) for distinguishing two dominant classes of pixels in a given data base image. To determine the (HCS), as it's shown in Figure 1, we take 5 images for each class of pixels and we define for each class Cj, $\mathrm{Wi,j}$ from a set of Ww representative pixels where $i = 1 \dots Nw$ and $j = 1.2$. In a given color space having d dimension, we characterize each pixel Wi,j belonging to class Cj by the observation $Xi,j = [X_{i,j}^1, \dots, X_{i,j}^k, \dots, X_{i,j}^d]^T$.

The rows of the matrix X correspond to $Nw \times 2$representative pixels, while the columns correspond to the levels of color components of each pixel. We can also express the matrix X by $X = [X^1 \dots X^k, \dots, X^d]^T$, where$X^k = [X_{1,1}^k \dots X_{Nw,1}^k, X_{1,2}^k \dots, X_{Nw,1}^k]^T$, contain intensities level ofk^{th} color component of $Nw \times 2$

representative pixels. Where $X_{i,j}^{k}$ is the k^{th} intensity level of color component. We represent all observations in the matrix form X:

$$X = \begin{pmatrix} X_{1,1}^{1} & \cdots & X_{Nw,1}^{1} & X_{1,2}^{1} & \cdots & X_{Nw,2}^{1} \\ \vdots & & \vdots & \vdots & & \vdots \\ X_{1,1}^{k} & \cdots & X_{Nw,1}^{k} & X_{1,2}^{k} & \cdots & X_{Nw,2}^{k} \\ \vdots & & \vdots & \vdots & & \vdots \\ X_{1,1}^{d} & \cdots & X_{Nw,1}^{d} & X_{1,2}^{d} & \cdots & X_{Nw,2}^{d} \end{pmatrix}$$

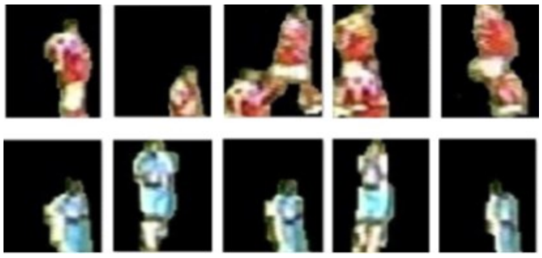

Figure 1. Training set image for two dominant classes

2.4. Minimization of color component correlation

To measure the level of correlation between the color components, we consider the $d-1$ couples of vectors with X^d and one of the vectors X^k, where $k = 1,\dots,d-1$. Let $cor(X^k, X^d)$, in (2) shows the correlation measure between $k^{th}$and d^{th} color component:

$$cor(X^k, X^d) = \frac{cov(X^k, X^d)}{\sigma^k \sigma^k} \tag{2}$$

Thus (3) defines the co-variance measurement$cor(X^k, X^d)$ between k^{th} and d^{th}level:

$$cov(X^k, X^d) = \frac{1}{Nclass*Nw} \sum_{j=1}^{Nclass} \sum_{i=1}^{Nw} (X_{i,j}^{k} - m^k)(X_{i,j}^{d} - m^d) \tag{3}$$

where m^k, m^d, $\sigma^k$and σ^drepresent respectively means and standard deviation of k^{th} and d^{th} color component, for k^{th}component they are defined by (4):

$$m^k = \frac{1}{Nclass*Nw} \sum_{j=1}^{Nclass} \sum_{i=1}^{Nw} (X_{i,j}^{k}), \sigma^k = \frac{1}{\sqrt{Nclass*Nw}} \sqrt{\sum_{j=1}^{Nclass} \sum_{i=1}^{Nw} (X_{i,j}^{k} - m^k)^2} \tag{4}$$

Correlation values are ranged between 0 and 1. When the correlation value close to 1, levels are considered to be correlated. The maximum of correlation between the d^{th} color component and all other $d-1$ color components is computed by (5) and it's considered as a correlation measure, denoted $J_{cor}(HS_a^d)$ between the d color components of the (HCS) HS_a^d:

$$J_{cor}(HS_a^d) = max \quad {}_{k=1}^{d-1} (cov(X^d, X^k)) \tag{5}$$

We consider only the (HCS) of dimension for which the correlation measure is below a given threshold, it is the candidate spaces that will be considered by the build process of the space most discriminating hybrid color, we consider only a limited number N_{cand}^{d} of hybrid candidate color space S_l^d having d dimension, where $l = 1 \cdots N_{cand}$ among all $N_{cand} - d + 1$ (HCS) HS_a^d.

2.5. Maximization of discriminating power

We present the sequential procedure for selecting color components that determines the (HCS). In each$\boldsymbol{d}$rank iteration of the construction process, we consider N_{cand}^{d} all candidate (HCS) S_l^d of dimension d, where $l = 1 \cdots N_{cand}^{d}$. We evaluate their discriminatory powers with a relevant criterion, and select the best one that is the (HCS) having dimension like the most discriminating one, denoted by S_d. This criterion, noted by$J_{dis}(S_l^d)$ measures the dispersion of the observations related to representative pixels in each hybrid candidate color space. On the first iteration $d = 1$, we consider the $d - dimensional$ d-dimensional candidates spaces defined by each of the N_{comp} available color components. The mono-dimensional space selected S^l is the one that maximizes the discriminative power $J_{dis}(S_l^1)$. During the second iteration of the procedure $d = 2$, the two-dimensional (HCS) are constituted by combining the color component issue from S^1 to each of the $N_{comp} - 1$ remaining color components. Among N_{cand}^2 these two-dimensional (HCS) S_l^2 where $l = 1 \cdots N_{cand}^2$ that obey to the correlation measure criterion, we select the one that maximizes $J_{dis}(S_l^2)$, this selected space S^2 **is** the most discriminating (HCS), this procedure is represented by Figure 2, it was iterated until $d = D$ indicating the dimension D of the suitable (HCS) S^D. The robustness power of a candidate (HCS) is evaluated by the measurement of compactness and separability of the involved classes. We use the intra-class dispersion matrix $W(S_l^d)$ given by (6).

$$W(S_l^d) = \frac{1}{Nclass*Nw}\sum_{j=1}^{Nclass}\sum_{i=1}^{Nw}(X_{i,j} - M_j)(X_{i,j} - M_j)^T \qquad (6)$$

Where $M_j = [m_j^1, \dots, m_j^k, \dots, m_j^d]^T$ are the vector containing gravities centre corresponding to Nw observation, and then $X_{i,j}$ serves to express cluster $C_j$by (7).

$$m_j^k = \frac{1}{Nw}\sum_{i=1}^{Nw} x_{i,j}^k \qquad (7)$$

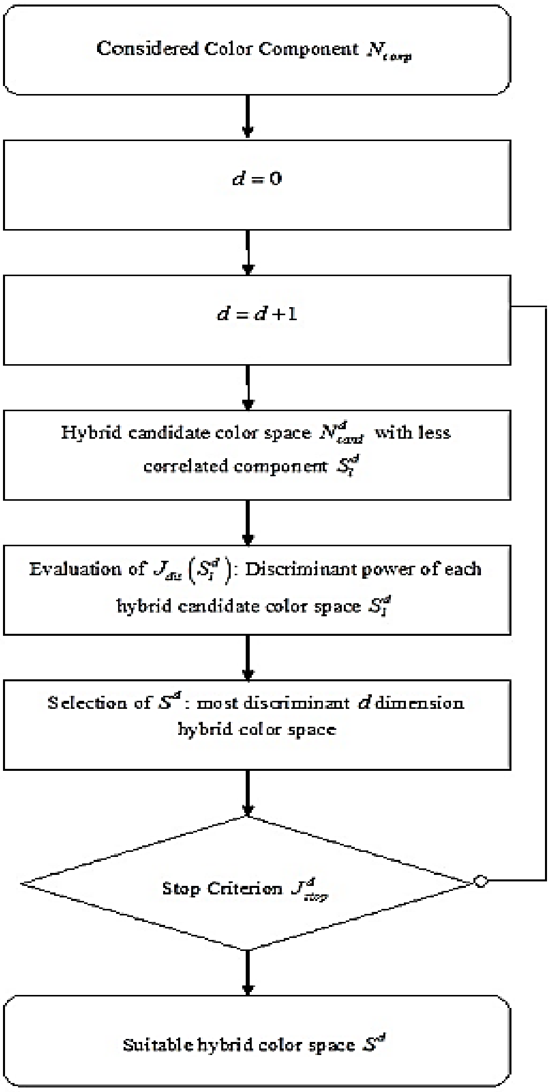

Figure 2. Iterative process of building suitable hybrid color space

In 8 represents the separability measurement between clusters was evaluated based on inter class dispersion matrix $B(S_l^d)$:

$$B(S_l^d) = \frac{1}{Nclass} \sum_{j=1}^{Nclass} (M_j - M)(M_j - M)^T \tag{8}$$

The discriminating power $J_{dis}(S_l^d)$ of each color component S_l^d was computed by trace criterion, at this end can be expressed by (9):

$$Jdis(S_l^d) = trace((W(S_l^d) + B(S_l^d))^{-1} W(S_l^d) = trace(T(S_l^d) W(S_l^d)) \tag{9}$$

where $T(S_l^d) = W(S_l^d) + B(S_l^d)$ designates total dispersion matrix. For each d rank iteration of proposed procedure, most discriminating hybrid color space S_l^d is the space constituted by components that maximize the $J_{dis}(S_l^d)$ criterion.

3. COLOR IMAGE SEGMENTATION PROCEDURE

The main idea of background suppression is to compare each image with a model of the background which is the reference image. Each pixel$pi$of the candidate image is compared with the corresponding pixel in the model. In our work, model of pixels density are estimated by Cauchy distribution as shown in (10).

$$F(x, \sigma) = \frac{1}{\pi} \left[\frac{a}{(x-\sigma)^2 + a^2}\right] \tag{10}$$

So for each pixel in the background, referring to the history of its intensity values and for the three densities functions based on Cauchy distributions for three color components representing intensity values (R, G and B) of color space of three dimension, our hybrid color space it is necessary to determine the five probability distributions. To slow the variation of intensities pixel on the scene, in (11) represents expression of the recursive filter to update recursively the background model because of occurred variation of intensities values:

$$B_{t+1} = B_t(1 - \alpha) + I_t \alpha \tag{11}$$

where B_{t+1} and B_t represent two successive intensities values of background pixel and α adaptation coefficient is between 0 and 1. Considering x_t the intensity value of a pixel at a given time t, its membership probability $P(x)$ at this time can be calculated by (12):

$$p(x) = \frac{1}{N} \sum_{i=1}^{N} \prod_{j=1}^{d} \left[\frac{a}{\pi(xtj - xij)^2}\right] \tag{12}$$

where$N$is the dimension of the training sample, $d$the dimension of the color space. According estimated probability and appropriate threshold, each pixel is classified into pixel of background or moving pixel.

4. EXPERIMENTAL RESULTS AND DISCUSSION

4.1. Partial data learning

We have implemented the proposed algorithm with many learning sample. in a first step we have randomly selected Nw pixels which represent various clusters that will be specified, so that for each cluster Cj, we considered a randomly sample constituted by the most representative 350 pixels of five images that represent the treated class, which gives a total amounts of pixels designed by $Nw = 350 * 5$ chosen randomly. After building the learning matrix$X$with observations in several color components which we will choose the most discriminating one. We denote that the results of this algorithm it's not stable in fact the small sample of learning pixels lead to uncertainly chromatic level. The most frequently obtained components are L(Luv), L(Lab), Y(YUV), Y(YIQ).

4.2. Full data learning

The second step consists to take account all pixels that constitute the learning image of each cluster, but pixels number related of each image they are not uniform. Thus, we consider Nb the low number of pixels that represent all learning image, taken account the size of handled sample we have extended the sets of data and then build Nw pixels constituted by $Nb * 5$ for each cluster Cj. The hybrid colour component brought out by this algorithm is Y(XYZ), v(Luv), S(HSL).

4.3. Data fusion theory

The mainly idea of this subsection is reducing number of interesting pixels, and thereafter reducing the learning matrix X, indeed the considered number of interesting pixels to be learned for each cluster is enough wide, let $Nw = Nb * 5$ where Nb equal to 1123, since we have two clusters, each row of learning matrix X contains $Nb * 5 * 2 = 11230$ pixels for each color component. For cluster Cj the N $b$interesting pixels corresponding of one image among the five others, are merged with the four Nb pixels issued from the other image, thus we have $Nb = Nw$ for each cluster Cj instead of $Nw = Nb * 5$, let $Nb * 2$ pixels number for two clusters and for each chromatic level instead of $Nb * 5 * 2$.

The essential value that we seek to calculate is the likelihood function $p(x|\theta)$, where$x$is a vector constituted by the aggregated information from different sources, and θ a real feature of the estimated system. To reach convincing fusion results we have to maximize this likelihood function [23, 24], assume that the data sources are conditionally independent.

The optimal parameters vector$\theta^*$for n sources is defined by (13):

$$\theta^* = \frac{\sum_{s=1}^{n} \sigma_s^{-1} * Xs}{\sum_{s=1}^{n} \sigma_s^{-1}} \tag{13}$$

where $\theta^*$is the estimation maximum likelihood of θ where σ_s is the variance related to the source measurement s and Xs is the observation provided by the same source. The applied procedure based on data fusion algorithm [25], allows selecting six hybrid chromatic levels, $Y(XYZ)$, $u(Luv)$, $L(HSL)$, $G(RGB)$, $S(HSL)$ and $V(YUV)$. Finally, to evaluate the effectiveness of our proposed approach for hybrid chromatic level section by iterative algorithm, we have used a non-parametric segmentation technique based on Cauchy distribution to learn the historical intensity state of each pixel belonging to background. Figures 3 and 4 show the effectiveness of obtained results.

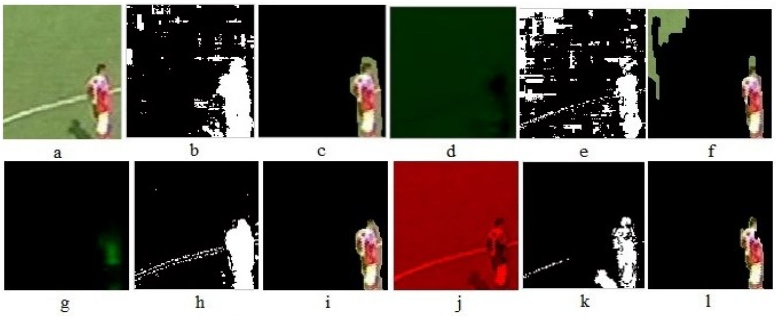

Figure 3. Original image of the first cluster. (a), (b) and (c): segmented image in RGB space.
(d), (e) and (f): segmentation results with full learning pixels.
(g), (h), (i), (j), (k) and (l): segmentation results with pixels fusion

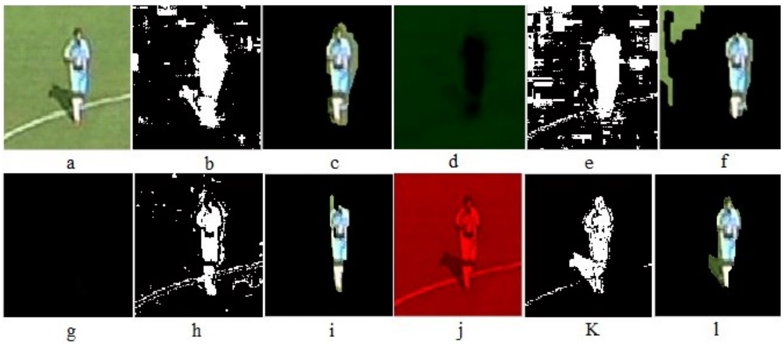

Figure 4. Original image of the second cluster; (a), (b) and (c): segmented image in RGB space.
(d), (e) and (f): segmentation results with full learning pixels.
(g), (h), (i), (j), (k) and (l): segmentation results with pixels fusion

5. CONCLUSION

In this paper we presented a segmentation method by statistical subtraction of the background, the new technique uses the Cauchy distribution to model and subtract the density of the background pixel intensity, the handled image are coded in hybrid color space based on supervised and iterative algorithm that use two ways to select significant chromatic level, the first one consists to learn respectively the partial and full amount of pixels, the second one consist to use the data fusion theory. Therefore, the proposed algorithm is suitable for many applications based on color information.

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BIOGRAPHIES OF AUTHOR

Mourad Moussa was born in Ben Arous, Tunisia in 1977. He received the Master degree in Automatic from the "Ecole Nationaled Ingnieurs de Monastir" in 2006 and the Ph.D. degree in Electrical Engeneering from the same school in 2011. He is currently an Assistant Professor in Signal and Image Processing at Sciences faculty of Gafsa. He is also a Researcher at the Networked Objects, Control and Communication Systems (NOCCS) Research Laboratory, National Engineering School of Sousse. His research is related to Image and video Processing, Machine learning.