A Colour Space Selection Scheme dedicated to Information Retrieval Tasks

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Abstract. The choice of a relevant colour space is a crucial step when dealing with image processing tasks (segmentation, graphic recognition…). From this fact, we address in a generic way the following question: What is the best representation space for a computational task on a given image? In this article, a colour space selection system is proposed. From a RGB image, each pixel is projected into a vector composed of 25 colour primaries. This vector is then reduced to a Hybrid Colour Space made up of the three most significant colour primaries. Hence, the paradigm is based on two principles, feature selection methods and the assessment of a representation model. The quality of a colour space is evaluated according to its capability to make colour homogenous and consequently to increase the data separability. Our framework brings an answer about the choice of a meaningful representation space dedicated to image processing applications which rely on colour information. Standard colour spaces are not well designed to process specific images (ie. Medical images, image of documents) so a real need has come up for a dedicated colour model.

1 Introduction

Colour representation is the basement of all colour image processing applications. In fact, many colour spaces were developed for graphics and digital image processing such as Red, Green, Blue (RGB) and Hue, Saturation. Intensity (HSI). Nevertheless, it is obvious that the performance of any colour-dependent system is highly influenced by the colour model it uses. The quality of a colour model is defined by its capacity to correctly distinct colour between them while being robust to variations inside a given chromatic cluster such as light changes. In term of datamining, this problem can be addressed as maximizing the distance inter-classes while minimizing the distance intra-class. These two criteria seem to be conflicting, which represents a real challenge to any colour representation scheme. Many information retrieval applications would benefit for a better representation space. The paper is organized as follows: In the second section, the question of finding the best colour space is introduced with a review of the related work. Thirdly, the global concept is described explaining the methodology of our contribution. Then, the fourth section presents the feature selection methods in use in this paper. The fifth section presents experimental results on colour classification according different colour models, in addition a

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comparative study on cadastral map segmentation is presented. Finally, a conclusion is given and future works are brought in section 5.

2 Related Work

In this section, reference to previous works on this field of science is done starting by classical colour spaces to finally present the selection of colour components.

2.1 Standard Colour Spaces

Most of acquisition devices, such as digital cameras or scanners, process signals in the RGB format. This is why RGB space is widely used in the applications of image processing. The R primary in RGB corresponds to the amount of the physical reflected light in the red band. However, RGB representation has several drawbacks that decrease the performance of the systems which depend on it. RGB space is not uniform; the relative distances between colours do not reflect the perceptual differences. Therefore, HSI space has been developed as a closer representation to the human perception system, which can easily interpret the primaries of this space. In HSI space, the dominant wavelength of colour is represented by the hue component. The purity of colour is represented by the saturation component. Finally, the darkness or the lightness of colour is determined by the intensity component. Eq.(1) shows the transformation between RGB and HSI spaces [1].

$$
\begin{aligned}
I &= \frac{1}{3}(R+G+B) \\
S &= 1-\frac{3}{R+G+B}[min(R,G,B)] \\
H &= \begin{cases} \theta & B \leq G \\ 360-\theta & B > G \end{cases} \\
& where\theta = \cos^{-1}\left\{\frac{0.5[(R-G)+(R-B)]}{\sqrt{(R-G)^2+(R-B)(G-B)}}\right\}
\end{aligned}
\tag{1}
$$

Although the HSI space is suitable for lots of applications based on colour images analysis, this colour space presents some problems. For example, there are non-avoidable singularities in the transformation from RGB to HSI, as shown in Eq.(1). The XYZ colour space developed by the International Commission on Illumination (CIE) in 1931 [2] is based on direct measurements of the human eye, and serves as the basis from which many other colour spaces are defined. The YUV colour is used in the PAL system of colour encoding in analogical video, which is part of television standards. The YUV model defines a colour space in terms of one luminance and two chrominance components. Another alternative of YUV is the YIQ which is used in the NTSC TV standard. On the other hand, Ohta, Kanade, and Sakai [3] have selected a set of "effective" colour features after analyzing 100 different colour features which have been used in segmenting eight kinds of colour images. Those selected colour features are usually names as I1I2I3 colour model. XYZ, YUV and I1I2I3 are non-uniform colour spaces; therefore CIE has recommended CIE-Lab and CIE-Luv as uniform colour spaces, as they are non-linear transformation of RGB space [4].

2.2 Hybrid Colour Spaces

Recently, the question of finding the best colour representation has generated a rich literature. In [5], a standard colour space is picked-up specifically for a given image however the process involved does not consider the possibility to combine colour components from several spaces. To solve this problem, in [6], dominant features from different colour spaces are selected to construct a DHCS (Decorrelated Hybrid Colour Space). A Principal Component Analysis (PCA) is performed from the covariance matrix composed with the total number of the candidate primaries. The 3 most significant axis are selected to reduce rate of correlation between colour components. On the other hand, our approach aims to maximise one criterion which is the colour recognition rate (Eq 2) while others methods [7] try to compromise indices (compacity and classes dispersion) in order to assess the suitability of a colour model.

$$\text{Rec} = \frac{\#\,\text{Correctly Classified Colour Pixels}}{\#\,\text{Colour Pixels}} \qquad \text{(Eq 2)}$$

These indices represent two competitive constraints, in other word, two conflicting objectives, the improvement of one of them leads to the deterioration of the other. Each image is like no other, so it deserves a dedicated colour representation. We believe, it is hardly possible to generalize the colour pixel distribution for a given image set. So it seems unlikely feasible to apply the same colour space on all the images contained in a database. Each image must be considered independently. in [8], soccer players are classified, according to their colour information, using supervised learning techniques, this training stage supposed to dispose of the user ground truth which is not often the case, and limit the flexibility of the system. Our framework is generic since it relies on a parsimonious use of machine learning algorithms. Furthermore, we handle different feature selection methods, we take advantages of their different ways to reach a single goal.

3 Methodology

The main architecture of our framework is presented in figure 1. It starts from an RGB image where each pixel is projected into nine standard colour spaces in order to build a vector composed of 25 colour components. Let C be a set of colour components. $C = \{C_i\}_{i=1}^{N} = \{R, G, B, I1, I2, I3, L^*, u^*, v^*, ...\}$ with Card(C)=25. From this point, pixels represent a raw database, an Expectation Maximization (EM) clutering algorithm is performed on those raw data in order to label them. Each feature vector is tagged with a label representing the colour cluster it belongs to.

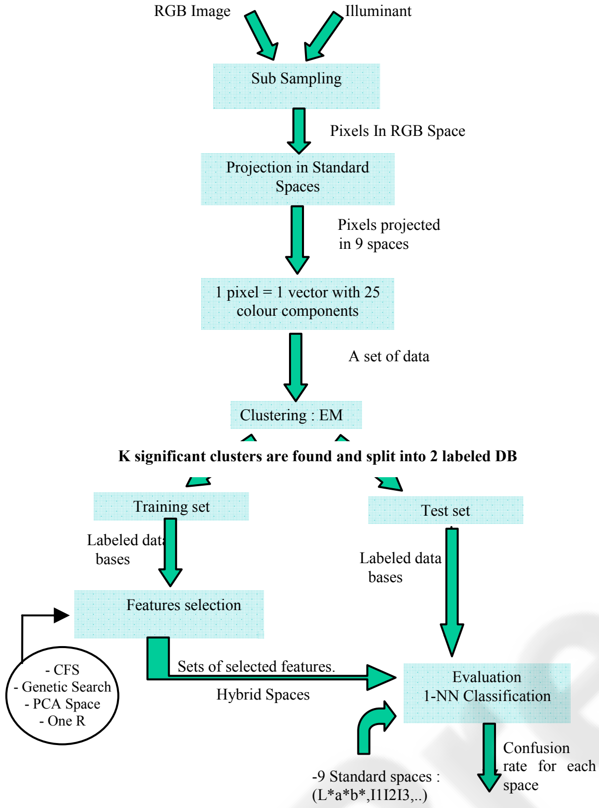

Fig. 1. A framework for colour space selection.

4 Feature Selection Methods

The selection of features is a very active area in recent years, especially in the context of data mining. Indeed, the data mining in very large databases is becoming a critical issue for applications such as image processing, finance, etc. It is important to summarize and intelligently retrieve the "knowledge" from raw data. The data mining is an area based on statistics, machine learning and the theory of databases. The variable selection plays an important role in data mining especially in the preparation of data prior to processing. Indeed, the interests of the variable selection are as follows:

- When the number of variables is just too great learning algorithm can not finish in a good time. The selection reduces the dimension of feature space.
- In terms of artificial intelligence, creating a classifier returns to create a model for the data. However, a legitimate expectation for a model is to be as simple as possible (principle of Occam's razor [9]).

Reducing the size of the space feature allows us to reduce the number of required parameters for the description of this model also avoiding the phenomenon of over-fitting and emphasizing the synthesize information.
- It improves the performance of the classification, its speed and power of generalization.
- It increases the data understanding: a better view of what are the processes that give rise to them. This selection consists of:

→ The elimination of independent variables of the class,
→ The elimination of redundant variables.

4.1 Global Concept

A general structure for selecting features can be offered in the way of figure 2 ([10]). Up to a certain criterion to be satisfied, sub sets are generated in browsing the feature space.

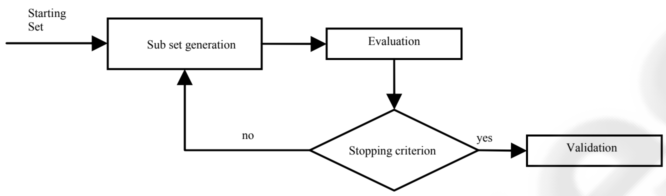

Fig. 2. Feature selection architecture.

The subsets generation is a searching process in the subset space of cardinality 2^N with N the number of features. All classical searching algorithms can be applied to that problem. For instance [11] proposes the methods forward addition and backward elimination (deletion), [12] and [13] have made a good use of evolutionary algorithms.

4.2 Searching Algorithm and Evaluation

Existing feature selection methods for machine learning typically fall into two broad categories—those which evaluate the worth of features using the learning algorithm that is to ultimately be applied to the data, and those which evaluate the worth of features by using heuristics based on general characteristics of the data. The former are referred to as wrappers and the latter filters.
1. Wrappers use classification algorithm to evaluate the pertinence of a given sub set of variables. Genetic Algorithms (GA) dedicated to colour space selection are wrappers based on heuristics. GA for Colour Space(GACS) encodes its individuals as vectors limited to three components specifically adapted to the colour representation [14]. 2. Filters are completely independent from the classification stage. They are based on statistical concepts: entropy, coherence… A good feature subset is one that contains feature highly correlated with predictive of the class and yet uncorrelated with the others [10].

The Wrappers. Although conceptually more simple than filters, wrappers were introduced more recently by John, and Kohavi Pfleger in 1994. Their principle is to generate subsets candidates and to evaluate them thanks to a classification algorithm. The score or merit will be a combination of a trade-off between the number of variables eliminated, and the classification rate on a test file. Thus, the "assessment" stage of the selection cycle is made by a call to the classification algorithm. In fact, the classification algorithm is called several times for each evaluation because a cross-validation is frequently used. By its very intuitive principle, this method generates subsets well suited to the classification algorithm. Recognition rates are high since the selection takes into account the intrinsic bias of data. Another advantage is its conceptual simplicity: there is no need to understand how the induction is affected by the selection of variables, it is sufficient to generate and test.
However, there are three reasons that the wrappers are not a perfect solution. First, they do not really have theoretical justification for the selection and they do not allow us to understand the conditional dependencies that may exist between the variables. On the other hand, the selection process is specific to a particular classification algorithm and find subsets are not necessarily valid if you change the method of induction. Finally, and this is the main defect of the method, the calculations quickly become quite long when the number of variable grows up.

The Filters. Filters don't have the defects of wrappers. They are much faster, they are based on more theoretical considerations, it allows a better understanding to the dependency relationships between variables. But, as they do not take into account the biases of the classification algorithm, the subsets of variables generated give a lower recognition rate. To give a score to a subset, the first solution is to give a score to each variable independently of the others and to do the sum of those scores [OneR Selection]. The alternative is to evaluate a subset as a whole [12]. We are closer here learning the Bayesian network structure. There is an intermediary between ranking and feature subset ranking based on an idea of Ghiselli and used with good results in the context of the CFS (correlation based feature selection) by Mr. Hall [10]. The score of a subset is constructed based on correlations variable-class and correlations variable-variable (Eq 3):

Equation. 3. Correlation score associated to each feature in CFS method

$$r_{zc} = \frac{k\overline{r}_{zi}}{\sqrt{k + k(k-1)\overline{r}_{ii}}}$$

Where r_{zc} is the correlation between the summed components and the outside variable (a given colour cluster – a class), k is the number of components, r_{zi} is the average of the correlations between the components and the outside variable, and r_{ii} is the average inter-correlation between components
This equation express that the merit of a given subset increase if the variables are highly correlated with the class and it decrease if features are highly correlated between each others. The idea is to state that a "good" subset is composed of variables highly correlated with the class (to discard independent variables) and loosely correlated between them/features (to avoid redundant components). It is an

approximation since it only takes into account the interactions of order 1. The correlation or dependency between two variables can be defined in several ways. Using the statistical correlation coefficient is too restrictive because it only captures the linear dependence. However, one can use a test of independence as the statistical test of χ^2 . It is also possible to combine wrapper and filter as presented in [13]

4.3 Stopping Criterion

The stopping criterion may take various forms: a computation time, a number of generations (for a genetic algorithm), a number of selected variables or a heuristic evaluation of the subset “value”.

Table 1. Selection feature methods in use.

Name	Type	Evaluation	Searching algorithm
CFS	Filter	CFS	Greedy stepwise
EHD	Filter	PCA*	Ranker
GACS	Wrapper	Classification	Genetic Algorithm
OneRS	Wrapper	Classification	Ranker

4.4 Hybrid Colour Space built by Genetic Algorithm. GACS

In Hybrid Colour Space (HCS) context, each individual has to encode a vector, where each component is an axis of the HCS. We consider a set C of features. $C = \{C_i\}_{i=1}^{N} = \{R, G, B, I1, I2, I3, L^*, u^*, v^*, ...\}$ with Card(C)=25. Practically, it is almost impossible to test all possible combinations, since they have a combinatory number equal to the factorial of the total number of the candidate primaries, hence, Genetic Algorithm are well suited to get rid off absurd combinations. From now, the first step is to initialize the population, each individual is made up picking randomly three elements of C. Concerning cross over operator, two individuals h1 and h2 share their genetic material, swapping one of their component; fig 3. Finally, to perform mutation on an individual, one component is selected and replaced at random by an element of C. Finally, the evaluation phase computes a 1NN classifier based on a Euclidian metric. A cross-validation system is run on the training base.

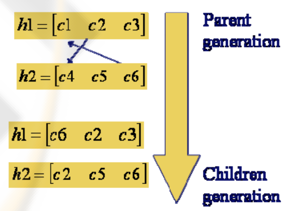

Fig. 3. HCS: cross over operator.

5 Experiments

5.1 Context

In the idea to assess our system, we perform two evaluation stages. The first one is a colour classification step to test if the colour representation found by our framework is interesting in term of colour distinction. The second step is a segmentation phase. Indeed, a better representation system should give better segmentation results.

5.2 Colour Classification

Our approach is applied on three different types of images. A natural scene, an image of the document and a synthetic image. Each colour space is evaluated on the test dataset through the use of a 1NN classification step. In table 2, the number of colour clusters found by the clustering algorithm(EM) is given. Table 4 shows the components selected by the several feature selection techniques.

Fig. 4. Images in use.

Table 2. Test images description.

Id	Image	Type	# of clusters
Im1	Lenna	Natural Scene	18
Im2	SatSnake	Synthetic image, discriminating by the saturation	23
Im3	Image of document	Ancient Cadastral Map	9

Table 3. Training and Test Databases.

	$\|X_{training}\|$ pixels	$\|X_{test}\|$ pixels
IM1	130107	130107
IM2	100951	100951
IM3	110424	110424

Table 4. Hybrid Colour Spaces found on the Image IM2.

Attributes	CFS	GACS	DHCS	OneRs
R	0	0	0	0
G	1	0	1	0
B	1	0	0	0
I1	0	0	0	0
I2	1	0	0	0
I3	0	0	0	0
T	1	1	0	1
S	1	1	0	1
I	0	0	0	0
L*	1	0	0	0
a*	1	0	0	0
b*	1	0	0	0
L*	0	0	0	0
u*	1	1	0	0
v*	1	0	0	0
A	0	0	0	0
C1	1	0	0	0
C2	1	0	0	0
X	0	0	0	0
Y	0	0	1	0
Z	1	0	1	0
Y	0	0	0	0
I	1	0	0	1
Q	1	0	0	0
Y	0	0	0	0
U	1	0	0	0
V	0	0	0	0
# of attributes	16	3	3	3

Table 5. Number of selected features.

	# of selected attributes			
	CFS	GACS	EHD	OneRS
IM1	16	3	3	3
IM2	16	3	3	3
IM3	12	3	3	3

Table 6. Confusion rate on Image 1.

IM1			
Colour Spaces	***Error***	***ColourSpaces***	***Error***
RGB	0.3608	TSI	0.3917
I1I2I3	0.3814	La*b*	0.4329
XYZ	0.3814	L*u*v*	0.4948
YIQ	0.4742	DHCS	0.3917
YUV	0.3195	CFS	0.0615
AC1C2	0.4123	**GACS**	**0.2680**
PCA	0.3711	OnRS	0.3608

Table 7. Confusion rate on Image 2.

IM2			
Colour Spaces	***Error***	***Colour Spaces***	***Error***
RGB	0.22	TSI	0.51
I1I2I3	0.24	La*b*	0.41
XYZ	0.23	L*u*v*	0.35
YIQ	0.43	DHCS	0.39
YUV	0.35	CFS	0.14
AC1C2	0.29	**GACS**	**0.19**
OnRS	0.39	PCA	0.35

Table 8. Confusion rate on Image 3.

IM3			
Colour Spaces	***Error***	***Colour Spaces***	***Error***
RGB	0.5444	TSI	0.3666
I1I2I3	0.2222	La*b*	0.2666
XYZ	0.5777	L*u*v*	0.3333
YIQ	0.3111	DHCS	0.36
YUV	0.3777	CFS	0.0333
AC1C2	0.3	**GACS**	**0.1888**
OnRS	0.4111	PCA	0.2444

5.3 Application to Segmentation and Evaluation

Once the source image is transferred into a suitable hybrid colour space, an edge detection algorithm is processed. This contour image is generated thanks to a vectorial gradient according to the following formalism. The gradient or multi-component gradient takes into account the vectorial nature of a given image considering its representation space (RGB for example or in our case hybrid colour space). The vectorial gradient is calculated from all components seeking direction for which variations are the highest. This is done through maximization of a distance criterion according to the L2 metric, characterizing the vectorial difference in a given colour space. The approaches proposed by DiZenzo[7] first, and then by Lee and Cok under a different formalism are methods that determine multi-components contours by calculating a colour gradient from the marginal gradients.

Given 2 neighbour pixels P and Q characterizing by their colour attribute A, the colour variation is given by the following equation:

$$\Delta A(P,Q) = A(Q) - A(P)$$

The pixels P and Q are neighbours, the variation ΔA can be calculated for the infinitesimal gap: dp = (dx, dy)

$$dA = \frac{\partial A}{\partial x}dx + \frac{\partial A}{\partial y}dy$$

This differential is a distance between pixels P and Q. The square of the distance is given by the expression below:

$$\begin{aligned} dA^2 &= \left(\frac{\partial A}{\partial x}\right)^2 dx^2 + 2\frac{\partial A}{\partial x}\frac{\partial A}{\partial y}dxdy + \left(\frac{\partial A}{\partial y}\right)^2 dy^2 \\ &= adx^2 + 2bdxdy + cdy^2 \\ a &= \left(G_x^{e1}\right)^2 + \left(G_x^{e2}\right)^2 + \left(G_x^{e3}\right)^2 \\ b &= G_x^{e1}G_y^{e1} + G_x^{e2}G_y^{e2} + G_x^{e3}G_y^{e3} \\ c &= \left(G_y^{e1}\right)^2 + \left(G_y^{e2}\right)^2 + \left(G_y^{e3}\right)^2 \end{aligned}$$

Where, E can be seen as a set of colour components representing the three primaries of the hybrid colour model. And where G_n^m can be expressed as the marginal gradient in the direction *n* for the *m*th colour components of the set E.

The calculation of gradient vector requires the computation at each site (x, y): the slope direction of A and the norm of the vectorial gradient. This is done by searching the extrema of the quadratic form above that coincide with the eigen values of the matrix M.

$$M = \begin{pmatrix} a & b \\ b & c \end{pmatrix}$$

The eigen values of M are:

$$\lambda_{\pm} = 0.5\left(a + b \pm \sqrt{(a-c)^2 + 4b^2}\right)$$

Finally the contour force for each pixel (x,y) is given by the following relation:

$$Edge(x,y) = \sqrt{\lambda_+ - \lambda_-}$$

These edge values are filtered using a two class classifier based on an entropy principle in order to get rid off low gradient values. At the end of this clustering stage a binary image is generated. This image will be called as contour image through the rest of this paper. Finally, regions are extracted by finding the white areas outlined by black edges. In order to compare the results between the segmented image generated by the computer and the user defined ground truth, the Vinet criterion[15] is chosen [Tab 9].

Table 9: Segmentation evaluation on Hybrid Colour Space.

Dizenzo Segmentation Colour Cadastral maps	*# of regions*	*Vinet criterion*
RGB image	1714	0.5703
HCS found by GACS	1596	0.5821

Another way to assess a segmentation process is to compute the Levin and Nazif (LN) criterion. It takes into parameters the segmented image and the original image and returns a score, the higher the better. This comparison is carried out on a set of 50 maps. Levin and Nazif criterion[15] is the union of two principles, the disparity intra and inter regions.

Table 10 : Comparison HCS and RGB spaces on a segmentation process using LN criterion.

Dizenzo Segmentation Colour Cadastral maps	*LN Criterion on 50 images*	
	Average	**Std deviation**
RGB	0.4770375	0.005396543
HCS	0.480325	0.007211647

5.4 Analyze

The quality of a colour model is judged by two decisive factors: "Robustness" and "Distinction". The robustness of the colour representation is an indication of the sensitivity of colour values to illumination and brightness variations. The “Distinction” capacity of a colour model is directly linked to its capacity to separate one colour to the others.
The colour space minimizing the error rate classification is the most discriminating space for a given image [Tab 6,7,8]. The space generating the least mistake will be retained to continue treatments on the image. The chosen space is minimizing the distance intra-class, within the same unit chromatic while maximizing the distance inter-classes. Such properties are helpful in post-processing stages such as segmentation, or graphics recognition. Thanks to a well suited colour model, the number of regions has been reduced by 118 decreasing the over-segmentation problem, moreover, the Vinet criterion has been improved by 2% getting closer to user ground truth. At the same time, the LN criterion results lead to the same conclusion, showing that the contrast inter regions and the homogeneity intra-region are slightly better in HCS than in the RGB case. These results are encouraging and they demonstrate how important it is to choose a “good” colour model.

6 Conclusions

In this paper, we have presented a colour space selection framework. Our contribution focuses on a “all-in-one” system to find a suitable colour space. Our tool can be seen as a pre-process to any colour information retrieval application (Segmentation, graphic recognition …). Our approach aims to maximise one criterion which is the colour recognition rate to unleash the colour information. Each image is like no other, so a dedicated colour representation is required. We believe, it is hardly possible to model a unique colour space from a given image set and then to apply this "mean model" individually, that's why our method computes independently a dedicated model to each image. Our framework relies on a wise use of different feature selection methods in order to take advantages of their diverse ways to reach a single goal. Finally, Hybrid Colour Spaces are particularly well suited while dealing with very specific images, such as medical images, images of documents where CIE spaces are not particularly well designed. We believe that much colour image software would get profit to the use of an adapted colour space.

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