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Progress in Pattern Recognition, Image Analysis, Computer Vision, and Applications

15th Iberoamerican Congress on Pattern Recognition, CIARP 2010
São Paulo, Brazil, November 8-11, 2010
Proceedings
Pattern recognition is a central topic in contemporary computer sciences, with continuously evolving topics, challenges, and methods, including machine learning, content-based image retrieval, and model- and knowledge-based approaches, just to name a few. The Iberoamerican Congress on Pattern Recognition (CIARP) has become established as a high-quality conference, highlighting the recent evolution of the domain.

These proceedings include all papers presented during the 15th edition of this conference, held in São Paulo, Brazil, in November 2010.

As was the case for previous conferences, CIARP 2010 attracted participants from around the world with the aim of promoting and disseminating ongoing research on mathematical methods and computing techniques for pattern recognition, computer vision, image analysis, and speech recognition, as well as their applications in such diverse areas as robotics, health, entertainment, space exploration, telecommunications, data mining, document analysis, and natural language processing and recognition, to name only a few of them. Moreover, it provided a forum for scientific research, experience exchange, sharing new knowledge and increasing cooperation between research groups in pattern recognition and related areas.

It is important to underline that these conferences have contributed significantly to the growth of national associations for pattern recognition in the Iberoamerican region, all of them as members of the International Association for Pattern Recognition (IAPR).

The scientific program included a tutorial day, with three topics addressed: an introduction to kernel machines, by Stéphane Canu; multimodal human–computer interaction for mobile computing, by Matthew Turk; and soft computing, f-granulation and pattern recognition, by Sankar Pal. We warmly thank the three speakers for having agreed to give these tutorials.

The next three days were organized in a single-track conference, with invited talks, oral presentations, and posters. We were very pleased to welcome four distinguished invited speakers: Alexandre Falcão on design of pattern classifiers using optimum-path forest with applications in image analysis; Stéphane Canu on recent advances in kernel machines; Matthew Turk on computational illumination; and Seth Hutchinson speaking on vision-based control of robot motion. We are very grateful and would like to thank them. The oral and poster sessions included 70 papers selected from 145 submissions. All submissions were double-blind reviewed by at least two reviewers. We thank all reviewers, who provided high-quality reviews in a short time.

To enhance the visibility of the best submissions and to stimulate further good scientific papers, some authors will be invited to submit an enhanced version of
their paper to a special issue of International Journal of Pattern Recognition and Artificial Intelligence, to be published in 2012.

In addition, an award, consisting of a cash prize, a trophy and a certificate, was given to the author(s) of the Best Paper registered and presented at CIARP 2010. The aim of this award is to acknowledge and encourage excellence and originality of new models, methods and techniques with an outstanding theoretical contribution and practical application to the field of pattern recognition and/or data mining. The selection of the winner was based on the wish of the author to be considered to the prize, the evaluation and recommendations from members of the Program Committee and the evaluation of the IAPR-CIARP Award Committee. This committee, carefully chosen to avoid conflicts of interest, evaluated each nominated paper in a second review process, which included the quality of the oral and/or poster presentation.

The conference was organized by the University of Sao Paulo. We would like to thank all participants of the organizing committee and auxiliary committee, at USP and UFABC, for their tremendous work, which made the conference a success.

Finally, we would like to thank all authors and participants, who contributed to the high quality of the conference and scientific exchanges.

November 2010

Isabelle Bloch

Roberto M. Cesar-Jr.
CIARP 2010 was organized by the Institute of Mathematics and Statistics—IME-USP, Brazil, and Telecom ParisTech, France; endorsed by the International Association for Pattern Recognition (IAPR); and sponsored by several scientific societies listed below.

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Table of Contents

Invited Talks

Recent Advances in Kernel Machines .................................................. 1
Stéphane Canu

Design of Pattern Classifiers Using Optimum-Path Forest with Applications in Image Analysis .................................................. 2
Alexandre X. Falcão

Vision-Based Control of Robot Motion ................................................. 3
Seth Hutchinson

Soft Computing, F-Granulation and Pattern Recognition ....................... 4
Sankar K. Pal

Computational Illumination .............................................................. 5
Matthew Turk

Color, Shape and Texture

Color Texture Analysis and Classification: An Agent Approach Based on Partially Self-avoiding Deterministic Walks ........................................ 6
André Ricardo Backes, Alexandre Souto Martinez, and Odemir Martinz Bruno

Characterizing 3D Shapes Using Fractal Dimension ................................ 14
André Ricardo Backes, Daulo Medeiros Eler, Rosane MInghim, and Odemir Martinez Bruno

Multiresolution Histogram Analysis for Color Reduction ...................... 22
Giovana Ramella and Gabriella Sanniti di Baja

Graphs and Hypergraphs

Graph of Words Embedding for Molecular Structure-Activity Relationship Analysis .......................................................... 30
Jaume Gibert, Ernest Valveny, and Horst Bunke

A Hypergraph Reduction Algorithm for Joint Segmentation and Classification of Satellite Image Content ........................................... 38
Alain Bretto, Aurélien Ducournau, and Soufiane Rital

A Static Video Summarization Method Based on Hierarchical Clustering .......................................................... 46
Silvio Jamil F. Guimarães and Willer Gomes
Biomedical Imaging

Histopathological Image Classification Using Stain Component Features on a pLSA Model .............................................. 55
Gloria Díaz and Eduardo Romero

Modified Expectation Maximization Algorithm for MRI Segmentation ......................................................... 63
Ramiro Donoso, Alejandro Veloz, and Héctor Allende

Generation of Synthetic Multifractal Realistic Surfaces Based on Natural Models and Lognormal Cascade: Application to MRI Classification ......................................................... 71
Mohamed Khider, Abdelmalik Taleb-Ahmed, and Boualem Haddad

Retrieval, Mining and Learning

Content-Based Emblem Retrieval Using Zernike Moments ......................................................... 79
Ezequiel Curra, Mariano Tepper, and Marta Mejail

A New Algorithm for Training SVMs Using Approximate Minimal Enclosing Balls ......................................................... 87
Emanuele Frandi, Maria Grazia Gasparo, Stefano Lodi, Ricardo Nanceuf, and Claudio Bartori

A Hybrid Face Recognition Approach Using GPUMLib ......................................................... 96
Noel Lopes and Bernardeste Ribeiro

Learning, Recognition and Clustering

Self-training for Handwritten Text Line Recognition ......................................................... 104
Volkan Frimen and Horst Bunke

Improving the Dynamic Hierarchical Compact Clustering Algorithm by Using Feature Selection ......................................................... 113
Reynaldo Gil-García and Aurora Pons-Porrata

Background Division, A Suitable Technique for Moving Object Detection ......................................................... 121
Walter Izquierdo-Guerra and Edel García-Reyes

Bayesian and Statistical Methods

Concept Formation Using Incremental Gaussian Mixture Models ......................................................... 128
Paulo Martins Engel and Milton Roberto Heinen

Integrating Phonological Knowledge in ASR Systems for Spanish Language ......................................................... 136
Javier Mike Olano and María Inés Torres

Inference of Restricted Stochastic Boolean GRN’s by Bayesian Error and Entropy Based Criteria ......................................................... 144
David Correa Martins Jr., Evaldo Araújo de Oliveira, Vitor Hugo Louzada, and Ronaldo Funio Hashimoto

Coding and Compression, Video, Tracking

Grid Smoothing: A Graph-Based Approach ......................................................... 153
Guillaume Noel, Karim Djonou, and Yskandar Hamam

A Quality Analysis on JPEG 2000 Compressed Leukocyte Images by Means of Segmentation Algorithms ......................................................... 161
Alexander Ralcón-Ruíz, Juan Paz-Viera, Alberto Taboada-Crispi, and Hichem Sahli

Comments on Matrix-Based Secret Sharing Scheme for Images ......................................................... 169
Essam Elsheikh and A. Ben Hamza

A Very Low Bit-Rate Minimalist Video Encoder Based on Matching Pursuits ......................................................... 176
Vitor de Lima and Helio Pedrini

An Unified Transition Detection Based on Bipartite Graph Matching Approach ......................................................... 184

A New Dissimilarity Measure for Trajectories with Applications in Anomaly Detection ......................................................... 193
Dustin L. Espinosa-Isidrón and Edel B. García-Reyes

Modelling Postures of Human Movements ......................................................... 202
Djamila Medjahed Gomaz, Houssem Eddine Gueziri, and Nazim Huachaine

Detection and Tracking of Driver’s Hands in Real Time ......................................................... 212
Raúl Crespo, Isaac Martín de Diego, Cristina Conde, and Enrique Cabello

Speech, Natural Language, Document

Speaker Verification in Noisy Environment Using Missing Feature Approach ......................................................... 220
Dayana Ribas, Jesús A. Villalba, Eduardo Lleida, and José R. Calvo
Fast k-NN Classifier for Documents Based on a Graph Structure .......................... 228
Fernando José Artigas-Fuentes, Reynaldo Gil-García, José Manuel Badía-Contelles, and Aurora Pons-Porrata

Comparative Analysis between Wavelets for the Identification of Pathological Voices ......................................... 236
Nathalie Cavalcanti, Sandro Silva, Adriano Bresolin, Heliana Bezerra, and Ana Maria G. Guerreiro

Comparison of HMM and DTW for Isolated Word Recognition System of Punjabi Language ........................................... 244
Kumar Raveendar

A Combination of Classifiers for the Pronominal Anaphora Resolution in Basque .......................................................... 253
Ana Zelasia Jauregi, Basilio Sierra, Olatz Arrregi Uriarte, Klaru Ceberio, Arantza Díez de Illurrazza, and Iakes Goenaga

Text Segmentation by Clustering Cohesion .................................................. 261
Raúl Abella Pérez and José Eladio Medina Pagola

Multiple Clues for License Plate Detection and Recognition ........................................ 269
Pablo Negri, Mariano Tepper, Daniel Acevedo, Julio Jacobo, and Marta Mejail

Image Filtering and Segmentation

Non Local Image Denoising Using Image Adapted Neighborhoods ................... 277
Álvaro Pardo

Pablo Meza, César San Martín, Esteban Vera, and Sergio Torres

Vessel Centerline Tracking in CTA and MRA Images Using Hough Transform .................................................. 295
Maysa M.G. Macedo, Choukri Mekkaoui, and Marcel P. Jackowski

Automatic Image Segmentation Optimized by Bilateral Filtering ................. 303
Javier Sánchez, Estibaliz Martinez, Agueda Arquero, and Diego Renza

Pan-sharpening of High and Medium Resolution Satellite Images Using Bilateral Filtering .................................................. 311
Diego Renza, Estibaliz Martinez, Agueda Arquero, and Javier Sánchez

Color Image Segmentation by Means of a Similarity Function ..................... 319
Rodolfo Alvarado-Cervantes, Edgardo M. Felipe-Riveron, and Luis P. Sánchez-Fernández

Image Segmentation Using Quadtree-Based Similarity Graph and Normalized Cut ........................................ 329
Marco Antonio García de Cervatillo, Anselmo Castelo Branco Ferreira, and André Luis Costa

A Genetic-Algorithm-Based Fusion System Optimization for 3D Image Interpretation ........................................ 338
Lionel Volet, Beatriz S.L.P. de Lima, and Alexandre G. Esvokoff

Feature Extraction, Shape, Texture, Geometry and Morphology

Quaternion Atomic Function Wavelet for Applications in Image Processing ........................................ 346
E. Ulises Moya-Sánchez and Eduardo Bayro-Corrochano

A Complex Network-Based Approach for Texture Analysis ...................... 354
André Ricardo Backes, Dalceimar Casanova, and Odemir Martinez Bruno

Enhancing Gabor Wavelets Using Volumetric Fractal Dimension ................... 362
Álvaro Gomez Zuniga and Odemir Martinez Bruno

Comparison of Shape Descriptors for Mice Behavior Recognition ................ 370
Jonathan de Andrade Silva, Wesley Nunes Gonçalves, Bruno Brandoli Machado, Henerson Pistori, Albert Schiaveto de Souza, and Kleber Padovani de Souza

Ridge Linking Using an Adaptive Oriented Mask Applied to Plant Root Images with Thin Structures ........................................ 378
Tabita Perciano, Roberto Hirata Jr., and Lúcio André de Castro Jorge

Parameter Estimation for Ridge Detection in Images with Thin Structures ........................................ 386
Tabita Perciano, Roberto Hirata Jr., and Lúcio André de Castro Jorge

Experimental Comparison of Orthogonal Moments as Feature Extraction Methods for Character Recognition .................. 394
Miguel A. Duval, Sandro Vega-Pons, and Eduardo Garea

Face Segmentation and Recognition, Biometry

Improving Face Segmentation in Thermograms Using Image Signatures ........ 402
Silve Filipe and Luis A. Alexandre
Color Image Segmentation by Means of a Similarity Function

Rodolfo Alvarado-Cervantes, Edgardo M. Felipe-Riveron, and Luis P. Sanchez-Fernandez

Center for Computing Research, National Polytechnic Institute, Juan de Dios Batiz w/n, Col. Nueva Industrial Vallejo, P.O. 07738, Mexico
Tel.: (52)-55-5729 6000; Ext. 56515
ateramex@gmail.com, edgardo@cic.ipn.mx, lsanchez@cic.ipn.mx

Abstract. An interactive, semiautomatic image segmentation method is presented which, unlike most of the existing methods in the published literature, processes the color information of each pixel as a unit, thus avoiding color information scattering. The process has two steps: 1) The manual selection of few sample pixels of the color to be segmented, 2) The automatic generation of the so called Color Similarity Image (CSI), which is a gray level image with all the tonalities of the selected color. The color information of every pixel is integrated by a similarity function for direct color comparisons. The color integrating technique is direct, simple, and computationally inexpensive. It is shown that the improvement in quality of our proposed segmentation technique and its quick result is significant with respect to other solutions found in the literature.

Keywords: Color image segmentation; Adaptive color similarity function; HSI parameter distances; Morphology in color images.

1 Introduction

Image segmentation consists of partitioning an entire image into different regions, which are similar in some predefined manner. Segmentation is an important feature of human visual perception, which manifests itself spontaneously and naturally. It is also one of the most important and difficult tasks in image analysis and processing [2] [6] [8] [9] [10]. All subsequent steps, such as feature extraction and objects recognition depend on the quality of segmentation. Without a good segmentation algorithm, objects of interest in a complex image are difficult (often impossible) to recognize using automated techniques [1] [2] [7] [8] [10]. At present, several segmentation techniques are available for color images, but most of them are just monochromatic methods applied on the individual planes in different color spaces where the results are combined later in different ways [5]. Their common problem is that when the color components of a particular pixel are processed separately the color information is so scattered in its components that most of the color information is lost [2] [5] [9].

In this work, an interactive, semiautomatic image segmentation method is presented which, in contrast with most of previously published algorithms, uses the color

* Corresponding author.
information for each pixel as a whole, thus avoiding color information scattering. In our method, the three color components (RGB) of every pixel transformed to the HSI
color model are integrated in two steps: in the definitions of distances in hue, saturation
and intensity planes \( [\Delta_h, \Delta_s, \Delta_l] \) and in the construction of an adaptive color
similarity function that combines these three distances assuming normal probability
distributions.

To obtain a consistent color model for direct color comparisons, some simple but
important modifications to the classical HSI color space were necessary. These modi-
fications eliminated the discontinuities occurring in the red hue (in 0 and 360 degrees)
and all the problems associated with them.

The segmentation method proposed basically relies on the calculation of a color
similarity function for every pixel in a RGB 24-bit true color image, its automatic
thresholding and finally the possible application of some simple morphological filters
to introduce geometric characteristics in some cases where it is needed.

2 Previous Works

There has been a considerable amount of research dedicated to the problem of color
image segmentation due to its importance and potential, and because color is an effec-
tive and robust visual cue for differentiating between objects in an image. The current
available techniques and approaches vary widely from extensions of classical mono-
chromatic techniques to mathematical morphology [2], clustering schemes [4] [12],
wavelets [3] and quaternions [11], among others. Until recently, the majority of pub-
lished approaches were based on monochromatic techniques applied to each color
component image in different color spaces, and in different ways to produce a color
composite [5].

Some color similarity measures and distances are presented in [10]. All these
measures compare color pixels as units. They are all based in three dimensional vector
representations of color in which each vector component corresponds to the RGB
color channels components.

A technique that combines geometrical and color features for segmentation extend-
concepts of mathematical morphology (for gray images) is developed in [2] to
process color images. The final segmentation is obtained by fusing a hierarchical
partition image and a text/graphic finely detailed image.

In [15] the authors present a mathematic and physic solid framework for the local
measure of texture in color images. They present a physic based color model using as
a starting point three dimensional energy density functions \( E(x, y, \lambda) \). From these
energy density functions they derive color texture measures in the wavelength – Fou-
rier domain using Gaussian derivative apertures integrating in this way texture and
color information. In their implementation they start with RGB images transforming
them to an opponent Gaussian color space \( (E_h, E_s, E_l) \) by a linear transform where
they process with each channel separately with a set of Gabor filters and integrate
later the results.

3 Description of the Method

The segmentation method proposed in this paper basically relies on the calculation
of a color similarity function for every pixel in a RGB 24-bit true color image to form
what we call a Color Similarity Image (CSI), which is a gray level image. A true color
image usually contains millions of colors and many thousands of them represent the
same perceived color of a single object due to the presence of additive noise, lack of
definition between color borders and regions, shadows in the scene, etc., [1] [8] [10].
The color similarity function proposed allows the clustering of the many thousands
colors representing the same perceived color in a single gray output image. This CSI
image is then automatically thresholded and the output can be used as segmentation
layer, or it can be used with morphological operators to introduce geometric en-
hancements if they are needed.

Firstly, we compute the color centroid and color standard deviation of a small
sample consisting of few pixels. The computed centroid represents the desired color to be
segmented using the technique we designed for that purpose.

Then, our color similarity function uses the color standard deviation calculated
from the pixel sample to adapt the level of color scattering in the comparisons. The
result of a particular similarity function calculation for every pixel and the color cen-
troid (meaning the similarity measure between the pixel and the color representative
value) generates the CSI. The generation of this image is the basis of our method and
preserves the information of the color selected from the original color image. This
CSI is a digital representation of a normalized function \([0 - 1]\) extended to the range
of \([0.0 - 255]\).

The CSI can be thresholded with any automatic method like Otsu’s [13] which was
our selection for the results presented in this work. In those cases where color is a
discriminating characteristic of objects of interest in a source image, only thresholding
the CSI could be necessary to complete the segmentation.

To generate a CSI we need: 1. A color image in RGB 24-bit true color format; and
2. A small set of arbitrarily located pixels forming a sample of the color desired to be
segmented. From this sample of pixels we calculate the statistical indicators according
to our HSI modified color model (see Section 3.1). This information is necessary to
adapt the color similarity function in order to obtain good results. To obtain the CSI
we calculate for every pixel \((i, j)\) in the image the following color similarity function \(S_i,j\):

\[
S_{i,j} = e^{-\frac{\Delta_h^2}{2\sigma_h^2}} * e^{-\frac{\Delta_s^2}{2\sigma_s^2}} * e^{-\frac{\Delta_l^2}{2\sigma_l^2}}
\]  

(1)

where \(\Delta_h\) is the hue Euclidean distance between \(\text{hue}(i, j)\) and the \(\text{average}_\text{hue}\); \(\Delta_s\)
is the saturation Euclidean distance between \(\text{saturation}(i, j)\) and the \(\text{average}_\text{saturation}\); \(\Delta_l\) is the intensity Euclidean distance between \(\text{intensity}(i, j)\) and the \(\text{average}_\text{intensity}\); \(\sigma_h\) is the hue standard deviation of the sample; \(\sigma_s\) is the Saturation standard deviation of the sample; \(\sigma_l\) is the Intensity standard deviation of the sample. In Eq. (1) the color information is integrated giving high importance to
perceptual small changes in hue, as well as giving wide or narrow tolerance to the intensity and saturation values depending on the initial sample, which is representative to the desired color to be segmented.

The common disadvantages attributed to the cylindrical color spaces such as the irremovable singularities of hue in very low saturations or the periodical nature of hue [5] (which is lost in its standard representation as an angle $\in [0^\circ, 360^\circ]$) are overcome in our technique using vector representation in $\mathbb{R}^2$ in the separation of chromatic and achromatic regions, and in the definition of the $\Delta_h$, $\Delta_s$, and $\Delta_l$ distances.

Two modifications on standard HSI color space were necessary in order to create a consistent model to represent colors and color centroids:

1. **Representation of hue.** Instead of standard representation of hue as an angle in the range $[0^\circ, 360^\circ]$, hue is represented here as a normalized vector in $\mathbb{R}^2$ (with magnitude 1 or 0). This representation has at least three advantages compared to an angle in the range $[0^\circ, 360^\circ]$ a) the existing discontinuity in 360 and 0 degrees is eliminated; b) the average hue of a group of pixels can be understood as the resulting angle of a vector addition of the color pixels in the chromatic region of the sample, giving a simple manner to calculate the average hue; c) setting magnitude to 0 or 1 works as a flag intended for distinction between chromatic or achromatic regions.

2. **Separation of chromatic and achromatic regions.** We use a separation of the region as described in [10] in order to calculate the average hue and $\Delta_h$. Once calculated $\Delta_h$, $\Delta_s$, and $\Delta_l$, this distinction is no longer necessary because in the formulation of $S_{ij}$ (Eq. 1) all the cases of color comparison between zones are accounted for and it is a simple matter to maintain consistency. The use of Gaussians in the definition of $S_{ij}$ (Eq. 1) reflects our belief that the color model modifications proposed in this paper allows normal distributions of the color characteristics in this modified HSI space according to the visual experience of color similarity.

The pixel sample is a representation of the desired color(s) to be segmented from a color image. From this pixel sample we obtain two necessary values to feed our segmentation algorithm: the color centroid and a measure of the dispersion from this centroid, in our case the standard deviation. These two values are represented accordingly to our modified HSI model.

The achromatic zone $G$ is the region in the HSI color space where hue is perceived by humans. This means that hue is perceived only as a gray level because the color saturation is very low or intensity is either too low (near to black) or too high (near to white).

Given the three-dimensional HSI color space, we define the achromatic zone $G$ as the union of the points inside the cylinder defined by $Saturation < 10\%$ of $MAX$ and the two cones $Intensity < 10\%$ of $MAX$ and $Intensity > 90\%$ of $MAX$, were $MAX$ is the maximum possible value as presented in [10]. Pixels inside this region are perceived as gray levels.

### 3.1 Calculation of Average Hue

In order to obtain the average of the hue ($H_m$) of several pixels from a sample, we take advantage of the vector representation in $\mathbb{R}^2$. Vectors that represent the hue values of individual pixels are combined using vector addition. From the resulting vector we obtain the average hue corresponding to the angle of this vector respected to the red axis. Thus $H_m$ is calculated in the following manner:

1. For every pixel $P(x, y)$ in the sample the following $\mathbb{R}^3$ to $\mathbb{R}^2$ transformation is applied:

$$V_1(P) = \begin{bmatrix} 1 - \cos(\pi / 3) & -\cos(\pi / 3) \\ \sin(\pi / 3) & -\sin(\pi / 3) \end{bmatrix} \begin{bmatrix} R \\ G \end{bmatrix} = \begin{bmatrix} f \\ y \end{bmatrix} \quad \text{if } P \in G \quad (2)$$

and $V(P) = V_1(P) / |V_1(P)|$;

In other case:

$$V(P) = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \quad \text{if } P \notin G$$

where $V(P)$ is the normalized projection of the RGB coordinates of the pixel $P$ to the perpendicular plane to the Intensity axis of the RGB cube when the x axis is collinear to the Red axis of the chromatic circle. On the other hand $G$ (see Section 3) represents the achromatic zone in the HSI space and $[RGB]^t$ is a vector with the color components of the pixel in the RGB color space.

To carry out this, the following code is executed:

```plaintext
Vector.x = 0; Vector.y = 0; // initialize vectors
For (i = 1; i <= n; i++) // for every pixel in the sample do
{
    (Vector.x = Vector.x + V(i).x); // x-component of the
    Vector.y = Vector.y + V(i).y); // y-component of the
    accumulated vector
    Vs = [Vector.x Vector.y]; // Accumulated vector
}
```

In this code we have a vector in $\mathbb{R}^2$, which accumulates the vector additions as index $i$ increments. Each of the vectors being added corresponds to the previous $\mathbb{R}^3$-to-$\mathbb{R}^2$ transformation for every pixel in the sample made in step 1.

2. The angle of the accumulated vector ($V_s$) with respect to the X-axis is the average hue:

$$H_m = \text{angle} (V_s, 0)$$

where 0 represents the Red axis.
Using the vector representation of Hue obtained by the $\mathbb{R}^3$-to-$\mathbb{R}^2$ transformation of RGB space points expressed in Eq. (2), we can calculate the hue distance $\Delta_h$ between two colors pixels or color centroids $C_1$ and $C_2$, as follows:

$$\Delta_h(C_1, C_2) = |V_1 - V_2|$$

$$= 0$$

if $C_1$ and $C_2 \notin G$

if $C_1$ or $C_2 \in G$

where $G$ is the achromatic region; $V_1$ and $V_2$ are the vectors in $\mathbb{R}^2$ calculated with the transformation on $C_1$ and $C_2$ given in Eq. (2).

Using the standard conversions for saturation and intensity from RGB space [10], normalized in the range [0, 1]:

$$saturation(P) = 1 - \left[ \frac{3}{R + G + B} \min(R, G, B) \right] .$$

$$intensity(P) = \frac{1}{3} (R + G + B) .$$

we define saturation distance $\Delta_s$ and intensity distance $\Delta_i$ between two pixels or color centroids as:

$$\Delta_s = abs[saturation(C_1) - saturation(C_2)],$$

$$\Delta_i = abs[intensity(C_1) - intensity(C_2)],$$

where $C_1$ and $C_2$ are color pixels or color centroids, respectively, in RGB space.

In Eq. (3) we defined the saturation equal zero in case of the black color.

The statistical values needed in Eq. (1) are calculated as follows [14]:

$$Saturation\_average = S_c = \frac{1}{n} \sum_{i=0}^{n} saturation(i) .$$

$$Intensity\_average = I_c = \frac{1}{n} \sum_{i=0}^{n} intensity(i) .$$

$$Hue\_standard\_deviation = \sigma_h = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \Delta_h^2(i)} .$$

$$Saturation\_standard\_deviation = \sigma_s = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \Delta_s^2(i)} .$$

$$Intensity\_standard\_deviation = \sigma_i = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \Delta_i^2(i)} .$$

where $n$ is the number of pixels in the sample; $\Delta_h$ is the hue distance between $hue(i,j)$ and $hue\_average$; $\Delta_s$ is the saturation distance between $saturation(i,j)$ and $saturation\_average$; $\Delta_i$ is the intensity distance between $intensity(i,j)$ and $intensity\_average$.

4 Results and Discussion

In this section we present the results of our segmentation method applied to two classical color images in RGB 24-bit true color format that are representative of many image processing and analysis applications. These experiments consisted of the segmentation of color regions according to the following three steps:

1) Selection of the pixel sample. In order to have a helping direction for this task the following considerations may be useful to select the number of pixels of the sample: If the color of the desired area to segment is solid (without additive noise) it is only necessary to have one pixel sample from the desired area. However, if we want to take in account the color lack of definition happening in the borders, we have to take a sample of the new colors that appear in that area due to the above condition. The pixels of the samples from the original images can be selected arbitrarily, that is, in any order, in any number and physically adjacent or not.

2) CSI calculation. This step is automatic; its output is a gray level image showing the similarity of each pixel of the RGB true color image to the color centroid formed with the chosen pixel sample taken from of the region of interest to be segmented, being white for 100% of similarity and black for 0%.

3) Thresholding and application of mathematic morphology. The user can threshold now the CSI and could be arranged as an automatic step by using, for example, the non-supervised Otsu's thresholding method [13]. After this step we can apply optionally any desired morphological tool if the thresholding results are not solid enough or geometric characteristics are needed to correctly separate the objects of interest.

Figure 1 shows a RGB color image (sized 200 x 200 pixels and with 33753 different colors) of the popular image of the baboon. In this image we can see four main hues of colors despite the many thousands of actual RGB values to represent them: The red part of the baboon's nose, the blue part of the nose, the orange eyes and the yellow-orange part of the fur.

Different pixel tonalities in the image depend on their particular saturation and on the unavoidable presence of additive noise. The proposed segmentation method is
practically immune to these conditions, although obviously there are some solutions to improve the quality of the segmented regions, as for example, preprocessing the image for smoothing noises of different types, applying some morphological operator to reduce objects with given characteristics, and so on.

In this experiment we took pixel samples for the blue color belonging to the edge of the perceived blue color. They are selected from an enlarged 21 x 21 pixels region as shown in Fig. 2. From this sample we calculated the color centroid and the standard deviation in our modified HSI space; with these two values we use the Eq. 1 to calculate for every pixel the pixel values of the CSI shown in Fig. 3. After applying Otsu’s thresholding method and an area closing with a box of 3x3 to eliminate small holes, we obtain the final segmentation shown in Fig. 4.

For the blue part of the nose we repeated part of the process. Figure 5 shows the pixels sample, its corresponding CSI is shown in Fig. 6 and after applying Otsu’s thresholding, an opening with a box of 3x3, a closing with the same box and eliminating remaining small areas, the final segmentation is shown in Fig. 7.

In Fig. 8 we show the pixel sample and in Fig. 9 the CSI for the orange color of the eyes. After thresholding the CSI, applying an opening with a disk 5x5 and eliminating the big area of the fur we obtain the final segmentation of the eyes shown in Fig. 10. The yellow-orange part of the fur shown in Fig. 11 was obtained as residue from the thresholding of the CSI and shown together in the composite of the segmentations of Fig. 4, 7 and 10.

5 Conclusions

The results in the previous section, demonstrate that the color segmentation method presented in this paper offers a useful and efficient alternative for the segmentation of objects with different colors in relatively complex color images with good performance in the presence of the unavoidable additive noise. The steps required to obtain a good segmentation of regions with different colors by using the proposed methodology are usually straightforward, simple and repetitive. If color is a discriminative characteristic in the layer of interest, only the selection of a given threshold to the color similarity function CSI is needed to obtain a good segmentation result. From many experiments we have observed that a good percentage of colors were obtained in a straightforward way only by thresholding the so called Color Similarity Image. In our method, the three RGB color components of every pixel transformed to the HSI color model are integrated in two steps: in the definitions of the Euclidean distances $[\Delta_h, \Delta_s, \Delta_l]$ in hue, saturation and intensity planes and in the construction of an adaptive color similarity function that combines these three distances assuming normal probability distributions. Thus the complexity is linear ($O(n)$) with respect to the number of pixels $n$ of the source image. The method discriminates whichever type of different color objects independently on their shapes and tonalities in a very straightforward way.

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On Combining Local DCT with Preprocessing Sequence for Face Recognition under Varying Lighting Conditions
Heydi Méndez-Vázquez, Josef Kittler, Chi-Ho Chan, and Edel García-Reyes

410

On Improving Dissimilarity-Based Classifications Using a Statistical Similarity Measure
Song-Woon Kim and Robert P.W. Duin

418

A Rotation Invariant Face Recognition Method Based on Complex Network
Wesley Nunes Gonçalves, Jonathan de Andrade Silva, and Odemir Martinez Bruno

426

Illumination Invariant Face Image Representation Using Quaternions
Dayron Rizo-Rodríguez, Heydi Méndez-Vázquez, and Edel García-Reyes

434

A Contrario Detection of False Matches in Iris Recognition
Marcelo Mottalli, Mariano Tepper, and Marta Mejía

442

Statistical Approaches, Learning, Classification, Mining

A Functional Density-Based Nonparametric Approach for Statistical Calibration
Noslen Hernández, Rolando J. Biscay, Nathalie Villa-Vialaneix, and Isneri Talavera

450

Feature Extraction Using Circular Statistics Applied to Volcano Monitoring
César San-Martín, Carlos Melgarco, Claudio Gallegos, Gustavo Soto, Millary Curilem, and Gustavo Fuentesalba

458

Improving the Accuracy of the Optimum-Path Forest Supervised Classifier for Large Datasets
César Castelo-Fernández, Pedro J. de Rezende, Alexandre X. Falcão, and João Paulo Papa

467

Assessment of a Modified Version of the EM Algorithm for Remote Sensing Data Classification
Thales Sehn Korting, Luciano Vieira Dutra, Guaraci José Erthal, and Leila Maria Garcia Fonseca

476

A Sequential Minimal Optimization Algorithm for the All-Distances Support Vector Machine
Diego Candel, Ricardo Nanculef, Carlos Concha, and Héctor Allende

484

Aerosol Optical Thickness Retrieval from Satellite Observation Using Support Vector Regression
Thi Nhat Thanh Nguyen, Simone Mentoveanu, Piero Campalani, Mario Capecchi, and Maurizio Bottini

492

An Overproduce-and-Choose Strategy to Create Classifier Ensembles with Tuned SVM Parameters Applied to Real-World Fault Diagnosis
Esteban Dazzi Wandelokem, Flávio M. Varejão, and Thomas W. Rauber

500

Multi-Objective Semi-Supervised Feature Selection and Model Selection Based on Pearson’s Correlation Coefficient
Frederico Coelho, Antonio Padua Braga, and Michel Verleysen

509

Introducing ROC Curves as Error Measure Functions: A New Approach to Train ANN-Based Biomedical Data Classifiers
Raúl Ramos-Pollán, Miguel Ángel Guevara-López, and Eugénio Oliveira

517

Partition Selection Approach for Hierarchical Clustering Based on Clustering Ensemble
Sandro Vega-Pons and José Ruiz-Shulcloper

525

The Imbalanced Problem in Morphological Galaxy Classification
Jorge de la Calleja, Gladis Huerta, Olac Fuentes, Antonio Benítez, Eduardo López Domínguez, and Ma. Auxiliadora Medina

533

Exploiting Contextual Information for Image Re-ranking
Daniel Carlos Guimarães Pedronette and Ricardo da S. Torres

541

Assessing the Role of Spatial Relations for the Object Recognition Task
Annette Morales-González and Edel García-Reyes

549

Automatic Representation of Semantic Abstraction of Geographical Data by Means of Classification
Rainer Larin Fonseca and Eduardo Garea Llanoo

557

Author Index

569
References

Author Index

Acevedo, Daniel 269
Alexandre, Luís A. 402
Allende, Héctor 63, 484
Alvarado-Cervantes, Rodolfo 319
Arquer, Agueda 303, 311
Arregi Uriarte, Olatz 253
Artigas-Fuentes, Fernando José 228
Backes, André Ricardo 6, 14, 354
Badía-Contelles, José Manuel 228
Bayro-Corrochano, Eduardo 346
Ben Hamza, A. 169
Benitez, Antonio 533
Bertocci, Heliana 236
Biscay, Rolando J. 450
Bottoni, Maurizio 492
Braga, Antonio Padua 509
Bresolin, Adriano 236
Brett, Alain 38
Bruno, Odemir Martinez 6, 14, 354, 362, 426
Bunke, Horst 30, 104
Cabello, Enrique 212
Calvo, José R. 220
Campalani, Piero 492
Candel, Diego 484
Canu, Stéphane 1
Casanova, Dalcimar 354
Castelo-Fernández, César 467
Cavalcanti, Náthalee 236
Cavicchi, Mario 492
Ceberio, Klara 253
Chan, Chi-Ho 410
Coelho, Frederico 509
Concha, Carlos 484
Conde, Cristina 212
Costa, André Luis 329
Crespo, Raúl 212
Cura, Ezequiel 79
Curilem, Millaray 458
da Silva, Henrique Batista 184
da S. Torres, Ricardo 541
de Andrade Silva, Jonathan 370, 426
de Carvalho, Marco Antonio Garcia 329
de Castro Jorge, Luís André 378, 386
de Diego, Isaac Martín 212
de la Calleja, Jorge 533
de Lima, Beatriz S.L.P. 338
de Lima, Vitor 176
de Oliveira, Evaldo Araújo 144
de Rezende, Pedro J. 467
de Souza, Albert Schiaveto 370
de Souza, Kleber Jacques Ferreira 184
de Souza, Kleber Padvani 370
Díaz, Gloria 55
Díaz de Illarrazu, Arantza 253
Djouani, Karim 153
Domínguez, Eduardo López 533
Donoso, Ramiro 63
do Patrocínio Jr., Zenilton
Kleber Gonçalves 184
Ducournau, Aurélien 38
Duin, Robert P.W. 418
Dutra, Luciano Vieira 476
Duval, Miguel A. 394
Eler, Danilo Medeiros 14
Elshah, Esam 169
Engel, Paulo Martins 128
Erthal, Guaraci José 476
Espinosa-Isidrón, Dustin L. 193
Evansoff, Alexandre G. 338
Falcão, Alexandre X. 2, 467
Falcón-Ruiz, Alexander 161
Felipe-Riveron, Edgardo M. 319
Ferreira, Anselmo Castelo Branco 329
Filipe, Silvio 402
Fonseca, Leila Maria Garcia 476
Fonseca, Rainer Larin 557
Frandi, Emanuele 87
Frinken, Volkmar 104
Fuentesalba, Gustavo 458
Fuentes, Olac 533
Gallegos, Claudio 458
García-Reyes, Edel B. 121, 193, 410, 434, 549