A Segmentation Scheme Based on a Multi-graph Representation: Application to Colour Cadastral Maps

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Abstract. In this paper, a colour segmentation process is proposed. The novelty relies on an efficient way to introduce a priori knowledge to isolate pertinent regions. Basically, from a pixel classification stage a suitable colour model is set up. A hybrid colour space is built by choosing meaningful components from several standard colour representations. Thereafter, a segmentation algorithm is performed. The region extraction is executed by a vectorial gradient dealing with hybrid colour space. From this point, a merging mechanism is carried out. It is based on a multi-graphs data structure where each graph represents a different point of view of the region layout. Hence, merging decisions can be taken considering graph information and according to a set of applicative rules. The whole system is assessed on ancient cadastral maps and experiments tend to reveal a reliable behaviour in term of information retrieval.

Keywords: Colour Segmentation, Colour Space, Graphics Recognition, Document Understanding.

1 Introduction

Technical documents have a strategic role in numerous organisations, composing somehow a graphic representation of their heritage. In the context of a project called “ALPAGE”, a closer look is given to ancient French cadastral maps related to the Parisian urban space during the 19th century. Hence, the data collection is made up of 1100 images issued from the digitalization of Atlas books and where each image contains a vast number of domain-objects, ie. Parcels, water collection points, stairs, windows/doors… From a computer science point of view, the challenge consists in the extraction of information from colour documents in the objective of providing a vector layer to be inserted in a GIS (Geographical Information System). Despite the large number of proposed document interpretation methods [1], only a handful of them focus in colour document analysis. In particularly, we state the case of Falco X.A [2] who proposed an object-line extraction method building a regular-mesh graph from a bitmap image where every pixel is treated as a node and putting an edge between every pair of adjacent nodes. Then the extraction problem can be considered

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as finding an optimal path between a start node and an end node. The limitation lies in the local aspect of this approach since the mesh graph construction is not achievable on the whole image; the start node is then user -defined to reduce the graph complexity. Among this reduced set of paradigms working with colour documents, the intention of Poh Kok Loo et al [3] is not much to deal with object extraction but more likely to distinguish text and graphic information. From this statement, a real place does exist for our system which aims to extract high level objects (parcel, water well …) in a noisy environment because of the presence strong time due degradations: colour degradation, yellowing of the paper, pigment fading… Our paradigm is structured around three main ideas. The first, one investigates the colour image restoration in the objective to power up ancient colours. Secondly, a comparative study explores the several colour spaces in order to choose the best model for the segmentation process. Finally, a knowledge-based segmentation method is proposed where a priori information is introduced through the use of a multi-graphs data structure.

2 Pre-processing Steps: Colour Restoration and Colour Spaces

2.1 Colour Restoration

In introduction, we expressed the difficulties to analyse ancient documents which were deprecated due to the time, usage condition or storage environment. So clearly, a real need for image restoration has come up. A pre-process, a faded colour correction has been executed to bring colours back to original or at least to unleash colour significance. It works automatically by increasing non-uniformly the colour saturation of washed-out pigments without affected the dominant colour.

Let X be the colour vector for a given pixel: X = $\begin{bmatrix} R \\ G \\ B \end{bmatrix}$

Let Y be the data in an independent system axis:

$$Y = T(X - \mu)$$

Where:

T are the singular vectors of the covariance matrix.
μ is the mean vector.

Let Y’ be the data extended according the direction the main factorial axis:

$$Y' = KY$$

$$K = \begin{bmatrix} k1 & 0 & 0 \\ 0 & k2 & 0 \\ 0 & 0 & k3 \end{bmatrix}$$ Coefficients are chosen experimentally.

Fig. 1. Original image

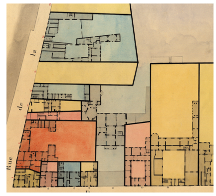

Fig. 2. Restored image

The restoration matrix is given as follow:

$$M = T^{-1}KT$$

Let X' be the vector containing the restored values: $X' = T^{-1}KT(X-\mu)+\mu$

2.2 Colour Space Selection

The choice of a relevant colour space is a crucial step when dealing with image processing tasks (segmentation, graphic recognition…). In this paper, a colour space selection system is proposed [Fig 3]. This step aims to maximize the distinction between colours while being robust to variations inside a given colour cluster. 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. $C = \{Ci\}_{i=1}^{N}$ = {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. Feature vectors are then reduced to a Hybrid Colour Space made up of the three most significant colour components. Hence, the framework can be split up in two parts: on one hand, the selection feature methods to decrease the dimension space and on the other, the evaluation of the suitability of a representation model. The quality of a colour space is evaluated according to its ability to make colour cluster homogenous and consequently to improve the data separability. This criterion is directly linked to the colour classification rate. The colour representation choice is done on-line after a pixel classification stage. Eleven colour spaces are evaluated according to their recognition rates [Table 2]. Hybrid spaces are built thanks to feature selection methods [4], [5], [6], [Table 1]. On all colour spaces, a 1-NN classifier using a Euclidian metric is performed in order to obtain the corresponding colour recognition rates.

Table 1. Selection feature methods in use

Name	Type	Evaluation	Searching algorithm
CFS [4]	Filter	CFS	Greedy stepwise
DHCS [6]	Filter	Principal Component Analysis(PCA)	Ranker
GACS [5]	Wrapper	Classification	Genetic Algorithm
OneRS [4]	Wrapper	Classification	Ranker

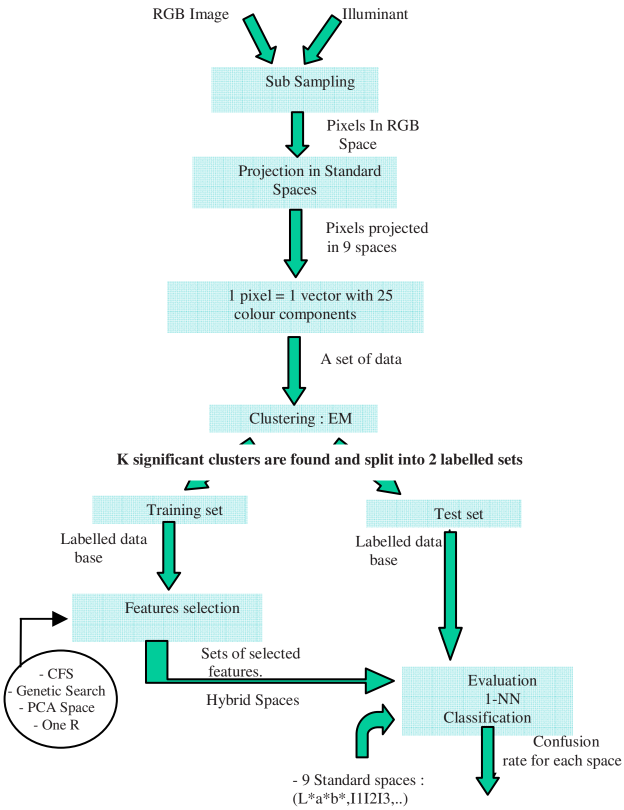

Fig. 3. A framework for colour space selection

Table 2. Pixel data bases description and Colour classification rate

Image	**Type**	**# of clusters**	$\lvert X_{training} \rvert$ **pixels**	$\lvert X_{test} \rvert$ **pixels**
Image of document	Ancient Cadastral Map	14	110424	110424

Cadastral Map			
Colour Spaces	*Rate*	*Colour Spaces*	*Rate*
RGB	0.4556	HIS	0.6334
I1I2I3	0.7778	La*b*	0.7334
XYZ	0.4223	L*u*v*	0.6667
YIQ	0.6889	**DHCS**	**0.64**
YUV	0.6223	**CFS**	**0.9667**
AC1C2	0.7	**GACS**	**0.8112**
PCA	0.7556	**OnRS**	**0.5889**

3 Indice Extractions

3.1 Black Layer and Colour Layer Separation

Basically, the black layer is extracted by using an Otsu binarization [9] on the luminance channel (Y channel of the YIQ colour space). Figure 4, 5 show the two extracted layers.

Fig. 4. Black layer

Fig. 5. Colour layer

3.2 Colour Segmentation from Hybrid Colour Space

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:

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

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:

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

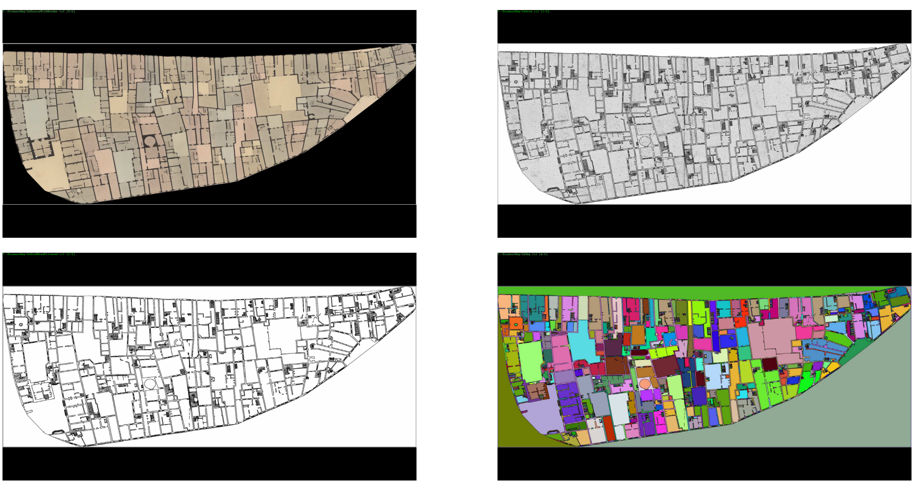

Fig. 6. Top Left: the source image; Top right: the gradient values; Bottom left: the binary image from edge values, Bottom right: the white connected components analysis

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 [Fig 6].

4 Syntaxic Level: A Multi Graph Data Structure

Each graph represents a point of view of the region layout. The three graphs in use rely on the same basement where one node corresponds to one region [Fig 7]. However, edges and edge attributes change from one graph to another. The graph definitions are explains to the next paragraph.

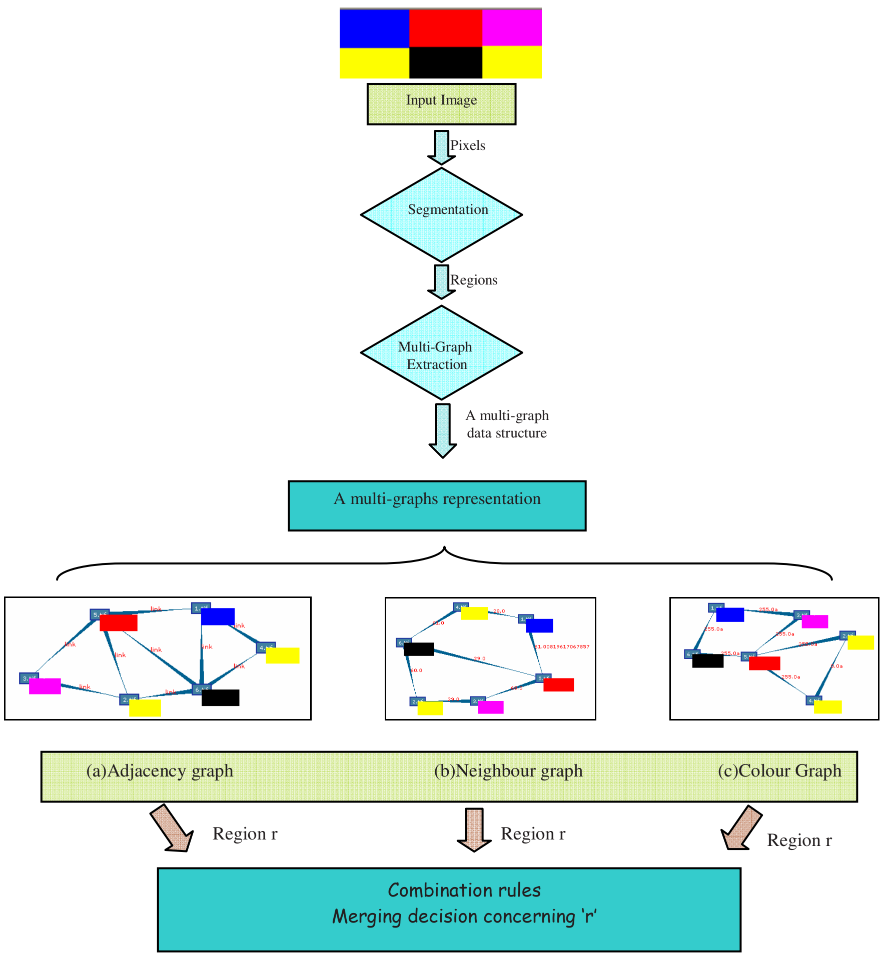

Fig. 7. Knowledge-Based Segmentation. A Study case.

4.1 Graph Definitions

4.1.1 Adjacency Graph Definition

Each region represents a vertex in this graph. Then, edges are built using the following rule: two vertices are linked with an undirected and an unlabelled edge if one of the nodes is connected to the other node in the corresponding image.

4.1.2 Neighbour Graph Definition

Each region represents a vertex in this graph. Then, edges are built using the following rule: two vertices are linked with an undirected edge if one of the nodes is one of the *h* nearest neighbours of the other node in the corresponding image. The *h* value, concerning the number of significant neighbours, is issued from a comparative study. This graph is a representation of the spatial layout of the regions. Edges are labelled with the spatial distance between the two region centres.

4.1.3 Colour Graph Definition

Each region represents a vertex in this graph. Then, edges are built using the following rule: two vertices are linked with an undirected edge if one of the nodes is one of the *k* closest neighbours of the other node in a colorimetric point of view. The colour graph expresses information concerning the colour distance between regions. This graph is an interpretation from the colour point of view of the region organisation. Edges are labelled with the colour distance between the two regions.

5 Semantic Level: Merging Rules

The segmentation process [7] is not enough to reconstruct high level information just because the black layer or an important colour difference can obstruct the spatial progression of the edge detection. From this fact, graphs are used to guide the region merging system. Each graph provides a context for a given node *n.* and this later is merged if it fulfils four rules [Fig 7], these conditions are a *priori* knowledge representation. The merging mechanism is described through the following algorithm:

Algorithm: Merging scheme for multi-graphs data structure

Require: the colour similarity threshold: T_{color}

Require: the spatial distance threshold: $T_{spatial}$

Ensure: A list of M Regions.

```
1: Start
2: MergingFlag=true
3: While MergingFlag == true do
4:         MergingFlag=false
5:         for i=1 to Number of Nodes do
6:           CurNode = GetCurrentNode(i)
```

```
            MNode=CombinationRules(CurNode, T_color, T_spatial)
              if MNode exist then
                MergeNodesInMultiGraphs(CurNode,MNode)
                MergingFlag=true
                break
              end if
          end for
end while
return the remaining nodes.
End
```

When a node $n1$ is merged with another one $n2$, the whole structure has to be updated, the three graphs have to be coherent, hence, the merged node n1 is deleted in the three graphs and its edges are linked to $n2$.

Elements:

Regions
Black layer

Syntax:

[element1] operator [element2]

Operators:

$\subset$: A region is inside another one
$\otimes$: Close Spatially: Threshold (Tspatial)
$\oplus$: Close Colour: Threshold (Tcolour)
$\bullet$: Connectedness
$\overline{x}$: Not.

Function:

Merge (R1,R2) $\equiv$ R1 $\cup$ R2

Merging rules:

[Rule 1] (R1 $\subset$ R2) $\wedge$ (R2 $\neq$ BlackLayer) $\longrightarrow$ R1 $\cup$ R2
[Rule 2] (R1 $\bullet$ R2) $\wedge$ (R1 $\oplus$ R2) $\longrightarrow$ R1 $\cup$ R2
[Rule 3] (R1 $\otimes$ R2) $\wedge$ (R1 $\oplus$ R2) $\longrightarrow$ R1 $\cup$ R2
[Rule 4] (R1 $\bullet$ R2) $\wedge$ (R1 $\overline{\bullet}$ BlackLayer) $\longrightarrow$ R1 $\cup$ R2

Fig. 8. Merging rules

6 Experimental Results

In order to compare the segmentation defined by an expert and the results generated by our segmentation algorithm, the Vinet [8] criterion is chosen.

The Vinet's measure is calculated by counting common pixels between the user defined image and the result computed by an image processing task. This can be expressed by the given formula:

$$Vinet = 1 - \frac{R_i - \left(R_i \cap V_j\right)}{R_i} \text{ between } [0, 1]$$

Where R_i, V_j are respectively a region from the ground truth image and a region from the image segmented by the computer. The higher is the measure the better is the segmentation. Figure 8 illustrates the segmentation results while in Table 3 Vinet measures are reported. Experiments highlight the profit to include different point of view of a single segmentation to guide a merging method.

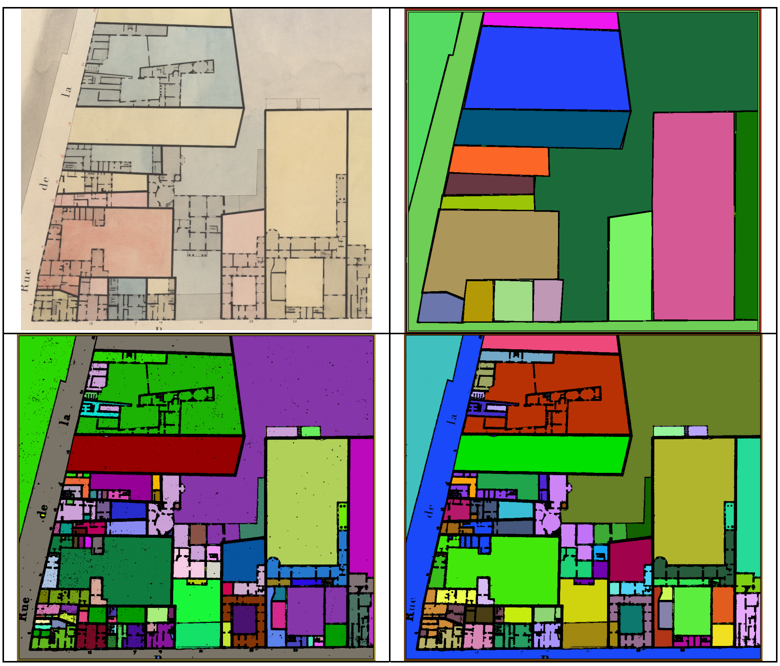

Fig. 9. Top left: Source Image; Top right: Ground truth composed of 17 regions; Bottom left: Segmentation without merging; Bottom right: Segmentation after the application of merging rules

Table 3. Segmentation results

Segmentation processes	*# of regions*	*Vinet measure*
Region growing[5]	1301	0.253
Our approach without merging	516	0.51794
Our approach with merging	74	0.64423

7 Conclusion

In this paper, we have been interested in an original problem, the colour graphic document analysis and an application to ancient cadastral maps. The aim was to identify graphic elements, which are defined by their colour homogeneity. Our contribution relies on a document oriented segmentation scheme. Firstly, a vectorial gradient working in a hybrid colour space is applied in order to achieve the partition in regions. Thereafter, a higher point view is given by a multi-graph representation, these multiple sources of information guide the merging mechanism. Finally, applicative rules condition the fusion of information to construct higher level objects. In addition, research perspectives are being explored to combine more efficiently black and colour layers. Ongoing works are dealing with the extraction of a visibility graph from the black layer to enrich the multi graph data structure.

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