Structural Clustering Multimedia Documents: An Approach based on Semantic Sub-Graph Isomorphism

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ABSTRACT

The works that used graphs to represent documents has referred to the richness of these expressive tools. However, the exploited graph theory could be of great interest concerning the evaluation of similarity between these documents, both in documentary classification and the information retrieval. In structural classification of the documents, object of this work, the similarity measure is a crucial step. In many applications, this step results in a sub-graph isomorphism problem. This problem is known in graph theory by a combinatorial explosion. To get around this problem, we propose to consider a graph as a set of paths that compose it. The matching, paths allows reducing the combinatorial cost.

We propose a structural measure based on the sub-graph isomorphism and we discuss the quality of our classifier, especially the separation of classes. We'd like to show that our measure is structural, not a "surface measure" and evaluate our approach on a corpus of multimedia documents extracted, randomly, from the INEX 2007 corpus.

Keywords

multimedia document, clustering, sub-graph isomorphism, structural similarity.

1. INTRODUCTION

Increasingly, documentary classification becomes a necessity in many domains of application both in industrials and academics. Generally, documents are classified for underlying purpose: to understand, reduce complexity, heterogeneity (size, type, form, etc), for easy retrieval, etc. The clusters are meaningful to him who created it. In a research laboratory, for example, documents can be grouped by team, by type (thesis, papers, etc.), by theme, etc. The same document can be manipulated differently by human agent or automatically. The multiple uses of a document, implies a multiplication of structures of it: logical, physical, semantic, etc. The definition of multiple structures of the same document arouses the problem of called *multi-structured documents* [3].

Multimedia documents are characterized by a rich content (image, text, sound, etc) and complex structures, which complicates access to specific granules (fine information) in such documents and therefore makes the evaluation of their similarity a tedious task. The complexity of multimedia documents involves problems related to their representation. In [11], the model *MVDM* "*Multi Views Document Model*" proposed by [6] allows a rich representation of the mutli-structured documents. In this model, the multi-structurality induces a representation of documents in graph forms (structures and their links).

We continue within *MVDM* and we consider that the document structure is sufficiently discriminating factor for classification. In our previous work [9], we have presented our classification process that is to automatically generate, in a documentary warehouse, clusters called generic views. These generic views grouped documents describing similar information (Cvs, documentary films, scientific papers, etc.). We used acyclic graphs to represent document. To compare structurally two documents means to compare the graphs that represent them. The graph theory could be of great interest in the evaluation of the structural similarity. In [13], to show graph equivalence or inclusion, may be done by looking for a sub-graph isomorphism. The problem of sub-graph isomorphism, known in graph theory, is a combinatorial problem. To get around this problem, we propose to consider a graph as a set of paths that compose it.

To evaluate the proximity between document structures, we proposed a similarity measure based on semantic sub-graph isomorphism taking into account the distribution (order, position, etc.) components of the structures compared and relationships between these components (preserve more sense). We show that our approach is based on structural similarity not on the "*surface similarity*" like as the case, for example, the Jaccard measure and Cosine measure. In [12], ignore the document structure means ignoring its semantic.

We have also proposed a cluster threshold separation as a parameter fixed previously by the user. This allows maintaining the cluster stability, minimizing inter-cluster similarity. Increase the dissimilarity between clusters can reduce noise and increase the precision of information retrieval systems (IRS). Indeed, when the clusters are very similar another problem arises. For example, consider two classes of documents: the first group documents discussing the world economic crisis and the second represents the documents on the crisis in Greece. In such a situation, there could be documents that are similar, at the same time, the two classes. In [1], two distant objects represent data belonging to different groups.

In [7], validation of a structure generated by an automatic classification is essential. In this context, we propose to recalculate the clusters once classifying is completed. This ensures that each document is attached at the right cluster.

In the next section we will give an overview, not exhaustive but representative measures of graph similarity. First we begin this section with some basic notions on graphs. We describe in the third section our approach of structural clustering of multi-structured multimedia documents.

2. RELATED WORKS

Graphs are widely used in many applications, its allow a rich modeling of complex and structured objects.

2.1 Basic notions on graphs

2.1.1 Definition

Definition**:** A graph *G* can be defined by a pair (*V*, *E*), where *V* is the set of nodes of *G* and $E \subseteq V$ x *V* represents the set of edges of *G* (relations between nodes).

2.1.2 Definition

Let the graphs *G*=(*V*,*E*) and G'=(*V',E'*) ;
G' is a sub-graph of $G \Leftrightarrow V' \subseteq V$ et $E' \subseteq E$.

2.1.3 Definition

let *G*=(*V*,*E*) and G'=(*V',E'*) Two graphs. *G* is isomorphic to a sub-graph of G' if there is an injection *f* from *V* to *V'* such:
$\forall (u,v) \in V^2$; $(u,v) \in E \Rightarrow (f(u),f(v)) \in E'$.

2.2 Similarity measures

Among the standard measures, from the most popular, we cite the Jaccard measure and the Cosine measure. These measures were used in various applications, to evaluate the similarity between two objects, represented by *X* and *Y*:

$$Jaccard(X,Y) = \frac{|X \cap Y|}{|X \cup Y|} \qquad (1)$$

$$Cosinus(X,Y) = \frac{|X \cap Y|}{\sqrt{|X| . |Y|}} \qquad (2)$$

Other measures were introduced in specific contexts and for specific goals. In this section, we present a representative overview of the works that used graphs (or trees) to represent objects to compare them.

[17] represent XML documents in tree form, and then they consider this tree as a set of paths. Thus, they calculate the frequency of these paths in order to ensure the classification of documents. The preprocessing steps, which is to reduce the number of paths, and the filter tag by replacing some tags and ignoring others can cause information loss that can be useful for classification. [16] use the frequency trees in their structural clustering process. It means to associate a document to a cluster by searching, in a corpus of trees, a set of frequently sub-trees to represent the document. The algorithms used in these approaches are complex and therefore their response time is generally very high. [5] use the labeled "tree summary". A tree summary is obtained by transformations (depth reduction, elimination of repeated nodes, etc) of trees. However, these transformations can cause loss of semantic information. To evaluate the similarity of two documents represented in tree forms *T* and *T'*, [10] has introduced the following measure:

$$Sim(T,T') = 1 - \frac{\sum_{vj} Danc(vj)}{\sum_{vj} Panc(vj)} \qquad (3)$$

Danc(v_j)*:* represents the distance alignment of the ancestors of node v_j.
Panc(v_j)*:* represents the weight of the ancestors of node v_j.

This measure allows calculating the degree of inclusion between two trees *T* and *T'* but it doesn't evaluate their similarity.

Approaches using trees to represent multimedia documents confronted with the problem of the boundary representation of multiple relationships between the same two nodes in a document. It is therefore necessary to find a model of representation appropriate to the multi-structured multimedia documents.
To compare medical images of a brain model brain [2], used graphs. Since the medical image is often noisy and over-segmented, the comparison of graphs in this context is based on a matching one-to-many (one region of the image model can correspond to several regions of the medical image). [14] have proposed a parameterized measure to evaluate the similarity of graphs representing images. They showed that the measure proposed by [4] can be seen as a particular case of their measurement. The authors have noted that the calculation of their similarity measure arouses a combinatorial explosion that makes searching for greater common sub-graph of two graphs restricted to small graphs. The measures used in these works are introduced in specific contexts; they can't easily be adapted for solving the general problems. To

$$Sim(G,G') = 1 - \frac{\sum_{\varepsilon,\varepsilon'} D_n(\varepsilon,\varepsilon')}{\sum_{\varepsilon} P_f(\varepsilon) + \sum_{\varepsilon'} P_f(\varepsilon')} \qquad (4)$$

calculate the similarity score between two graphs *G* and *G'*, representing XML documents, [6] proposed the following measure:

D_n : alignment function of relationships ε and ε'
P_f : function to calculate the final weight of a relationship (arc of a graph) and which is equal to the product of three functions P_{str}: structural weight, P_{Adap}: weighting adaptation and P_{Rep}: weights reflecting the representation of relationships. Calculating the final weight, which is product of these three functions, requires a response time that increases with the size of the graphs.

The choice of modeling objects greatly affects the quality of the classification of these objects. Graphs have a rich expressiveness power, which explains their presence in many application areas. In the next section, we describe our approach of structural clustering of multimedia documents based on structural and semantic similarity of graphs. In [15], many applications involve matching two graphs in order to compute their similarity.

3. STRUCTURAL CLUSTERING OF DOCUMENTS

In [6], the notion of structure can be encompassed in a wider concept which is that of view. A view is a particular description of a document which expresses one or more special needs of this document. It reflects one of the structures of a multi-structured document. Multiple descriptions, (multiple views) of the same content, allows combining several criteria to access precisely to the information deemed relevant by the user. For example in Figure 1, the document "Discours_P" contains the discourses of French presidents. It can be described by "President" and "occasion" (two structures of the same nature).

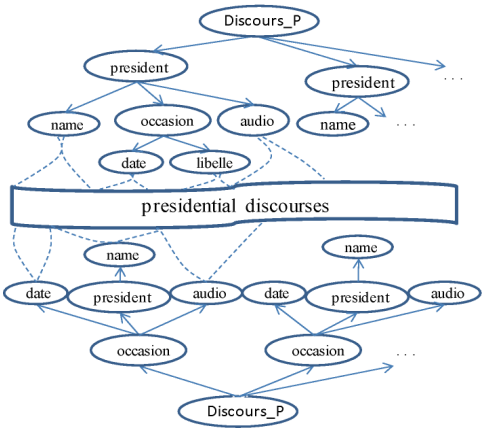


Fig 1: Two same nature structures for the same document

Formally, a view is a description of a document, by a set of components connected with each other. It can be represented using a directed graph where nodes represent components of the view documentary and arcs of the graph represent the relationships between these components (example Figure 1). A document d_i can be described by a set $\{Vsp_j\}_{j\in[1,ni]}$ of specific views where each view $Vsp_j=(N_j,E_j)$ with N_j is a set of components of d_i *and* E_j is the set of relationships between these components.

For describing document structures, we use the *MVDM*. This model is organized on the concept of view. It is composed of two layers: a specific layer where each specific view, characterizing the organization of a particular document, is represented in tree form and a generic layer where the generic views are represented by graphs (Figure 2).

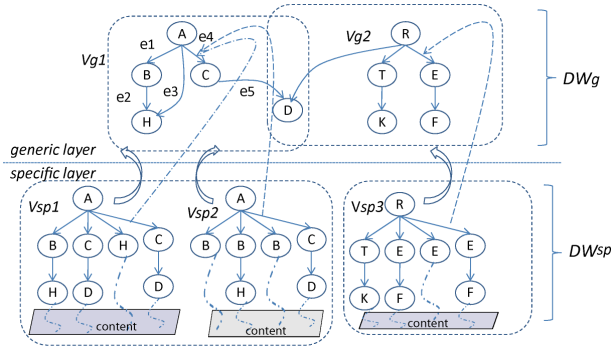
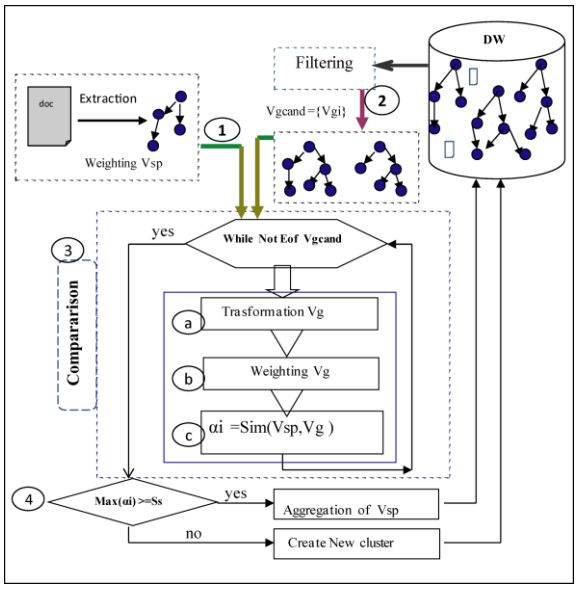


Fig 2: Example of the documentary warehouse (DW).

Formally, we can write : $DW=DWg \cup DWsp$ where *DWg* represents a layer genéric of *DW* and *DWsp* repesents its specific layer. A generic view summarizes the overall characteristics of specific views it represents. A cluster C_i, represented by Vg_i (see Figure 2), groups a set of specific views structurally similar. These views describe specific information thematically similar. Access to the cluster represented by Vg_i permits access targeted to the sub-collection of documents, represented by it. In our previous works [8], we have presented the steps of our document integration process in the documentary warehouse (see Figure 3). Due to lack of space, we can't detail our approach to structural clustering, but we refer the reader to these works. The basic idea of our integration process of a new multimedia document in DW is to extract the specific view *Vsp* of this document then calculate the similarity between *Vsp* and each generic view *Vg* of Dw_g. then, depending on the results of this step either aggregating *Vsp* in the cluster most similar (attach the specific components nodes, relations, of document, to the generic components similar of *Vg*, example Figure 2) or create a new cluster. Clusters aren't defined previously; they are created automatically along with the integration of documents.

Fig 3: Overall architecture of the clustering process



In the following, we present our similarity measure based on sub-graph isomorphism and show that this measure is structural.

Let $G=(V,E)$ and $G'=(V',E')$ two labeled, acyclic and , ordered digraphs. *G* can be considered as a set of simple paths where one path is a sequence of adjacent nodes *p* ($p>0$) from the root node u_1 to u_p : $chm_i= u_1/u_2/u_3/\ldots\ldots/u_p$ where $(u_k,u_{k+1}) \in E$, $k\in\{1,2,\ldots,p-1\}$. And we consider a path of G as a sub-graph of G. Matching two graphs is therefore to match their paths.

Let $CH_G=\{chm_1,chm_2, \ldots,chm_n\}$ the set of paths of *G and* $CH_{G'}=\{chm'_1,chm'_2, \ldots,chm'_{n'}\}$ the set of paths of graphs.
n (*resp. n'*): number of paths of *G (resp. G')*.

We define the alignment function of paths D_{ch} from GxG' *(resp. from* $G'xG$*)* to [0,1] as follows:

$$D_{ch}: G \times G' \rightarrow [0,1]$$
$$(chm, chm') \ \alpha \ D_{ch}(chm, chm')$$

$$where\ D_{ch}(chm, chm') = \frac{\sum_{e_i \in chm} | P_e(e_i) - w_i |}{\sum_{e_i \in chm} P_e(e_i)} \qquad (5)$$

$$and\ w_i = \begin{cases} P_e(e'_k)\ if\ \exists\, e'_k \in chm'\ \ \varphi_e(e_i) = e'_k \\ 0\ \text{otherwise} \end{cases} \qquad (6)$$

- P_e is the weighting function which allows weighting the relationship of a graph and we have defined as:

$$P_e: E \rightarrow]0,1[$$
$$(u,v) \ \alpha \ P_e(u,v)$$

where

$$P_e(u,v)=\begin{cases}1-\dfrac{ord(v)}{k} & \text{if depth(v)=1} \\ P_e(x,u)-\dfrac{ord(v)}{k^{depth(v)}} & \text{otherwise ; u is the incident node of (x,u)}\end{cases} \quad (7)$$

- *depth(v)*: designates the depth of the node *v,*
- *ord(v)*: designates the order of the node *v* (its position relative to its brothers nodes),
- *k* is a parameter (a power of 10) fixed by the user and that designates the maximum number of nodes son (son number <*k*) for each node graphs manipulated.
- φ_e bidirectional alignment function of relations from *E* to *E' (resp. from E'* to *E),* which aligns a relation of *G* to the relation of *G'* most similar.

For example in G_2 of Figure 4, $P_e(C,H)= P_e(A,C) - ord(H) / 1000 =0.779$.

Corollary: the path *chm* of *G* is similar to *the path chm'* of *G' iff* $D_{ch}(chm,chm')=min(D_{ch}(chm,chm'_j))_{j\in[1,n']}$ and $D_{ch}(chm,chm')<1$.

To evaluate the structural similarity between graphs *G* and *G'*, we have proposed the following measure:

$$Sim(G,G')=1-\frac{d_{GG'}+d_{G'G}}{2} \quad (8)$$

$$\text{where } d_{GG'}=\frac{1}{n}\sum_{i\in[1,n]}\min_{k\in[1,n']}(D_{ch}(chm_i,chm'_k)) \quad (9)$$

$$\text{and } d_{G'G}=\frac{1}{n'}\sum_{j\in[1,n']}\min_{k\in[1,n]}(D_{ch}(chm'_j,chm_k)) \quad (10)$$

Division by *n* (number of paths of *G)* allows a standardization the value of $d_{GG'}$ ($d_{GG'}\in[0,1]$).
In the following, we describe our search algorithm for sub-graph isomorphism between two graphs *G* and *G ':*

let $CH_G=\{chm_1, chm_2, \ldots\ldots, chm_n\}$ the set of paths of *G,*
let $CH_{G'}=\{chm'_1, chm'_2, \ldots\ldots, chm'_{n'}\}$ the set of paths of *G',*
let $CH_{App}=\phi$ *where* CH_{App} the set of the matched paths of *G.*

begin
  for each $chm_i \in CH_G$
    if $\exists\, chm'_j \in CH_{G'}$ / chm_i *similar to* chm'_j *then*
      $CH_{App} = CH_{App} \cup \{ chm_i \}$,
      $CH_G = CH_G - \{ chm_i \}$,
    endif
  endfor
  if $card(CH_{App})=card(CH_G)$ *then*
    G is isomorphic to a sub-graph of G'
  endif
end

In the following, we show that our measure takes into account the contextual and structural aspects of documents to compare. We also show our contribution to the cost reduction of combinatorial matching graphs.

3.1 The impact of our weighting on the proposed measure

The similarity measure proposed is based on path matching of graphs to compare. We show through the example of figure 4, that it takes into account the distribution of the components of matched graphs.

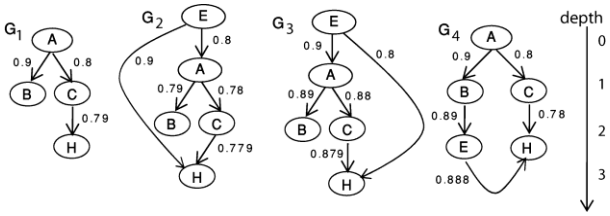


Fig4: Example of weighting graph relations.

Thus in this example of figure 4, the paths G_2*:E/A/B* and G_3 *:E/A/B* are similar to 88% (according to our approach). In fact:

$$D_{ch}(G_2:E/A/B,G_3:E/A/B)=\frac{(0.9-0.8)+(0.89-0.79)}{0.79+0.8}=0.12$$

The distance (greater than zero) between these two paths is due to the fact that the two paths don't have the same position in the two graphs. Despite consisting of the same elements, these two paths aren't identical (similar 100%) because they haven't got the same role in both graphs.

In a multimedia document, the order of components, the synchronization between and within components and the links between these components are crucial parameters concerning the sense of this document.

3.2 The particularities of our measure

In a comparison process of document structures, we believe that the structural information is essential and that two documents composed of the same words doesn't imply they are similar.

We explain, through the example of structures represented by graphs in figure 4, that measures of Jaccard and Cosine don't take into account the distribution of components (order, level of depth, etc) of the matched graphs:

Table 1. Comparison of our measure with those of Jaccard and Cosine

Jaccard	Cosine	Our measure
$J(G_1,G_2)=0.67$	$Cos(G_1,G_2)=0.81$	$Sim(G_1,G_2)=0.64$
$J(G_1,G_3)=0.67$	$Cos(G_1,G_3)=0.81$	$Sim(G_1,G_3)=0.652$
$J(G_1,G_4)=0.67$	$Cos(G_1,G_4)=0.81$	$Sim(G_1,G_4)=0.668$

The results represented in Table 1 show that measures of Jaccard and Cosine don't take into account the distribution of components of the graphs matched.

Unlike measures of Jaccard and Cosine, our measure is structural (not a surface measure). In fact in a multimedia document, the sense is not only the significance of the structural elements of this document but it also concerns the relationships, carrying information implied, between these elements. Our measure reflects both the contextual and structural aspects of objects matched (which justifies the

difference between the lines of the third column of Table 1). In our context, we consider that the relationship between the structural components of a document, represent additional information that complement the overall and contextual meaning of these components. For example, the same image in two different documents can't express the same context and therefore may not have the same importance in both documents. We also show that the existing standard measures can't effectively respond to our problem.

For example in the Figure 5, $G=(V,E)$, $G'=(V',E')$ Where : $V=\{book,author,name,address,street,city\}$, $V'=\{book,author,name,address,number,editor,street,city\}$, $CH_G=\{chm_1, chm_2, chm_3\}$ and $CH_{G'}=\{chm'_1,chm'_2,chm'_3, chm'_4, chm'_5, chm'_6, chm'_7\}$

Where:

chm_1=book/author/name,
chm_2=book/author/adress/street,
chm_3 =book/author/adress/city,
chm'_1= book/author/name,
chm'_2=book/author/adress/number,
chm'_3=book/author/adress/street,
chm'_4=book/author/adress/city,
chm'_5=book/editor/address/number,
chm'_6=book/editor/adress/number,
chm'_6=book/editor/adress/street
and chm'_7= book/editor/adress/city.

In this example, G is isomorphic to a sub-graph of G' (according our approach). Let f an injection function from V to V', such:

- (*book,author*) of G is similar to (*f*(*book*),*f(author))= (book,author)* of G',
- (*author,name*) of G is similar to *f*(author),*f(name))= (author,name)* of G',
- (*author,address*) of G is similar to (*f*(author),*f(address))= (author,address)* of G',
- (*address,street*) of G is similar to (*f*(address),*f(street))= (address,street)* of G',
- (*address,city*) of G is similar to (*f*(address),*f(city))= (address,city)* of G',

Therefore:

- the path chm_1=*book/author/name* of G is similar to the path *f(book)/f(author)/f(name)=*chm'_1 of G',
- the path chm_2=*book/author/address/street* of G is similar to the path *f(book)/f(author)/f(address)/f(street)=*chm'_3 of G',
- the path chm_3=*book/author/address/street* of G is similar to the path *f(book)/f(author)/f(address)/f(street) =*chm'_4 of G'.

On the other side, the paths chm_3 and chm'_7 are not similar. More precisely, we have $D_{ch}(chm_3,chm'_7)$= 0.105 and $D_{ch}(chm_3,chm'_4)=0.00038$,therefore chm_3 is the most similar to chm'_4. Then, the relationship *(address,city)* of chm_3 can't be matched to the relationship *(address,city)* of chm'_7 because this paths aren't similar (according to our approach). However, for measures based on the alignment of nodes, without considering the relationships between the nodes, these two relationships are similar. Consequently, the existing standard measures can't fully respond to our problem.

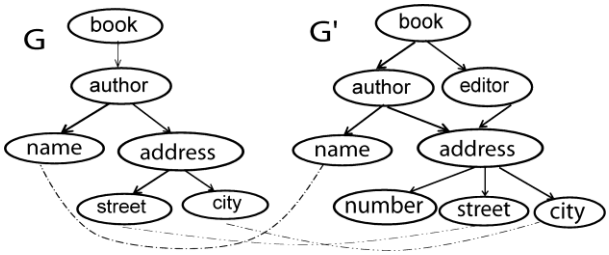


Fig 5: Example of semantic matching paths.

The graph matching leads to a combinatorial explosion which increases with the size of graphs: known problem in graph theory. In the next section, we explain our contribution which aims to reduce this combinatorial.

3.3 The reduction of the combinatorial cost of matching graphs

We explain, through the structures of the example in Figure 5, that the matching paths allows contributing to the reduction of the cost of combinatorial, as discussed above. Calculating the similarity between graphs G and G' is looking for a sub-graph isomorphism. So this is to check all possible injective matchings between G (composed of 6 nodes and 3 paths) and G' (composed of 12 nodes and 7 paths). The number of injections (allowing to match the nodes of two graphs) possible between these two graphs can be calculated using the formula A^p_n (number of permutations of p objects from n objects). In this example, there exists A^6_{12} =12*11*10*9*8*7=665280 injectifive matching possible between G and G' to explore. However, there are A^3_7 =7*6*5*4=840 possible injections, for mapping a path of G to one path of G'(one-to-one). The difference between the number A^6_{12} and A^3_7 shows clearly the interest of our proposal. More generally, let G a graph consisting with *p and* G' a graph consisting with *n paths* (where n>=p). Since a path is a set of nodes, therefore the number of path in a graph is less than the nodes number of this graph. Consequently $A^p_n < A^{|V|}_{|V'|}$ (where $|V|$ is the number of G nodes and $|V|<|V'|$).

In the following, we describe our algorithms that allow evaluating the distance between two graphs G and G':

```
real Dist(graph G, graph G')
let CH_G={chm_1, chm_2, ...,chm_n }the set of G paths,
let CH_G'={chm'_1, chm'_2, ...,chm'_n'} the set of G' paths,
begin
  let d_GG'=0
  for each chm_i of CH_G          //* i ∈[1,n]
    for each chm'_k of CH_G'      //*k ∈[1,n']
      d_i=D_ch(chm_i,chm'_k )
    endfor
    d=min(d_i )
    d_GG'= d_GG' +d
  endfor
    let d_G'G=0
    for each chm'_i of CH_G'
      for each chm_k of CH_G
        d_i=D_ch(chm'_i,chm'_i )
      endfor
      d=min(d_i )
      d_G'G= d_G'G +d
    endfor
  if (d_GG' * d_G'G ≠ 0) then return (d_GG'+ d_G'G)/2
      else return (d_GG'+ d_G'G)
    endif
end
```

To test the separation of a given view over all generic views of Dw_g, we propose the following algorithm:

```
boolean Separat(graph V1)
begin
  boolean View_sep=true
  for each V2 in DW_g
    if (Dist(V1,V2) < S_sep and V1≠V2) then
                View_sep=false
                exit for
    endif
  endfor
  return View_sep
end
```

In the following, we describe our algorithm for the integrating of documents into *DW*:

```
let S_s the similarity threshold
let S_sep the separation threshold.
S_s and S_sep two parameters fixed a previously by user.
let D={d1,d2,.....dn} a set of documents
let C a set of clusters of Dw_g
begin
  for each d_i in D
    Extraction of the specific view Vsp of d_i
    if card(C )=0 then
          C = { C1 }     //* create a new cluster
    otherwise
    for each Vg in Dw_g
       //Transformating Vg
      if (Separat(Vg) then
        α_i =Sim(Vsp,Vg ) //* Sim(Vsp,Vg )=1-Disp(Vsp,Vg)
      endif
    endfor
    α=max(α_i)
    if ∃k / Sim(Vsp, Vg_k)=α>=S_s then
              aggregate Vsp into Vg_k
        otherwise   j= card(C )
          C = C ∪ { C_{j+1} }   //* create a new class C_{j+1}
    endif
  endif
  endfor
  reclassify
end
```

This algorithm allows to receive a set of documents $D=\{d_1,d_2,...,d_n\}$(where a document d_i is represented by a specific view Vsp_i *as* input and generating a set of clusters $C=\{c_1,c_2, ...,c_k\}$ at the output. Each cluster groups a set of structurally similar documents.

Concerning the threshold of similarity S_s, several tests were realized to determine the optimal value. We noticed that the increase of the value of S_s leads to the creation of numerous clusters. On the other hand, the decrease of this value implies the growth of the number of documents associated to each cluster that arouses heterogeneousness between documents of the same class. We noticed that the value of 0.8 (80 % of similarity) gave good results (Idarrou and al., 10).
Our measure is parameterized by a similarity threshold S_s fixed previously by the user to choose the degree of document similarity of generated clusters.

Formally:
$\forall i \in [1,k]\ ;\ \forall d_x \in c_i \Rightarrow Sim(Vsp_x, c_i) >= S_s$ (where Vsp_x is the specific views of documents d_x).
$\forall i, j \in [1,k]\ ;\ i \neq j \Rightarrow Sim(c_i, c_j) < S_s$ (separation of clusters).

4. EXPERIMENTAL RESULTS

To validate our approach, we conducted an evaluation based on a corpus of multimedia documents in XML format (described in Table 1) randomly extracted from INEX 2007 corpus.

Table 2: description of the used corpus

Number of documents	**1200**
Total number of nodes	55708
Total number of elements	25417
Total number of attributes	30291
Average number of nodes/*Vsp*	25.24
Average number of paths /*Vsp*	11.96
Average depth / *Vsp*	6.12

To study the impact of similarity threshold on the quality of classification, we have conducted two experiments on the same corpus of documents (Table 2): The first test with a similarity threshold of 80% and the second with a similarity threshold of 78%. Initially, we have fixed the cluster separation threshold of 20% for both tests.

4.1 First test

The 1200 documents integrated into the documentary warehouse are grouped into 15 clusters of documents. We obtained the results shown in Table 3:

Table 3: Results of our structural clustering process of documents.

Clusters	Nbr of *Vsp*/ cluster	Nbr of Nodes/ cluster	Nbr of Paths / cluster	Average similarity	Standard dervation
C_1	17	1816	344	0.96	0.051105
C_2	85	6535	1302	0.98	0.021720
C_3	52	3430	805	0.95	0.033968
C_4	122	6241	1670	0.98	0.016195
C_5	68	5465	1191	0.98	0.013503
C_6	19	1655	125	0.95	0.051093
C_7	226	9930	2607	0.98	0.014977
C_8	49	1506	483	0.96	0.012697
C_9	34	1913	467	0.99	0.009701
C_{10}	11	800	172	0.98	0.025761
C_{11}	328	8262	2724	0.98	0.009255
C_{12}	16	1142	251	0.99	0.011985
C_{13}	115	3213	960	0.99	0.009555
C_{14}	15	798	179	0.94	0.021291
C_{15}	43	3002	669	0.99	0.010890

The Grouping of 1200 documents as clusters allows access (using cluster representatives) to 55693 fragments (relationships), in average 3712.9 fragments per cluster. It also allows access to 13949 paths (documentary passages) distributed in average 929.93 paths per cluster. The cluster represented by C_{11} is much richer in terms of representativeness. It allows you to navigate in a sub-collection of views, structurally similar, describing 328 documents. Access to C_{11} thus allows access to 8261 fragments (relationships). 8261 fragments composed in 2724

paths distributed in 328 specific views. The standard deviation in average 2%, shows the cluster homogeneity.

4.2 Second test

In this case, the 1200 documents integrated into the documentary warehouse are grouped into 12 clusters of documents (Table 4).

Table 4: Results of our structural clustering process of documents

Clusters	Nber views / cluster	Standards derivation
C_1	27	0.056
C_2	340	0.014
C_3	13	0.011
C_4	3	0.02
C_5	4	0.08
C_6	178	0.01
C_7	3	0.06
C_8	587	0.009
C_9	2	0
C_{10}	7	0.023
C_{11}	33	0.01
C_{12}	3	0.001

We have observed that the number of clusters decreased (12 clusters instead to 15), against the average standard deviation intra-cluster has increased 3.16% rather than 2% in the first test. The cluster C_8 represents 48.8% of the documents. The average standard deviation 3.16%, shows that the clusters are more heterogeneous than in the first test (Table 3).

As we have described in our previous works (Idarrou and al., 10), representatives of clusters can be enriched (addition of fragments: transforming step of generic views) as and when the classification. This increases the representativeness of the clusters and therefore optimizes the storage volume of documentary warehouse. However, this transformation can lead to another problem: approximation of clusters (minimizing the distance inter-cluster) and therefore perturbing clusters. To maintain stability of clusters and preserve their quality, we propose to fix beforehand a threshold of inter-cluster separation.

We proposed to recalculate the clusters once classifying is completed. This ensures that each document is attached at the right cluster. Indeed, a document may not be attached to the right cluster for example in the case where the cluster to which it should be attached is not yet created at the time of integration of this document.

During the experiments we conducted in this work, we noted, after recalculation of clusters, that several documents have changed their cluster. They were misclassified.

We have noted the positive impact of the cluster threshold separation on the quality of clusters obtained. Specifically, when the clusters are separated sufficiently, that allows excluding the possibility of belonging of the same document to two different clusters. That's what we noticed during this experiment.

5. CONCLUSION AND OUTLOOKS

This work is a continuation of our previous works on the structural clustering of multi-structured multimedia documents. Compared to the works that we have studied in Section 2, our approach is part of the category of approaches using graphs to represent objects for comparison. This choice is justified by the fact that the graphs are appropriate to the multimedia documents. Our approach aims to regroup a collection of heterogeneous documents and from different sources, in cluster forms of structurally homogeneous documents (while keeping the characteristics of each document: content and structure). This allows, for example, optimizing access to information relevant in a large mass of homogeneous data.

We have demonstrated that: (1) Our approach is based on a *structural* similarity and not on a "surface similarity". We consider that the taking into account of the relations (supplementary information), between components of documents, is a crucial parameter in our process of structural comparison. In fact, the sense of a multimedia document depends not only on the content of its components but it also depends on relations between these components. (2) The proposed measure is based on a sub-graph isomorphism based on the semantic matching paths. The path matching graphs, allows both, to preserve the *contextual* and *hierarchical* aspects of matched components, and it allows reducing the cost of combinatorial: a problem frequently discussed in the graph comparison. (3) The standard measures can't fully respond to our problematic.

We also presented our algorithms of graph comparison and clustering of documents and we showed, through the results obtained the interest of our approach.

In our future work, we will make a comparative study with other approaches to demonstrate the quality and effectiveness of our classifier

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