Indexation of Document Images Using Frequent Items

Eugen Barbu, Pierre Heroux, Sebastien Adam and Eric Trupin

Laboratoire Perception Systemes Information CNRS FRE 2645, University Of Rouen, Place E. Blondel, 76 821 Mont Saint Aignan cedex, France

Abstract. Documents exist in different formats. When we have document images, in order to access some part, preferably all, of the information contained in that images, we have to deploy a document image analysis application. Document images can be mostly textual or mostly graphical. If, for a user, a task is to retrieve document images, relevant to a query from a set, we must use indexing techniques. The documents and the query are translated in a common representation. Using a dissimilarity measure (between the query and the document representations) and a method to speed-up the search process we may find documents that are from the user point of view relevant to his query. The semantic gap between a document representation and the user implicit representation can lead to unsatisfactory results. If we want to access objects from document images that are relevant to the document semantic we must enter in a document understanding cycle. Understanding document images is made in systems that are (usually) domain dependent, and that are not applicable in general cases (textual and graphical document classes). In this paper we present a method to describe and then to index document images using frequently occurences of items. The intuition is that frequent items represents symbols in a certain domain and this document description can be related to the domain knowledge (in an unsupervised manner). The novelty of our method consists in using graph summaries as a description for document images. In our approach we use a bag (multiset) of graphs as description for document images. From the document images we extract a graph based representation. In these graphs, we apply graph mining techniques in order to find frequent and maximally subgraphs. For each document image we construct a bag with all frequent subgraphs found in the graph-based representation. This bag of "symbols" represents the description of the document.

1 Introduction

A document image analysis (DIA) system transforms a document image into a description of the set of objects that constitute the information on the document and which are in a format that can be further processed and interpreted by a computer [1]. Documents can be classified in mostly graphical or mostly textual documents [2]. The mostly textual documents also known as structured documents respect a certain layout and powerful relations exist between components. Examples of such documents are technical papers, simple text, newspapers, program, listing, forms,… Mostly graphical documents do not have strong layout restrictions but usually relations exist between

Barbu E., Heroux P., Adam S. and Trupin E. (2005).
Indexation of Document Images Using Frequent Items.
In *Proceedings of the 5th International Workshop on Pattern Recognition in Information Systems*, pages 164-174
DOI: 10.5220/0002576001640174

different document parts. Examples of this type of documents are maps, electronic schemas, architectural plans …

For this two categories of documents graph based representations can be used to describe the image content (e.g. region adjacency graph [3] for graphical and Voronoi-based neighborhood graph [4] for textual document images).

This paper presents an approach similar with the “bag of words” method from Information Retrieval (IR) field. We describe a document using a bag of symbols found automatically using graph mining [5] techniques. In other words, we consider as “symbols” the frequent subgraphs of a graph-based document representation and we investigate if the description of a document as a bag of “symbols” can be profitably used in a indexation and retrieval task.

The approach has the ability to process document images without knowledge of, or models for document content. Frequent items are used in clustering of textual documents [6], or in describing XML documents [7] , but we do not know any similar approch in the DIA field.

This paper is one step from a plan that has as aim to study if the bag of symbols approach can be successfully used in document image supervised classification, indexation and clustering (see Fig. 1).

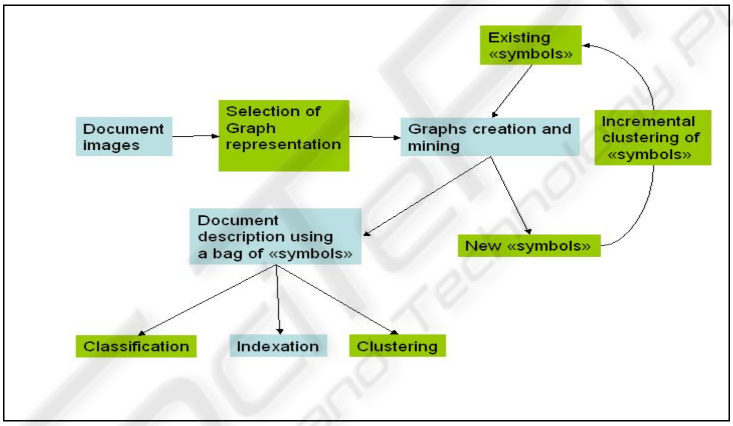


Fig. 1. The “ bag of symbols” applications on document images

The outline of this paper is as follows. In section 2 we present a graph representation and how we create this representation from a document image. Section 3 presents the graph-mining method used, in section 4 we describe how we search documents based on dissimilarities between bags of objects. Section 5 shows experimental results. We conclude the paper and outline perspectives in section 6.

2 Graph representation

Eight levels of representation for document images are proposed in [8]. These levels are ordered in accordance with their aggregation relations. Data array, primitive, lexical, primitive region, functional region, page, document, and corpus level are the representation levels proposed.

Without loosing generality, in the following paragraphs we fix our attention on a graph-based representation build from the primitive level. The primitive level contains objects such as connected components (set of adjacent pixels with the same color) and relations between them. From a binary (black and white) document image we extract connected components. The connected components will represent the graph nodes. On each connected component we extract features. In the actual implementation the extracted characteristics are rotation and translation invariant features based on Zernike moments [9]. The invariants represents the magnitudes of a set of orthogonal complex moments of a normalized image.

Let *I* be an image and *C(I)* the connected components from *I*, if $c \in C(I)$, *c is described as* $c=(id,P)$, where *id* is a unique identifier and *P* the set of pixels the component contains. Based on this set *P*, we can compute the center for the connected component bounding box and also we can associate a feature vector to it. Based on that, $c=(id,x,y,v), v \in R^n$. Subsequently using a clustering procedure on the feature vectors we can label the connected component and reach the description $c=(id,x,y,l)$ where *l* is a nominal label . The graph *G(I)* representing the image is $G=G(V(I),E(I))$. Vertices *V(I)* correspond to connected components and are labeled with component labels. An edge between vertex *u* and vertex *w* exists *iff* $((u.x-w.x)^2+(u.y-w.y)^2)^{1/2}<t$,where *t* is a threshold that depends on the image *I* global characteristics (size, number of connected components,…).

The following paragraph presents the clustering procedure used to associate each connected component a label.

2.1 Labeling connected components

The two main categories of clustering methods are partitional and hierarchical. Partitional methods can deal with large sets of objects (“small” in this context means less than 300) but needs the expected number of clusters in input. Hierarchical methods can overcome the problem of number of clusters by using a stopping criterion [10] but are not applicable on large sets due to their time and memory consumption.

In our case the number of connected components that are to be labeled can be larger than the limit of applicability for hierarchical clustering methods. In the same time we cannot use a partitional method because we do not know the expected number of clusters. Based on the hypothesis that a “small” sample can be informative for the geometry of data, we obtain in a first step an estimation for the number of clusters in data. This estimation is made using an ascendant clustering algorithm with a stopping criterion. The number of clusters found in the sample is used as input for a partitional clustering algorithm applied on all data.

We tested this “number of cluster estimation” approach using a hierarchical ascendant clustering algorithm [11] that employes Euclidean distance to compute the dissimilarity matrix, complete-linkage to compute between-clusters distances, and

Calinsky-Harabasz index [10] as a stopping criterion. The datasets (T_1, T_2, T_3) (see Table 1.) are synthetically generated and contain well separated (not necessary convex) clusters.

Table 1. Data sets description

T	|T|	no. of clusters
T1	24830	5
T2	32882	15
T3	37346	24

Table 2. Proposed number of clusters

T \ |S|	50	100	300	500	600	700
T1	[6, 8, 7, 6, 5, 6, 6, 6, 5, 5] **6**	[5, 7, 9, 7, 5, 5, 7, 5, 5, 7] **5**	[7, 5, 7, 8, 7, 5, 5, 5, 7, 7] **7**	[8, 7, 5, 5, 5, 5, 5, 5, 5, 5] **5**	[5, 5, 5, 5, 5, 7, 7, 7, 7, 5] **5**	[5, 5, 7, 5, 7, 5, 5, 7, 5, 5] **5**
T2	[9, 15, 15, 14, 13, 15, 13, 13, 14, 15] **15**	[15, 15, 13, 15, 15, 15, 15, 15, 15, 15] **15**	[15, 15, 15, 15, 15, 15, 15, 15, 15, 14] **15**	[15, 15, 15, 15, 15, 15, 15, 15, 15, 15] **15**	[15, 15, 15, 15, 15, 15, 15, 15, 15, 15] **15**	[15, 15, 15, 15, 15, 15, 15, 15, 14, 15] **15**
T3	[11, 7, 9, 18, 7, 7, 6, 4, 14, 8] **7**	[6, 14, 23, 21, 7, 17, 23, 16, 12, 11] **23**	[22, 24, 23, 19, 23, 24, 24, 21, 21,24,] 24] **24**	[21, 25, 25, 24, 22, 24, 23, 24, 24, 24] **24**	[20, 25, 21, 24, 19, 23, 24, 25, 24, 22] **24**	[23, 20, 21, 20, 25, 24, 24, 21, 25, 24] **24**

Considering *S* the sample extracted at random from a test set, in Table 2 we present predicted cluster numbers obtained for different sample sizes. After repeating the sampling procedure for *10* times if the test set is for example |*S*|=*50*, we obtain a set of estimations for the number of clusters. We can see that by using a majority voting decision rule we can find the good number of clusters in most of the cases and even when the sample size is very small (*50 or 100*) compared to the data set size.

We employed our sampling approach combined with the k-medoids clustering algorithm [12] on the connected components data set from images in our corpus (see section 5). The k-medoids clustering algorithm is a more robust version of the well known k-means algorithm. The images from our corpus contain *6730* connected components. The proposed number of clusters using ten samples of size *600* is *[16,14,17,16,16,19,7,17,15,16]* and by considering the majority we use *16* clusters as input to the partitional clustering algorithm.

After labeling the connected components (nodes in the graph) subsequently we describe the way we add edges to the graph. The edges can be labeled or not (if unlabeled the significance is Boolean: we have or have not a relation between two connected components) and can be relations of spatial proximity, based on “forces” [13], orientation or another criterion.In our actual implementation the distance between centers of connected components is used (see Fig. 2). If the distance between two connected components centers is smaller than a threshold, then an edge will link the two components (nodes).

3 Graph mining

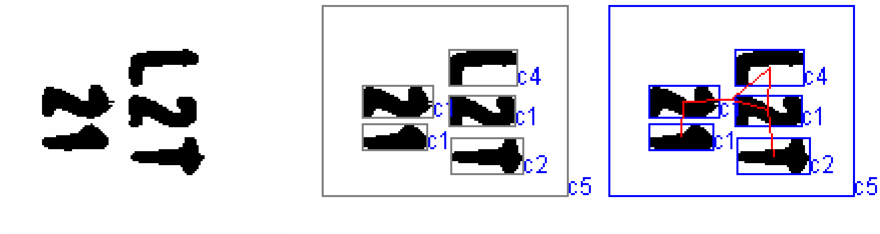
"The main objective of graph mining is to provide new principles and efficient algorithms to mine topological substructures embedded in graph data" [5].

Mining frequent patterns in a set of transaction graphs is the problem of finding in this set of graphs those subgraphs that occur more times in the transactions than a threshold (minimum support). Because the number of patterns can be exponential this problem complexity can also be exponential. An approach to solve this problem is to start with finding all frequent patterns with one element, then all patterns with two elements, etc in a level-by-level setting . In order to reduce the complexity different constraints are used: the minimum support, the subgraphs are connected, and not overlapped.

The first systems emerged from this field are SUBDUE and GBI [5]. These approaches use greedy techniques and hence can overlook some patterns. The SUBDUE system search subgraphs in a single graph using a minimum description length-based criterion. Complete search for frequent subgraphs is made in an ILP framework by WARMR [5]. An important advance is the introduction of the concept of closed subgraph. A graph is said to be closed or maximal if it does not have a super-graph with the same number of apparitions in the dataset [14]. The graph-mining systems were applied to scene analysis, chemical components databases and workflows. A system that is used to find frequent patterns in graphs is FSG (Frequent Subgraph Discovery) that "finds patterns corresponding to connected undirected subgraphs in an undirected graph database"[15].

In our document image analysis context we are interested in finding maximal frequent subgraphs because we want to find symbols but to ignore their parts.

The input for the FSG program is a list of graphs. Each graph represents a transaction. We present subsequently how we construct the transactions list starting from a set of document images. Using the procedure presented in section 2 we create for each document an undirected labeled graph.




```
t #DocId=1
#distance treshold = 30
v 0 c4
v 1 c1
v 2 c1
v 3 c1
v 4 c2
v 5 c5
u 0 2 E
u 0 5 E
u 1 3 E
u 1 5 E
u 2 4 E
u 2 5 E
```

Fig. 2. An image (width=123, height=96) and associated graph transaction

Every connected component of this graph represents a transaction. We can further simplify the graphs by removing vertices that cannot be frequent and their adjacent edges. Using FSG we extract the frequent subgraphs and we construct a bag of graphs occurring in each document. In the following paragraphs we consider that the frequency condition is sufficient for a group of connected components to form a symbol and we will conventionally make an equivalence between the frequent subgraphs found and symbols. As we can see in the example (Fig. 2) the proposed symbols are far from being perfect due to the image noise, connected components clustering procedure imperfections, … however we can notice the correlation between this artificial symbol and the domain symbols.

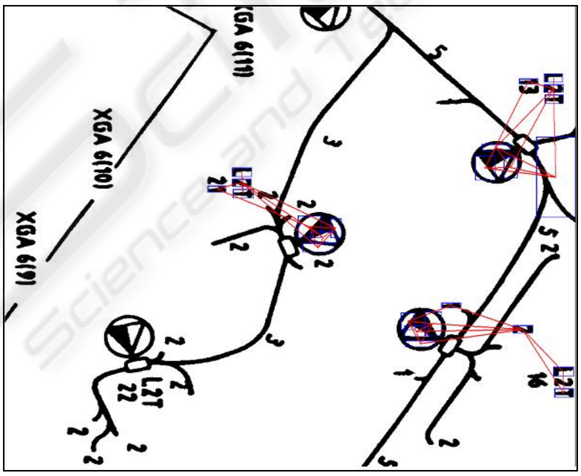


Fig. 3. Frequent subgraph and its occurences in an image

In conclusion, the subgraphs proposed as frequent are used to model a document as a bag of symbols. Because some documents may not contain any symbols the document representation is based on two vectors containing connected components labels, and symbols labels.

$$A: (c_{i1}, c_{i2}, \ldots, c_{in}), (s_{j1}, s_{j2}, \ldots, s_{jm}), i_1 \le i_2 \ldots \le i_n, j_1 \le j_2 \ldots \le j_m.$$

4 Dissimilarity between document descriptions

In this paragraph we present the dissimilarity measure employed between the documents descriptions that we used.

A collection of documents is represented by a symbol-by-document matrix **A**, where each entry represents the occurrences of a symbol in a document image, $\mathbf{A} = (a_{ik})$, where a_{ik} is the weight of symbol *i* in document *k*. Let f_{ik} be the frequency of symbol *i* in document *k*, *N* the number of documents in the collection, and n_i the total number of times symbol *i* occurs in the whole collection. In this setting conform with [16] one of the most effective weighting scheme is entropy-weighting. The weight for symbol *i* in document *k* is given by :

$$a_{ik} = \log(1 + f_{ik}) * (1 + \frac{1}{\log(N)} \sum_{j=1}^{N} \frac{f_{ij}}{n_i} \log(\frac{f_{ij}}{ni}))$$

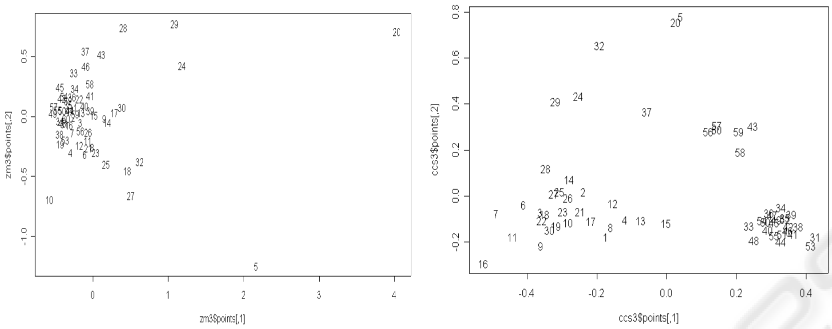
Now, considering two documents A, B with the associated weights $A = (a_1, a_2, \ldots, a_t), B = (b_1, b_2, \ldots, b_t)$ where *t* is the total number of symbols, then

$$d(A,B) = 1 - \frac{\sum_{i=1}^{t} a_i * b_i}{(\sum_{i=1}^{t} a_i^2 \sum_{i=1}^{t} b_i^2)^{1/2}}$$

represents a dissimilarity measure based on the cosine correlation.

5 Experiments

The corpus used for evaluation contains 60 images from 3 categories: electronic (25 images) and architectural schemas (5 images) and engineering maps (30 images) (see Fig. 5). In order to present a corpus summary we employed a multidimensional scaling algorithm to represent in a two dimensional plot the dissimilarities between documents (see Fig. 4). Each document image is described with one of the following types of features : Zernike moments for the whole image (a vector with 16 components) or the connected components and symbols lists described above. In Fig. 4.a) we present the dissimilarities between images represented by Zernike moments. In Fig. 4.b) are plotted the dissimilarities between the document images computed using the cosine correlation presented in section 4. Each image from the corpus has an id from 1 to 60. The engineering maps have identifiers from 1 to 30, electronic images from 31 to 55, and the arhitectural schemas from 56 to 60. We can see in Fig. 6 that the bag of symbols representation separate better the image classes. This fact has an important influence on the quality of the query results.



a.) **b.)**

Fig. 4. Documents ids presented in a two dimensional space with respect to their reciprocal dissimilarities

A query can be an image, a list of symbols and connected components, or only one of the later lists.

$$query: \left(c_{i1}, c_{i2}, \ldots, c_{in}\right), \left(s_{j_1}, s_{j_2}, \ldots, s_{j_m}\right), i_1 \le i_2 \ldots \le i_n,\ j_1 \le j_2 \ldots \le j_m.$$

$$query: \left(s_{j_1}, s_{j_2}, \ldots, s_{j_m}\right), j_1 \le j_2 \ldots \le j_m.$$

$$query: \left(c_{i1}, c_{i2}, \ldots, c_{in}\right), i_1 \le i_2 \ldots \le i_n.$$

In order to extract the formal description of a given query image we label the connected components of the query image, construct the graph, and employ graph matching to detect which symbols occur in the query image. At the end of this process the query image is described by the two lists of connected components and symbols.
In order to evaluate experimental results we used precision and recall measures. If A is the set of relevant images for a given query, and B is the set of retrieved images then :

$$precision = \frac{|A \cap B|}{|B|}, \quad recall = \frac{|A \cap B|}{|A|}$$

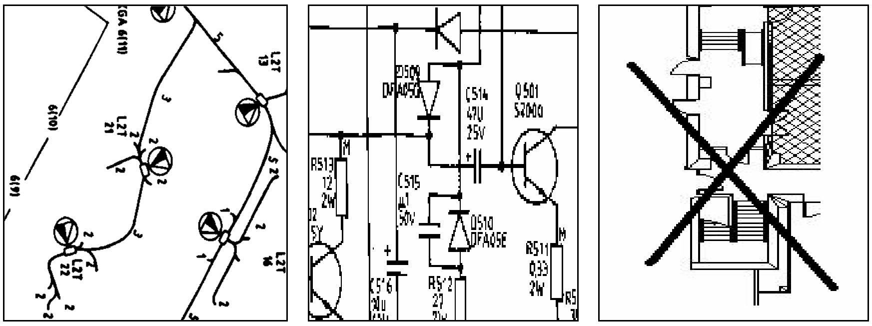


Fig. 5. Corpus images

This corpus contains images that are scanned and contain real and artificial noise.

Table 3. Queries recall and precision

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10
recall	0.75	0.5	0.48	0.55	0.56	0.76	0.6	0.4	0.32	0.16
precision	0.6	0.31	0.8	0.73	0.87	0.95	0.88	0.5	0.42	0.4

Queries Q1-4 represents symbol queries , i.e. as input is a list of symbols. The other queries are document images.

6 Conclusions

The research undertaken represents a novel approach for indexing document images. The approach uses data mining techniques for knowledge extraction. It aims at finding image parts that occurs frequently in a given corpus. These frequent patterns are part of the document model and can be put in relation with the domain knowledge.

Using the proposed method we reduce in an unsupervized manner the semantic gap between a user representation for a document image and the indexation system representation.

The exposed method can be applied to other graph representations of a document. In the near future, we will apply this approach to layout structures of textual document images.

Another follow up activity is to quantify the way noise affects the connected components labeling, and the manner in which an incorrect number of clusters can affect the graph mining procedure. Based on this error propagation study we can ameliorate our method. Other possible improvements can be obtained if we would employ a graph-based technique that can deal with error tolerant graph matching.

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