Address block localization based on graph theory

Djamel GACEB, Véronique Eglin, Frank LEBOURGEOIS and Hubert EMPTOZ
LIRIS INSA de Lyon – 20, av. Albert Einstein 69621 VILLEURBANNE CEDEX
E-Mail: {djamel.gaceb1, veronique.eglin, flebourg, hubert.emptoz @insa-lyon.fr}

ABSTRACT

An efficient mail sorting system is mainly based on an accurate optical recognition of the addresses on the envelopes. However, the localizing of the address block (ABL) should be done before the OCR recognition process. The location step is very crucial as it has a great impact on the global performance of the system. Currently, a good localizing step leads to a better recognition rate. The limit of current methods is mainly caused by modular linear architectures used for ABL: their performances greatly depend on each independent module performance. We are presenting in this paper a new approach for ABL based on a pyramidal data organization and on a hierarchical graph coloring for classification process. This new approach presents the advantage to guarantee a good coherence between different modules and reduces both the computation time and the rejection rate. The proposed method gives a very satisfying rate of 98% of good locations on a set of 750 envelope images.

Keywords: Text location, physical segmentation, real time processing, business documents processing, graph coloring.

1. INTRODUCTION

Automatic mail sorting machines of most recent systems process about 17 mail pieces per second that requires a fast and precise block address OCR\(^1\) based recognition. This recognition is mainly conditioned by a correct address line organization. The address block location (noted ABL) is a non trivial operation due to the very large variability of characteristics of this image region and to the significant number of parasitic informative blocks.

Once the envelope image has been acquired by a linear CCD camera, three principal modules contribute to the task of the ABL (see figure 1): Envelope image segmentation, envelope layout analysis, blocks interpretation and recognition.

Following a binarizing step of the envelope image, a first module detects the connected components (CCs) including all textual and graphical objects of the page. The second module carries out the hierarchical analysis of the layout of these CCs to recompose the blocks and establish their descriptions. Lastly, a decisional phase inspects the whole of the data obtained to recognize the address block. Practically, a dysfunction of one of these modules reduces the performances of the others, and consequently leads to a bad location of address block (AB) and so to a false optical character recognition of their contents.

---

\(^1\) OCR: (Optical Character Recognition) used to convert scanned text document to editable text
is the case for most of the mails of our study): some page settings do not respect this strict layout (see figure 2) and must be taken into account.

Moreover, the presence of stamps, post office marks, printed logos, various advertisements and other parasitic information on the mail makes the task of localization more difficult (figure 2). Other constraints particularly related to our industrial application can also be pointed out, namely:

- Very large mail variety (quality, color and different paper textures),
- Obligation for results (in a very competitive market, the system must be the most powerful possible to avoid expensive manual interventions),
- Real time constraints (limited processing time) and high spatial resolution of the images (200–300 dpi).

Although the performances of the ABL systems do not stop growing, some limits are always present, most of time depending on a linear modular architecture limited by the above mentioned constraints. This represent the global framework of this study.

Taking into account all of these limits, we propose in this paper an original and robust ABL architecture resulting from multi-resolution representations and based on classification modules related to graph theory. The high level stages are based on the hierarchical graphs coloring (which are noted HGC), allowing to manage, through a pyramidal data organization, the compound rules governing the interpretation of the decomposition into connected components of interest zones. As for now, no other work in this field has made use of the power of this tool. In opposite to traditional methods that use linear architectures, our strategy consists in increasing the performances of each module and their coherence with the other tasks of the ABL process in order to reduce mail rejection and to reduce time processing to the maximum.

The remainder of this paper is organized as follows: The various existing ABL methods are quoted in section 2 in which the previous works and the set limits are presented. In the third section, the formal aspects of graphs coloring are detailed. The fourth section describes the application of the coloring to the ABL problem. The results of ABL are then commented and discussed.

2. EXISTING ADDRESS-BLOCK LOCATION SYSTEMS

A significant number of works have been devoted in the recent years to the improvement of the ABL. All suggested methods can be divided into two great categories: the methods that select the AB among several candidate blocks and those that directly extract the AB starting from the image of the envelope. The methods of the first category use various segmentation techniques to let emerge perceptible informative blocks of the envelope image. The principle consists in extracting descriptors for each block, in order to identify the one which explicitly contains the destination address. The methods of the second category are limited to a direct AB location without segmenting the envelope image into several blocks. In spite of a processing speed that is slightly higher than that of the first category methods, the rate of bad localization remains the highest. This is why we were interested, within the context in the first category methods.

In 1988, an expert system was proposed by Wang and al [1] to sort mail automatically. The authors use a blackboard to preserve and exploit the geometrical features of the blocks obtained in the data processing stage of various types of envelope images. A few years after, Viard-Gaudin and Barba proposed in [2] a new approach of ABL based on a pyramidal data structure construction, in which, a downward analysis was used to extract the spatial relationships between the different segmented blocks with their features on each level of the pyramid. Yu [3] adapted an almost similar principle to complex mails. The approach suggested by Jeong [4] is based on the grouping of the connected components resulting from the binary image, where each group is assigned to one of the nine classes: the destination...
address block is given by selecting only some classes. Eiterer [5], recently and without segmenting the image, proposed a new track through an approach based on fractal dimensions. A classification by the K-Means method is used to label the grey level pixels as background, noise or semantic objects which constitute the basic classes defining the stamps, the postmarks, and the address blocks.

We present here the various existing techniques used at each stage of the ABL: binarisation, connected components (CCs) detection and physical layout segmentation.

2.1 Binarisation and connected components detection

The binarisation (or thresholding) is applied in the first stage of the ABL process and has a very strong impact on the performances of the sorting system. The thresholding methods are in general divided into two categories: Global (eg: Otsu’s method [6]), and local (eg: Sauvola’s method [7]). Obviously global techniques can not produce satisfactory results when the grey-levels input image has non-uniform shading or multi-modal histogram. Local algorithms usually involve more computation and so are slower when running on a single-processor computer. For more details, a comparison of several binarisation techniques is presented in [19].

After the binarisation stage, an analysis of CCs is carried out to extract various vital information for the later stages. Formally, a connected component is a set of foreground pixels immediately adjacent to each other. Typically, in a machine printed ABL under ideal digitizing conditions, each alphanumeric character is a separate CC. In order to reduce the processing time necessary to the CCs detection, several methods were developed. A good state of the art is presented in [9]. In our study we concerned ourselves with the work of Pavlidis [8] which modeled the problem of CCs detection by a line adjacency graph (LAG). This method is based on run-length representation and is quite efficient when implemented in software form. To increase its speed further, the algorithm was modified to generate components directly from the bit-packed image.

2.2 Physical layout segmentation

Generally, the physical layout segmentation of the envelope image indicates its separation into its constitutive elements containing homogeneous data. These elements are often spaced and form elementary geometrical blocks, based on a rectangle in the large majority of the cases. To obtain this segmentation, one proceeds either by recursive splitting starting from spaces, or by recursive merging of the objects progressively or still by the combination of both [20]. The CCs merging segmentation methods (progressive regrouping of CCs, RLSA, segmentation by scaling method of cumulated gradients) are more used by the bottom-up strategies [13] [10], whereas the methods of segmentation by splitting (profile projection, segmentation by spaces analysis, Hough’s transform) are adapted to the top-down strategies [12]. Other methods, known as hybrid, benefit from the two strategies at the same time [12].

Déforges and Barba [10] presented a bottom-up generic method based on a multi-resolution description of the document image used for ABL. An almost similar structure was used by Wang [11] to distinguish the text blocks from graphic blocks, and to represent them in a structural model. Shi and Govindaraju [12] proposed an algorithm based on the application of "fuzzy directional run-length".

2.3 Various errors of the physical segmentation

It is evident that the blocks resulting from the traditional segmentation methods can contain parasitic elements. Generally, this segmentation encounters several types of errors (described in [18] and in Figure 3) strongly related to the bad application of the segmentation technique given the presence of parasitic objects near the address block (noise, small tables fragments, logos, publicity text, or other markings or graphics).
These errors are summarized in the following points:
- Horizontal or vertical merging of text blocks or lines,
- Horizontal or vertical splitting of text blocks or lines,
- Text fusion or confusion with graphics or noise,
- Bad detection of textual blocks or lines.

The physical segmentation and ABL methods cited above all use a complex data structures. The management of the criteria and knowledge becomes more difficult to control given the great variability on the envelopes to be sorted. For more robustness, we focused our work on the pyramidal data representation by introducing graph coloring.

### 3. FORMAL ASPECTS OF THE GRAPH COLOURING

Various practical classification problems can be modeled by the graph coloring. The general form of these applications requires the formation of a graph by the nodes (vertex) which represent the objects of interest and the edges (arcs) which define the relations between these objects.

One wants for example to break up a set of items into several homogeneous classes without knowing their a priori number. In doing so, it is sufficient to represent each item \( i \) by a node \( V_i \) and to add an edge \( E(\{i, j\}) \) between each pair of sufficiently different individuals. The finite graph \( G=(V, E) \) is defined by the finite set \( V=\{v_1, v_2, ..., v_n\} \) whose elements are called nodes, and by the finite set \( E=\{e_1, e_2, ..., e_m\} \) whose elements are called edges.

The coloring of the nodes of the graph \( G(V, E) \) consists in assigning to all nodes a color so that two adjacent nodes do not carry the same color. These colors will correspond to the various classes of items. A coloring with \( K \) colors is thus a partition of \( \{V\} \) into \( K \) subsets of elements.

The number of colors used to color the graph \( G \) of \( N \) nodes is called chromatic number which represents the smallest integer \( K \) for which there is a partition of \( V \) into \( K \) subsets.

On the graph \( G \) of order \( \mid V \mid = 8 \) of figure 4, whose set of nodes is \( V=\{1, ..., 8\} \), three colors were needed to color the nodes so that two adjacent nodes can not have the same color. This number is the minimal chromatic number.

The adjacency matrix \( M_a \) of \( G \) is the symmetrical square matrix \( 8 \times 8 \) defined as follows:

\[
M_a = \begin{bmatrix}
  x1 & x2 & x3 & x4 & x5 & x6 & x7 & x8 \\
  x1 & 0 & 1 & 0 & 0 & 0 & 0 & 1 \\
  x2 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\
  x3 & 0 & 1 & 0 & 0 & 1 & 0 & 0 \\
  x4 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\
  x5 & 0 & 1 & 1 & 0 & 0 & 0 & 0 \\
  x6 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
  x7 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
  x8 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
\end{bmatrix}
\]

A complete consultation of \( M_a \) takes a time: \( \Gamma = O(0.5 \times |V| \times |V|) - |V| \)

The coloring is called b-coloring, if for each color \( Ci \), there exists at least a colored \( Vi \) node \( Ci \) whose neighborhood is colored by all the other colors. The \( Vi \) node is known as a dominating node for color \( Ci \). The example of figure 5 presents the possibility of b-coloring of the nodes of a color class using the other colors.
The b-chromatics number of a graph $G$, defined by $b(G)$, is the maximum integer number of colors $K$ so that $G$ can have a b-coloring by the $K$ colors. It can be easily noticed that:

$$\chi(G) \leq b(G) \leq \Delta(G) + 1$$

Where $\Delta(G)$ is the maximum degree of $G$, called the degree of node $V_i$, and its number of incidental edges is noted $d(vi)$. The majority of the evaluations of $\chi(G)$ and $b(G)$ come from coloring algorithms. There exist many of them, and so that not to drown ourselves with this question, we will limit ourselves to quoting the fastest and most recent ones.

New graph coloring and b-coloring algorithms have been proposed by Effantin and Kheddouci [14, 17]. More details on the approximation of the b-chromatic number were proposed by Corteel [16]. All of these algorithms were efficiently introduced into Elghazel’s works [15] who proposed a new unsupervised classification method of medical data based on graph b-coloring where the number of the classes is not known a priori. On the same database the comparison between the accuracy of this method and that of the method of agglomerative hierarchical classification, of the approach of Hansen and the classification of DRG, showed that this technique offers a true representation of the classes by the dominant individuals and guarantees a better interclass disparity.

4. APPLICATION OF GRAPH COLORING TO OUR PROBLEM

The ABL strongly depends on the parasitic objects’ density near the address block. The knowledge delivered by the features of the block description resulting from the physical segmentation stage, is not efficient to discriminate heterogeneous blocks (containing parasitic elements). To efficiently locate AB on envelopes known as difficult, it has been necessary to choose an even more advanced tool of progressive grouping of CCs and of AB identification. So, we have taken the power of the graph coloring into account to automatically separate the elements into homogeneous groups (figure 6) and in that sense to considerably improve the ABL system.
4.1 The used thresholding and connected components detection methods

The separation between the text zones and the location stages considerably increase the computation time and lead to an over-segmentation of the noise and of the paper texture on empty zones of the image. Indeed, none of the traditional methods (whether global or local) efficiently meets all the required conditions, in particular, a certain efficiency on all the images during a limited computing time. We have managed to optimize this stage by applying a local threshold only near the text zones (Figure 8) that can be located by the cumulated gradients method with the multiresolution and mathematical morphology [19].

After this binarization step, we detect CCs of foreground of the binary and block layers. The method used is inspired from Pavlidis’ studies [8] based on the LAG (Line Adjacency Graph) structure, a structure particularly adapted to a line by line image scan. It consists in connecting the black pixels runs of two consecutive lines of a sliding window. Each CC is represented by the coordinates of its bounding box with: \( CC(i) = (x_i^1, y_i^1, x_i^2, y_i^2) \). Let \( V(L_j) \) (or \( V(L_j) \)) be the set of the CCs
of the binary layer (or of the block layer) which represents the finest (or the coarsest) level $L_1$ (or $L_3$) of the pyramid. With $V(L_k)=\{CC_k(i)_{i=1...N_k}\}$, $N_k$ is the number of CCs in the layer $k=1,2,3$. The physical layout segmentation is then based on a hierarchical analysis on each pyramid level of the bounding boxes. Each level contains different features. This CCs, constitutes a significant information source, very often used during the description process.

![Fig.9. Bounding boxes of connected components of binarized envelope image.](image)

### 4.2 Hierarchical analysis and block description strategy

Each block can be described by a set of the features resulting from the hierarchical analysis of the three levels of the data pyramid. To manage knowledge that are associated to them, each group of objects has features and a strategy of classification. At the bottom of the hierarchy (corresponding to the high resolution image) there are the binary layer CCs. The progression in the hierarchy makes it possible, at each level, to acquire more precise knowledge on the image contents. Each set of features can be visible at various levels of perception. For example, the alignment of the text lines is not perceived on the same level as the character spacing, nor that of the blocks position on the envelope (see figure 10 and table 1).

![Fig. 10. Hierarchical extraction of features.](image)

Our idea consists in making the block description phase cooperate with the physical segmentation phase and allowing, at any level of the hierarchy, the use of all information expressed in the other levels (Figure 10). In that way, the description can take advantage of the two phases. Let $Vd_{L_k}(i)$ be the descriptor-vector of block $i$ at the levels $k=1,2$ and 3. The complete description of this block is given by the combination of the descriptions of three levels $L_1$, $L_2$, and $L_3$ (see Formula 1)

$$Vd_{Total}(i) = Vd_{L_1} \cup Vd_{L_2} \cup Vd_{L_3}$$ (1)

Table 1. Features perception at the various pyramid levels

<table>
<thead>
<tr>
<th>Features on the CCs layer $Vd_{L_1}$</th>
<th>Features on the lines layer $Vd_{L_2}$</th>
<th>Features on the blocks layer $Vd_{L_3}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Position</td>
<td>Position</td>
<td>Position</td>
</tr>
<tr>
<td>CCs height</td>
<td>Line height</td>
<td>Block width</td>
</tr>
<tr>
<td>CCs width</td>
<td>Line width</td>
<td>Number of lines</td>
</tr>
<tr>
<td>Inter-character space</td>
<td>Inter-line space</td>
<td>Eccentricity</td>
</tr>
<tr>
<td></td>
<td>Alignment</td>
<td>Spatial relations</td>
</tr>
<tr>
<td></td>
<td>Eccentricity</td>
<td>Density</td>
</tr>
<tr>
<td></td>
<td>Overlapping degree</td>
<td>Uniformity</td>
</tr>
</tbody>
</table>

Using the PCA, we could select a minimal number of features while ensuring a perfect disparity between the objects of different natures.
4.3 Application of the graph coloring to the physical layout

The segmentation techniques can not systematically produce uniform and well located blocks in complex environments. One speaks about over-segmentation when constitutive components are fragmented and about under-segmentation when several constitutive components can not be isolated. Consequently, the presence of parasites or incomplete information in an address block can introduce errors into its description and can lead to a bad interpretation. Segmentation methods by merging and splitting can all have both advantages and disadvantages [20].

Hybrid segmentation approaches (or mixed approaches) gather both strategies in the same time (top-down and bottom-up) and can benefit from the advantages of one strategy to fill the disadvantages of the other. Our concept of physical layout segmentation is based on the same principle of a hybrid strategy. High stages of our approach lies on the Hierarchical graph coloring (HGC), that largely makes use of all the levels of the pyramidal structure and the coloring power, so as to extract, to characterize and precisely to group objects of same nature (see Figure 11). Therefore, our idea consists in forming at each level of the hierarchy groups of components that must as homogeneous as possible in order to lead to a more precise description.

Let G be a non oriented graph at three levels independent but coherent defined by the following relationship:

\[
G(V, E) = \bigcup_{k=1}^{3} G_k(vd_{L_k}, E_{L_k > S_k})
\]  

(2)

With \(vd_{L_k} = \{vd_{L_k}(i}\}_{i=1,N_k}\) the finite set of represented nodes starting from the descriptors of the set \(V(L_k)_{k=1,2,3}\) of \(N_k\) constitutive elements of level \(k\) of the data pyramid (figure 7), and \(E_{L_k > S_k}\) the finite set of edges represented by the pairs of adjacent nodes, we define the first state of the graph. Taking into account the fact that each node is represented by a features vector, two nodes are then considered as adjacent if and only if their dissemblance \(d_{i,j}\) (distance between their two features vectors) is strictly greater than the threshold \(S_k\) (the optimization mechanism of the thresholds \(S_k\) is detailed in section 4.4.). This definition is given by the following relationship:

\[
E_{L_k > S_k}[vd_{L_k}(i), vd_{L_k}(j)] = \begin{cases} 
1 & \text{si } d_{i,j} > s_k \\
0 & \text{si non}
\end{cases}
\]  

(3)

The hierarchical coloring of graph \(G\) is used here to split-up the set of nodes of each level \(K\) into homogeneous subsets. It focuses on the dissemblance of the objects (represented by nodes) of the same level of the data pyramid to make their resemblances emerging. The coloring process uses a hybrid strategy of progression into the hierarchy of the graph: the colors of a level take part in the formation and the description of the nodes of the next level (see Figure 11).

The coloring steps for the graph \(G_k\) coloring are given by the following algorithm [17]:

**Algorithm 1: Graph_coloring (Graph)**

Begin
If \(c(i) \neq \emptyset\) then
  Let \(M := Nc(i) \cup \{c(i)\}\);
  \(q := 0\);
  For every node \(j \in N(i)\) such that \(c(j) := \emptyset\) do
    \(q := \min \{k|k > q, k \in M \text{ and } k \notin c(j)\}\);
    If \(q \leq \Delta + 1\) then \(c(j) := q\);
    Else \(c(j) := \min \{k|k \notin Nc(j)\}\);
  Endif
Enddo; Endif; End.
Where \( c(i) \) is the color of node \( i \), \( N(i) \) is the set of nodes adjacent to node \( i \). \( Nc(i) \) is the set of node colors of \( N(i) \), 
\[ d(i) = |N(i)| \] is its degree, and 
\[ \Delta = \max \{d(i) | i \in V \} \].

At the starting point, our method of physical layout segmentation is based on the first stage graph construction (which is noted \( G1 \)) based on the CCs layer \( V(L1) \) of the first data pyramid level. The graph \( G1(VdL1,E>SL1) \) is then colored by the algorithm 1 to form \( G3(VdL3,E>SL3) \). Then these colors are superimposed on the blocks layer \( V(L3) \) to subdivide each block that contains several colors and also each color that contains several blocks. By exploiting those new knowledge, we apply once again a second coloring of graph \( G3(VdL3,E>SL3) \) formed by \( VdL3 \) set of fragments descriptors that we merge to form a uniform blocks layer noted \( V(L3^*) \). Finally, the total description of each block is improved by a new set of features extracted from the second layer resulting from the coloring process of the graph \( G2(VdL2,E>SL2) \) with \( VdL2 \) the set of descriptors defined by the analysis of \( V(L3^*) \) and \( V(L3) \) (see the stages in figure 12). The following algorithm summarizes all the segmentation stages:

**Algorithm 2 : Physical_segmentation()**

```plaintext
Begin
Level1: regrouping of similar CCs
For every CC1 (i)/i:=1…N1 Extract VdL1(i)
Endfor
V(L1)={VdL1(i)/i=1…N1}; G1:= G(V(L1),E(L1)>SL1); Execute: Graph_coloring(G1);
Level2: homogenization of the blocks layer
Let M := G1 \( \setminus \) V(L3) 
For every item i of M Extract VdL3(i) endfor
G3:= G(M, E(M)>SL3); Execute: Graph_coloring(G3);
Level3: emergence of the text lines
Let M:= V(L1) \( \setminus \) G3 
For every item i of M Extract VdL2(i) endfor
G2:= G(M, E(M)>SL2); Execute: Graph_coloring(G2); V(L2)=G2; V(L3)=G3;
Extract VdL1 := VdL1 \( \setminus \) G2 and G3;
Extract VdL3 := G3 \( \setminus \) V(L1) and G2;
For every block find \( Vd_{max}(\theta) \)={ \( Vd_{iwa} \) }\( \cup \{ Vd_{iwa3} \} \cup Vd_{iwa3} \);
End
```

The various stages of segmentation are thus illustrated by the following example:

![Figure 12. Example of various stages of physical segmentation.](image-url)

### 4.4 Optimisation of dissemblance thresholds

In a preparatory phase of auto-parameter setting, the system uses the Levine and Nazif [21] combination of intraclass and interclass disparities to automatically adjust all the threshold values necessary for the coloring process. The principle consists in choosing the thresholds that maximize the following cost function:

\[
F = M_{\text{Inter\_groups}} + M_{\text{Intra\_groups}} \tag{4}
\]

Where, \( M_{\text{Inter\_groups}} \) represents the sum of dissimilarities between the groups (colors) pondered by their areas:

\[
M_{\text{Inter\_groups}} = \sum_{i \in G} \sum_{j \in G} \frac{AiCi}{Ai} \text{ where } Ci = \sum_{li} \frac{lj |mi - mj|}{|mi + mj|} \tag{5}
\]
mi is the average of group Gi, lij, the length of the common border between Gi and Gj; and Li, the perimeter of group Gi. The criterion \( M_{\text{para groups}} \) computes the sum of the standardized variances of the groups (cut down to 1).

4.5 Training based on the b-coloring

In order to prepare a representative training basis, 400 blocks of several categories (AB, stamp, logos…), resulting from the physical segmentation of a large variety envelope images have been selected. The training graph (noted \( G_{\text{Training}} \)) is constructed just after the description of each block of the base by a discriminating features vector (section 4.2). After the \( G_{\text{Training}} \) coloring process by the algorithm1, some results colors do not have any dominating node. We use then the algorithm3 [17] for the b-coloring of the non-dominating colors of \( G_{\text{Training}} \).

**Algorithm 3: b-coloring_Graph()**

\[
\text{BEGIN} \\
\text{Repeat,} \\
q := \max\{k | k \in NDm\}; L := L\{q\}; NDm := L\{Dm\}; \\
\text{For each vertex } v_i \text{ such that } c(v_i) := q \text{ do} \\
\text{K := } \{k | k \in L \text{ and } k \notin Nc(v_i)\}; \\
c(vj) := \{c | \text{dist}(vi, c) := \min_k \text{dist}(vi, k)\}; \\
\text{Enddo;} \\
\text{For each vertex } v_j \text{ such that } c(vj) \notin NDm \text{ do} \\
\text{Update(Nc(vj));} \\
\text{If Nc(vj) := L\{c(vj)\} then Add(c(vj),Dm);} \\
\text{EndIf; Enddo;} \\
\text{Until } (ND := \emptyset); \\
\text{END.}
\]

Where \( NDm \), is the set of the non-dominating colors, \( Dm \) is the set of the dominant colors, and \( C(vi) \) is the colors of node \( i \).

Whereas a supervised classification technique requires from the supervisor the introduction of the classes number (knowing that an imprecision of this number can easily force the classifier to make classification errors), a non supervised technique does not present this kind of disadvantage. The b-coloring process perfectly decomposes the set of blocks into uniform subsets (colors), without knowing their optimal a priori number. Moreover, this process offers a good representation of the classes by the dominant nodes (representatives of the blocks) what ensures a great interclass disparity (Figure13). These representative nodes will thus be used in the ABL phase to identify in real time the block addresses among several candidates.

![Fig.13. Features separability and training: block classification by b-coloring and detections of the representatives centers of classes](image)

4.6 Real-Time Identification of the Address-Block Based on the Graph B-Coloring

To select the AB in a list of the candidate blocks \( S = \{V_{i=1...N}\} \), we compare in the space of features the description of each blocks representatives (dominant nodes) \( S' = \{W_{j=1...M}\} \) resulting from the training phase. The matching algorithm
determines in real time for each block of $S$ the designation of its adjacent nodes of $S^*$. This interpretation provides new knowledge on the spatial relationships between the envelope zones that are necessary to take a final decision. The dissimilarity between $V_i$ and $V_j$ is given by the generalized Minkowski distance of order $\alpha$ ($\alpha = 1$).

$$d_{i,j} = \left( \sum_{k=1}^{N_f} g_k(V_i^k, V_j^k)^\alpha \right)^{1/\alpha}$$  \hspace{1cm} (6)

If $\alpha = 1 \Rightarrow d_{i,j}$ is the City Block distance, $\alpha = 2 \Rightarrow d_{i,j}$ is the Euclidean distance and the more $\alpha$ increases, the more $d_{i,j}$ tends to the Chebyshev distance. $N_f$ is the length of the vectors of the characteristics. $g_k$ is the dissemblance function that compares each pair of features.

5. EXPERIMENTATION

The evaluation of the performances of our approach has been achieved on a corpus of 750 envelope images (considered as difficult and noisy) and more than 98% of good localization has been obtained. Others tests were carried out, as well, on a basis of 100 images rejected by the currently most powerful system of localization, all these rejections being due to the failure of one of the localization phases. The following curve shows that 18 envelopes were rejected because of a bad binarisation, 53 because of a bad physical segmentation and 29 because of a bad identification of the address block. 93% of good localization was obtained using our approach.

![Figure 14. Performances of our method](image)

Thanks to its robustness to the parasitic elements, the HGC method is definitely more efficient for noisy images (see figure 15 and figure 16) segmentation by comparison to classical approaches like RLSA and projection profiles based methods.

![Figure 15. Noisy block address (a), emergence of the lines by the RLSA method (b), Perception of the lines by coloring (c).](image)

![Figure 16. Text line segmentation: fusion of line 2 with line 3 by the method of profile projection (Left), correct segmentation of the text lines inclined by the method based on the HGC (Right).](image)
6. CONCLUSION

We have presented in this paper a new approach of address-block localization based on a hierarchical graph coloring and a pyramidal data organization. We have shown that the hierarchical graph coloring give a great robustness with parasitic objects considered as principal factors of physical segmentation error, and that the b-coloring leads to a noticeable improvement of the interpretation step of candidate blocks. Moreover, we also intend to increase coherences between the various modules so as to reduce the computing times and the rejection rates. This work is granted by CESA Company (www.cesa.fr).

REFERENCES

17. Brice Effantin and Hamamache Khedouci, a distributed algorithm for a b-coloring of a graph, the fourth international symposium on parallel and distributed processing and applications (ISPA’2006), serrento, Italy, 2006.