Towards Efficient Horizontal Multimedia Database Fragmentation using Semantic-based Predicates Implication

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Abstract. Partitioning techniques are traditionally used in distributed system design to reduce accesses to irrelevant information by grouping data frequently accessed together in specific fragments. Here, we address the primary horizontal fragmentation of textually annotated multimedia data. In this study, we discuss the issue of identifying semantic implications between textual-based multimedia predicates, as a crucial phase in the efficient partitioning of multimedia data. Our proposal integrates knowledge bases as a framework for assessing the semantic relatedness between predicate values and operators. We developed a prototype implementing the various aspects of multimedia semantic predicates implications. Experimental results show that the proposed method is polynomial in the number of user predicates as well as the sizes of the knowledge bases being employed. Real-world multimedia fragmentation tests are ongoing.

1. Introduction

Video and audio-on-demand, video conferencing, distance e-Learning and cartography are only few examples of multimedia applications emerging on the web. In such a distributed environment, many technical problems need to be solved in order to obtain a full-fledged distributed multimedia database system. These problems concern all layers of the multimedia system, in particular the storage and retrieval layers.

Traditionally, partitioning techniques are used in distributed system design to improve data storage and retrieval efficiency. Three main fragmentation techniques have been defined for relational databases: horizontal, vertical and hybrid. More recently, some researchers have extended these techniques for partitioning object oriented databases. In essence, fragmentation consists of dividing the database objects and/or entities into fragments, on the basis of common queries accesses, in order to distribute them over several distant sites. The fragmentation enhances system performance [Ezeife and Barker, 1995] by:

- Reducing the amount of irrelevant data accessed by applications, (because applications usually access portions of entities and objects),
- Allowing parallel execution of a single query, dividing it into a set of sub-queries that operate on segments of an entity/class,
- Reducing the quantity of data transferred when migration is required,
- Decreasing data update cost and storage space.

Several continuing studies are aimed at building distributed MultiMedia DataBase Management Systems MMDBMS [Kosch 2004]. Nevertheless, most existing systems lack a formal framework to provide full-fledged multimedia operations. In particular, multimedia
fragmentation remains a relatively complicated issue owing to the complexity of the multimedia data itself; different multimedia data types (video, audio, image and/or text), frequently used with various formats, as well as the integration of metadata (consisting of semantic descriptors such as event, location, which person appears in a picture, etc., and/or low-level descriptors such as color, texture, shape, etc.) to describe the multimedia content.

In this paper, we address primary horizontal fragmentation (cf. Section 2) in distributed multimedia databases. We particularly address semantic-based predicates implication required in current fragmentation algorithms, such as \textit{Make\_Partition} and \textit{Com\_Min} \cite{Oszu and Valduriez 1991}, \cite{Navathe et al. 1995}, \cite{Belatreche et al. 1997}, in order to partition multimedia data efficiently. Since predicate implications are of crucial impact in traditional fragmentation techniques, we believe that the identification of semantic implications between multimedia predicates will improve the multimedia fragmentation process (as we will show in the motivation section). In this study, we introduce a set of algorithms for identifying semantic implications between predicate values, predicate operators, and consequently multimedia semantic-based predicates. We also present our prototype with some preliminary experiments to test and evaluate our approach. The remainder of this paper is organized as follows. Section 2 reviews background in DB fragmentation. In Section 3, we present a motivation example. Section 4 defines the concepts to be used in our approach. In Section 5, we detail our semantic implication algorithms and their usage in multimedia fragmentation. Section 6 presents our prototype and timing analysis. Finally, Section 7 concludes.

2. Background and Related Work

Fragmentation techniques for distributed DB systems aim to achieve effective resource utilization and improved performance \cite{Chinchwadkar and Goh 1999}. This is addressed by removing irrelevant data accessed by applications and by reducing data exchange among sites \cite{Baiao and Mattoso 1998}. In this section, we briefly present traditional database fragmentation approaches, and focus on horizontal fragmentation algorithms. We also report recent approaches targeting XML as well as multimedia data fragmentation.

In essence, there are three fundamental fragmentation strategies: Horizontal Fragmentation (HF), Vertical Fragmentation (VF) and Mixed Fragmentation (MF). HF underlines the partitioning of an entity/class in segments of tuples/objects verifying certain criteria. The generated horizontal fragments have the same structure as the original entity/class \cite{Oszu and Valduriez 1991}. VF breaks down the logical structure of an entity/class by distributing its attributes/methods over vertical fragments, which would contain the same tuples/objects with different attributes \cite{Baiao and Mattoso 1998}. MF is a hybrid partitioning technique where horizontal and vertical fragmentations are simultaneously applied on an entity/class \cite{Navathe et al. 1995}.

Horizontal fragmentation is generally categorized in two types: Primary HF and Derived HF. PHF is the partitioning of an entity based on its attributes’ values \cite{12}. DHF denotes the partitioning of an entity (called member) based on links with other entities (called owners) \cite{12}. In other words, it is the partitioning of an entity/class in terms of the PHF of another entity/class \cite{1} taking into consideration their inner-links. In this paper, we only focus on PHF which is, to the best of our knowledge, has been addressed mainly by two main algorithms: \textit{Com\_Min} developed in \cite{Oszu and Valduriez 1991} and \textit{Make\_Partition} Graphical Algorithm developed in \cite{Navathe and Ra 1989} (used essentially for vertical fragmentation). The \textit{Com\_Min} algorithm generates, from a set of simple predicates applied to a certain entity, a complete and minimal set of predicates used to determine the minterm fragments corresponding to that entity. A minterm is a conjunction of simple predicates \cite{Belatreche et al. 1997} associated to a fragment. \textit{Make\_Partition} generates minterm fragments by grouping predicates having high affinity towards one another. The number of minterm fragments generated by \textit{Make\_Partition} is relatively smaller than the number of \textit{Com\_Min} minterms \cite{Navathe et al.}.
(the number of minterms generated by Com-Min being exponential to the number of simple predicates considered). Similarly, there are two main algorithms for the PHF of object oriented DBMS: one developed by in [Ezeife and Barker 1995] using Com_MIN [Oszu and Valduriez 1991], and the other developed in [Bellatreche et al. 1997] on the basis of Make_Partition [Navathe and Ra 1989]. The use of Com_MIN or Make_Partition is the major difference between them.

Recent works have addressed XML fragmentation [Sub 2001], [Gertz and Bremer 2004] due to the various XML-oriented formats available on the web. The usage of XPaths and XML predicates forms the common basis of all these studies. Yet, XML fragmentation methods are very specific and hardly applicable to multimedia databases.

A recent address to address multimedia database fragmentation is provided in [Saad. et al. 2006]. The authors here discuss multimedia primary horizontal fragmentation and provide a partitioning strategy based on the low-level features of multimedia data (e.g. color, texture, shape, etc., represented as complex feature vectors). They particularly emphasize the importance of multimedia predicates implications in optimizing multimedia fragments.

### 3. Motivation

In order to fragment multimedia databases, several issues should be studied and extended. Multimedia queries contain new operators handling low-level and semantic features. These new operators should be considered when studying predicates and particularly predicate implications [Saad et al. 2006]. For example, let us consider the following predicates used to search for videos in the movie database IMDB1.

<table>
<thead>
<tr>
<th>Predicate</th>
<th>Attribute</th>
<th>Operator</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1</td>
<td>Keywords</td>
<td>=</td>
<td>“Football”</td>
</tr>
<tr>
<td>P2</td>
<td>Keywords</td>
<td>=</td>
<td>“Tennis”</td>
</tr>
<tr>
<td>P3</td>
<td>Keywords</td>
<td>=</td>
<td>“Sport”</td>
</tr>
<tr>
<td>P4</td>
<td>Location</td>
<td>=</td>
<td>“Coliseum”</td>
</tr>
<tr>
<td>P5</td>
<td>Location</td>
<td>Like %</td>
<td>“Rome”</td>
</tr>
</tbody>
</table>

In current fragmentation approaches, these predicates are considered different and are analyzed separately. Nonetheless, a multimedia query consisting of $P_1$ and $P_2$ would retrieve movies belonging to the result of $P_3$, the value/concept Sport encompassing in its semantic meaning Football and Tennis. Thus, we can say that $P_1$ and $P_2$ imply $P_3$ ($P_1, P_2 \Rightarrow P_3$). Consequently, the fragmentation algorithm should only consider $P_3$, eliminating $P_1$ and $P_2$ while generating fragments. A similar case can also be identified with $P_4$ and $P_5$. The value/concept Rome covers in its semantic meaning Coliseum. However, the operator used in $P_4$ is not the same as that utilized in $P_5$, which raises the question of operator implication. Since the operator Like % covers in its results those of the operator equal (Like % returning results that are identical or similar to a given value, where equal returns only the results identical to a certain value), the results of $P_5$ would cover those returned by $P_4$. Hence, we can deduce that $P_4$ implies $P_5$ ($P_4 \Rightarrow P_5$). As a result, the fragmentation algorithm should only consider $P_5$, disregarding $P_4$. Note that ignoring such implications between predicates can lead, in multimedia applications, to higher computation costs when creating fragments, bigger fragments which are very restrictive for multimedia storage, migration, and retrieval, as well as data duplication on several sites [Saad et al. 2006].

In [Navathe et al. 1995], [Belatreche et al. 1997], the authors have highlighted the importance of implication, but have not detailed the issue. As mentioned before, the authors in [Saad et al. 2006] have only addressed implications between low-level multimedia predicates.

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1 Available at http://www.imdb.com/
(based on complex feature vectors). In this study, we go beyond low-level features provided in [Saad et al. 2006] and present a complementary semantic implication approach (Figure 3).

4. Preliminaries

In the following, we define the major concepts used in our approach. We particularly detail the notions of Knowledge Base (KB) and Neighborhood (N) which will be subsequently utilized in identifying the implications between semantic predicates.

4.1. Basic Definitions

Definition 1 - Multimedia Object: is depicted as a set of attribute \((a_i, v_i)\) doublets: \(O = \{(a_1, v_1), (a_2, v_2), \ldots, (a_n, v_n)\}\). Multimedia attributes and values can be simple (numeric or textual fields), complex (color histogram, texture, shape, etc.) or contain raw data (BLOB files) of multimedia objects. Note that in horizontal multimedia fragmentation, multimedia objects constitute the basic reference units (similarly to ‘objects’ in object oriented DB partitioning and ‘tuples’ in relational DB fragmentation).

Definition 2 - Multimedia Type: allocates a set of attributes used to describe multimedia objects corresponding to that type [Saad et al. 2006]. Two objects, described by the same attributes, are of the same type.

Definition 3 - Multimedia Query: is written as follows [Belatreche et al. 1997], [Saad et al. 2006]: \(q = \{\text{Target clause}, \text{Range clause}, \text{Qualification clause}\}\)
- **Target clause**: contains multimedia attributes returned by the query,
- **Range clause**: gathers the entities (tables/classes) accessed by the query, to which belong target clause and qualification clause attributes,
- **Qualification clause**: is the query restriction condition, a Boolean combination of predicates, linked by logical connectives \(\wedge, \vee, \neg\).

Definition 4 - Multimedia predicate: is defined as \(P = (A \theta V)\), where:
- \(A\) is a multimedia attribute or object,
- \(V\) is a value (or a set of values) in the domain of \(A\),
- \(\theta\) is a low-level multimedia operator (Range and KNN operators), a comparison operator \(\theta_c\) (\(=, <, \leq, >, \geq, \neq, \) like) or a set operator \(\theta_s\) (in and \(\theta_s\) qualifier where the quantifiers are: any, some, all).

4.2. Knowledge Base

In the fields of Natural Language Processing (NLP) and Information Retrieval (IR), knowledge bases (thesauri, taxonomies and/or ontologies) provide a framework for organizing entities (words/expressions [Richardson and Smeaton 1995], [Lin 1998], generic concepts [Rodriguez and Egenhofer 2003] [Ehrig and Sure 2004], web pages [Maguitman 2005], etc.) into a semantic space. Subsequently, knowledge bases are utilized to compare/match the considered entities with respect to their corresponding similarity/relevance degrees with one another. In our approach, we employ knowledge bases as a reference for identifying semantic implications between predicates, which is not addressed in existing approaches. As shown in the motivating example, implication between semantic predicates relies on the implications between corresponding values and operators. Hence, two types of knowledge bases are used here: i) value-based: to represent the domain values commonly used in the application, and ii) operator-based: to organize operators used with semantic-based predicates. We will also give the semantic relations commonly used in the literature [Richardson and Smeaton 1995], [Lin 1998], [WordNet 2005], to organize entities and concepts in a KB. We detail them below.
4.2.1. Knowledge Base

In our study, a Value Knowledge Base (VKB) is domain-oriented and comes down to a hierarchical taxonomy with a set of concepts representing groups of words/expressions (which we identify as value concepts), and a set of links connecting the values, representing semantic relations.

As in WordNet, we consider that a VKB concept consists of a set of synonymous words/expressions such as \{car, auto, automobile\}. Value concepts are connected together via different semantic relations, which will be detailed subsequently. Formally, \(VKB=(Vc, E, R, f)\) where:

- \(Vc\) is the set of value concepts (synonym sets as in WordNet [Miller 1990]).
- \(E\) is the set of edges connecting the value concepts, where \(E \subseteq Vc \times Vc\).
- \(R\) is the set of semantic relations, \(R = \{\Omega, \prec, \succ, \ll, \gg\}\) (cf. Table 2), the synonymous words/expressions being integrated in the value concepts.
- \(f\) is a function designating the nature of edges in \(E\), \(f:E \rightarrow R\) (cf. Figure 1).

4.2.2. Operator Knowledge Base

As stated previously, operators should also be considered when studying the implication between semantic predicates. Therefore, an operator knowledge base of four descriptors \(OKB=(Oc, E, R, f)\) is also defined where:

- \(Oc\) is the set of operator concepts, consisting of mono-valued comparison operators \(\theta_c\) (=, \(\neq\), \(>\), \(<\), and like) as well as multi-valued ones \(\theta_s\) (in and \(\theta_s\) qualifier where the quantifiers are: any, some, all).
- \(E\) is the set of edges connecting the operators, where \(E \subseteq Oc \times Oc\).
- \(R\) is the set of semantic relations, \(R = \{\Omega, \prec, \succ, \ll, \gg\}\).
- \(f\) is a function designating the nature of edges in \(E\), \(f:E \rightarrow R\).

We designed the operator knowledge base \(OKB\) as shown in Figure 2.

In the mono-valued operator taxonomy, we can particularly observe that the pattern matching operators Like and Not Like (considered as antonyms) make use of the parameters ‘_’ and ‘%’, to represent one and zero/multiple optional characters respectively. Hence, we represent this fact by a semantic IsA \(\prec\) relation following these operators, i.e. Like_ \(\ll\) Like%
and Not Like_ ≺ Not Like%. On the other hand, ‘<’ and ‘>’ implicitly denote the operator ‘≠’ (commonly represented by < >), thus are considered as sub-operators of this later.

![](image)

**Figure 2. Our proposed operator knowledge base**

In the multi-valued operator taxonomy, the *any* and *some* quantifiers are considered as synonyms, as well as the operators ≠All and Not In, and =Any (or Some) and In. The >All and <All operators are considered as sub-operators of ≠All (like mono-valued operators) and thus are linked to this later using IsA relations. In addition, the >All and >Any operators are linked together because if the condition is valid for all comparison values, it must be for any value inside the comparison set. Likewise for <All and <Any, and ≠All and ≠Any.

### 4.3. Semantic Relations

Hereunder, we develop the most popular semantic relations employed in the literature, which are included in the WordNet knowledge base [30, 31, 32]:

- **Synonym (≡):** Two words/expressions (likewise for operators) are synonymous if they are semantically identical, that is if the substitution of one for the other does not change the initial semantic meaning.
- **Antonym (Ω):** The antonym of an expression is its negation.
- **Hyponym (<):** It can also be identified as the subordination relation, and is generally known as the Is Kind of relation or simply IsA.
- **Hypernym (>):** It can also be identified as the super-ordination relation, and is generally known as the Has Kind of relation or simply HasA.
- **Meronym (≺):** It can also be identified as the part-whole relation, and is generally known as PartOf (also MemberOf, SubstanceOf, ComponentOf, etc.).
- **Holonym (≻):** It is basically the inverse of Meronym, and is generally identified as HasPart (also HasMember, HasSubstance, HasComponent, etc.).

Table 2 reviews the most frequently used semantic relations along with their properties [Richardson and Smeaton 1995] [Lin 1998], [WordNet 2005]. Note that the transitivity property is not only limited to semantic relations of the same type and could also exist between heterogeneous relations. For example:

- **Brake system ≺ car and car = automobile transitivity infer Brake system ≺ automobile.**
- **ABS ≺ Brake system and Brake system ≺ car transitivity infer ABS ≺ car** (Figure 1).

Formally, let Cᵢ, Cⱼ and Cₖ be three concepts connected via semantic relations Rᵢⱼ and Rᵢₖ in a given KB. Table 3 details the transitivity properties for all semantic relations defined in the previous subsections, identifying the resulting relation Rᵢₖ transitively connecting concepts Cᵢ and Cₖ. The relevance of identifying transitivity between different semantic relations will be...
demonstrated when defining the neighborhood of a concept, subsequently recognizing the concept implications.

<table>
<thead>
<tr>
<th>Property Relation</th>
<th>Symbol</th>
<th>Reflexive</th>
<th>Symmetric</th>
<th>Transitive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Synonym</td>
<td>≡</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Antonym</td>
<td>Ω</td>
<td>×</td>
<td>✓</td>
<td>×</td>
</tr>
<tr>
<td>Hypernym</td>
<td>≺</td>
<td>✓</td>
<td>×</td>
<td>✓</td>
</tr>
<tr>
<td>Hypernym</td>
<td>≺</td>
<td>✓</td>
<td>×</td>
<td>✓</td>
</tr>
<tr>
<td>Meronym</td>
<td>≺</td>
<td>✓</td>
<td>×</td>
<td>✓</td>
</tr>
<tr>
<td>Holonym</td>
<td>≻</td>
<td>✓</td>
<td>×</td>
<td>✓</td>
</tr>
</tbody>
</table>

4.4. Neighborhood

In our approach, the neighborhood notion is used to compute the implication between values, operators, and consequently predicates. The implication neighborhood of a concept $C_i$ is defined as the set of concepts $\{C_j\}$, in a given knowledge base $KB$, related with $C_i$ via the synonym ($\equiv$), hyponym ($\prec$) and meronym ($\ll$) semantic relations, directly or via transitivity. It is formally defined as:

$$N_{KB}^\equiv(C_i) = \{C_j \mid C_i \text{ R } C_j \text{ and } R \in \{=,\prec,\ll\}$$

When applying the neighborhood concept to some value concepts in Figure 1, we obtain the following implication neighborhood examples:

- $N_{KB}^\equiv(car) = \{car, auto, automobile\}$
- $N_{KB}^\equiv(ABS) = \{ABS, brake system\}$
- $N_{KB}^\ll(tire) = \{tire, wheel, vehicle, machine\}$ (transitivity between $\ll$ and $\prec$)

Moreover, we define the global implication neighborhood of a concept to be the union of each implication neighborhood with respect to the synonym ($\equiv$), hyponym ($\prec$) and meronym ($\ll$) semantic relations:

$$N_{KB} (C_i) = \bigcup R R_{KB}^\equiv (C_j) / R \in \{=,\prec,\ll\}$$

Note hereunder the corresponding global neighborhoods of the same examples:

- $N_{KB}^\equiv(car) = N_{KB}^\equiv(car) \cup N_{KB}^\ll(car) \cup N_{KB}^\ll(car) = \{car, auto, automobile, vehicle, machine\}$
- $N_{KB}^\ll(ABS) = \{ABS, brake system, car, auto, automobile, vehicle, machine\}$

Similarly, the implication neighborhood can be applied to operator concepts:

- The global neighborhood of the Like operator: $N_{OKB} (Like) = \{=, Like, Like, Like\%\}$.
- The global neighborhood of $\neq All$: $N_{OKB} (\neq All) = \{\neq All, Not In, \neq Any, \neq Some\}$.
- The global implication neighborhood of $> All$:
  $$N_{OKB} (> All) = \{> All, > Any, > Some, \neq All, Not In, \neq Any, \neq Some\}.$$
5. Semantic Implication Between Predicates

Finding implication between predicates is crucial to cutback the number of predicates involved in the fragmentation process [Navathe et al. 1995], [Belatreche et al. 1997] (a large number of unnecessary fragments would notionally achieve low system performance especially when using multimedia data). When a predicate \( P_i \) implies a predicate \( P_j \) (denoted by \( P_i \Rightarrow P_j \)), \( P_i \) can be removed from the minterm fragment to which it belongs and can be replaced by \( P_j \). In the following, we detail the rules that can be used to determine implication between semantic predicates. As mentioned earlier, the semantic implication between two predicates depends on the implications between their corresponding values and operators. Therefore, we develop value and operator implications before introducing our predicate implication algorithm. Our Semantic Implication Algorithm (SPI) is complementary to that developed in [Saad et al. 2006] and thus could be coupled with its overall process (cf. Figure 3) in order to enable relevant multimedia fragmentation. Due to the space limitation, value and operator neighborhood computation will not be detailed here since the main definitions have been already covered previously.

\[
\text{Multimedia\_fragmentation\_pre-processing}() \quad // \text{Developed in [Saad et al. 2006] to the exception} \\
\quad // \text{of semantic implication.}
\]

\[
\begin{align*}
\text{Begin} \\
\text{Multimedia\_Types\_Classification()} & \quad // \text{Classifying multimedia objects according to their types} \\
\text{Predicates\_Grouping()} & \quad // \text{Grouping low-level and semantic predicates together} \\
\text{Multimedia\_Predicates\_implication()} & \quad // \text{Low-level predicates implications} \\
\text{Semantic\_Predicates\_Implication()} & \quad // \text{Contribution of our study.} \\
\text{End For} \\
\text{End}
\end{align*}
\]

Figure 3. Multimedia fragmentation pre-processing phase introduced in [Saad et al. 2006], which is to be executed prior to applying the classic fragmentation algorithms [Ozsu and Valduriez 1991], [Navathe et al. 1995]

5.1. Value Implication

A value \( V_i \) implies \( V_j \) if the corresponding value concepts \( V_{C_i} \) and \( V_{C_j} \) are such as the global neighborhood of \( V_{C_j} \) includes that of \( V_{C_i} \) in the used value knowledge base:

\[
V_i \Rightarrow V_j \quad \text{If} \quad N_{V_{ka}}(V_{C_j}) \subset N_{V_{ka}}(V_{C_i}) \quad (3)
\]

Note that when \( V_i \) and \( V_j \) are synonyms, that is when \( V_{C_i} \) and \( V_{C_j} \) designate the same value concept (e.g. car and automobile), implication exists in both directions: \( V_i \Rightarrow V_j \) and \( V_j \Rightarrow V_i \). Known as equivalence implication, it is designated as \( V_i \Leftrightarrow V_j \).

\[
V_i \Leftrightarrow V_j \quad \text{If} \quad N_{V_{ka}}(V_{C_i}) = N_{V_{ka}}(V_{C_j}) \quad , \quad \text{i.e.} \quad V_{C_i} \quad \text{and} \quad V_{C_j} \quad \text{are the same} \quad (4)
\]

Our Value Implication algorithm is developed in Figure 4. The algorithm returns values comprised in \{0, -1, 1, 2\} where:

- ‘0’ denotes the implication absence between the compared values,
- ‘-1’ designates that value \( V_j \) implies \( V_i \),
- ‘1’ designates that value \( V_i \) implies \( V_j \),
- ‘2’ designates that values \( V_i \) and \( V_j \) are equivalent.

A special case of value implication to be considered is when sets of values are utilized in multimedia predicates. This occurs when set operators come to play (e.g. \text{Keywords = ANY} \{“Eiffel Tower”, “Coliseum”\} and \text{Keywords = ANY} \{“Paris”, “Rome”\}). The algorithm for determining the implication between two sets of values is developed in Figure 6. It considers each set of values in isolation and, for each value in the set, computes the neighborhood of the value. Subsequently, it identifies the union of all the neighborhoods of values for the current set (cf. Figure 6, lines 1-7), and compares the ‘unioned’ neighborhoods of the two sets being treated.
so as to determine the implication (cf. Figure 6, lines 8-17). In other words, when comparing sets $VS_1$ and $VS_2$:

- If $|VS_1| < |VS_2|$ and all values of $VS_2$ imply (or are equivalent to) those of $VS_1$, then the set $VS_2$ implies $VS_1$ (i.e. the neighborhood of $VS_2$ includes that of $VS_1$).
- If $|VS_1| > |VS_2|$ and all values of $VS_1$ imply (or are equivalent to) those of $VS_2$, then the set $VS_1$ implies $VS_2$ (i.e. the neighborhood of $VS_1$ includes that of $VS_2$).
- Otherwise if $|VS_1| = |VS_2|$, then:
  - $VS_1$ is equivalent to $VS_2$ when all values of $VS_1$ are equivalent to those of $VS_2$ (i.e. the neighborhoods of $VS_1$ and $VS_2$ are identical).
  - $VS_1$ implies $VS_2$ when all values of $VS_1$ imply those of $VS_2$, i.e. the neighborhood of $VS_1$ encompasses that of $VS_2$: $N_{\theta_{VS_1}}(VS_2) \subseteq N_{\theta_{VS_1}}(VS_1)$
  - $VS_2$ implies $VS_1$ when all values of $VS_2$ imply those of $VS_1$, i.e. $N_{\theta_{VS_2}}(VS_1) \subseteq N_{\theta_{VS_2}}(VS_2)$
  - Otherwise, there is no implication between $VS_1$ and $VS_2$.

For example, applying Value Set implication to sets $VS_1 = \{\text{"Eiffel Tower"}, \text{"Coliseum"}\}$ and $VS_2 = \{\text{"Paris"}, \text{"Rome"}\}$ yields $VS_1 \Rightarrow VS_2$ having:

- $|VS_1| = |VS_2|
- all values of $VS_1$ imply those of $VS_2$: Eiffel Tower $\Rightarrow$ Paris and Coliseum $\Rightarrow$ Rome (cf. Figure 1).

5.2. Operator Implication

Similarly to values, the general implication concept remains unchanged with operators. An operator $\theta_i$ implies $\theta_j$ ($\theta_i \Rightarrow \theta_j$) if the corresponding operator concepts $O_{c_i}$ and $O_{c_j}$ are such as the global neighborhood of $\theta_i$ includes that of $\theta_j$, following the operator knowledge base defined in Section 4.1.2. We formally write it as:

$$\theta_i \Rightarrow \theta_j \quad \text{If} \quad N_{\theta_{O_{c_i}}}(O_{c_i}) \subseteq N_{\theta_{O_{c_j}}}(O_{c_j})$$

(5)

Similarly to value implication, when $\theta_i$ and $\theta_j$ are synonyms (e.g. =any and =some following $\theta_{KB}$), equivalence implication exists in both directions:

$$\theta_i \Leftrightarrow \theta_j \quad \text{If} \quad N_{\theta_{O_{c_i}}}(O_{c_i}) = N_{\theta_{O_{c_j}}}(O_{c_j}), \text{ i.e. } O_{c_i} \text{ and } O_{c_j} \text{ are the same}$$

(6)

The Operator_Implication algorithm is developed in Figure 5. It returns values comprised in \{0, -1, 1, 2\}:

- ‘0’ denoting the lack of implication between the operators’ values,
- ‘-1’ designating that operator $\theta_j$ implies $\theta_i$,
- ‘1’ designating that operator $\theta_i$ implies $\theta_j$,
- ‘2’ when operators $\theta_i$ and $\theta_j$ are equivalent

5.3. Predicate Implication

$$P_i \Rightarrow P_j \quad \text{if} \quad \begin{cases} \theta_i \Rightarrow \theta_j \text{ and } V_i \Rightarrow V_j, \text{ or} \\ \theta_i \Leftrightarrow \theta_j \text{ and } V_i \Rightarrow V_j, \text{ or} \\ \theta_i \Rightarrow \theta_j \text{ and } V_i \Leftrightarrow V_j \end{cases}$$

(7)

Let $P_i = A_i \theta_i V_i$ and $P_j = A_j \theta_j V_j$ be two predicates employing comparison or set operators. The implication between $P_i$ and $P_j$, denoted as $P_i \Rightarrow P_j$, occurs if the operator and
value (set of values) of $P_i$ ($\theta_i$ and $V_i$) respectively imply those of $P_j$ ($\theta_j$ and $V_j$), or the value (set of values) part of $P_i$ ($V_i$) implies that of $P_j$ ($V_j$) when having equivalent operators.

When both pairs of values (sets of values) and operators are equivalent, the corresponding predicates are equivalent as well:

$$P_i \Leftrightarrow P_j \text{ if } \left[ \theta_i \Leftrightarrow \theta_j \text{ and } V_i \Leftrightarrow V_j \right]$$

### Value Implication:

**Input:** $V_i, V_j, V_{KB}$  // $V_{KB}$ is the reference value KB  
**Output:** $\{0, -1, 1, 2\}$  // A numerical value indicating 

1. If $N_{V_{KB}}(V_i) = N_{V_{KB}}(V_j)$ Return 2  // synonyms, $V_i \leftrightarrow V_j$
2. Else If $N_{V_{KB}}(V_i) \subset N_{V_{KB}}(V_j)$ 
   Return 1  // $V_i \Rightarrow V_j$
3. Else If $N_{V_{KB}}(V_i) \supset N_{V_{KB}}(V_j)$ 
   Return -1  // $V_j \Rightarrow V_i$
4. Else Return 0  // There is no implication

### Value Set Implication:

**Input:** $V_{S1}, V_{S2}, V_{KB}$  // value sets to be compared w.r.t. $V_{KB}$  
**Output:** $\{0, -1, 1, 2\}$  // A numerical value indicating 

1. For each value $V_i$ in $V_{S1}$  // Neighborhood of $V_{S1}$  
   $N_{V_{KB}}(V_i) = N_{V_{KB}}(V_{S1}) \cup N_{V_{KB}}(V_{S2})$
2. End for

3. For each value $V_j$ in $V_{S2}$  // Neighborhood of $V_{S2}$  
   $N_{V_{KB}}(V_j) = N_{V_{KB}}(V_{S2}) \cup N_{V_{KB}}(V_{S1})$
4. End For

5. If $N_{V_{KB}}(V_{S1}) = N_{V_{KB}}(V_{S2})$ Return 2  // $V_{S1} \leftrightarrow V_{S2}$
6. Else If $N_{V_{KB}}(V_{S1}) \subset N_{V_{KB}}(V_{S2})$ 
   Return 1  // $V_{S1} \Rightarrow V_{S2}$
7. Else If $N_{V_{KB}}(V_{S2}) \subset N_{V_{KB}}(V_{S1})$ 
   Return -1  // $V_{S2} \Rightarrow V_{S1}$
8. Else Return 0  // There’s no implication between $V_{S1}$ and $V_{S2}$

### Operator Implication:

**Input:** $\theta_i, \theta_j, O_{KB}$  // $O_{KB}$ is the reference operator KB  
**Output:** $\{0, -1, 1, 2\}$  // A numerical value indicating 

1. If $N_{O_{KB}}(O_{S1}) = N_{O_{KB}}(O_{S2})$ Return 2  // synonyms, $\theta_i \leftrightarrow \theta_j$
2. Else If $N_{O_{KB}}(O_{S1}) \subset N_{O_{KB}}(O_{S2})$ 
   Return 1  // $\theta_i \Rightarrow \theta_j$
3. Else If $N_{O_{KB}}(O_{S2}) \subset N_{O_{KB}}(O_{S1})$ 
   Return -1  // $\theta_j \Rightarrow \theta_i$
4. Else Return 0  // There is no implication between $\theta_i$ and $\theta_j$

### Figure 4. Identifying semantic implications between textual values

### Figure 5. Identifying implications between operators

Our *Semantic Predicate Implication (SPI)* algorithm, developed in Figure 7, utilizes the preceding rules to generate the semantic predicate Implications Set ($IS$) for a given multimedia type. The implications are designated as doublets $(P_i \Rightarrow P_j)$. Note that in *SPI*, the input
parameters of Value_Implication and Value_Set_Implication between brackets, i.e. \( V_i \) and \( V_{i+1} \), designate single values and set values respectively following the considered predicate (cf. Definition 4).

**Semantic Predicate Implication (SPI):**

| Input: | \( P, V_{KB}, O_{KB} \) // \( P \) is the set of predicates utilizing semantic operators, \( V_{KB} \) is the concept knowledge base, \( O_{KB} \) is the concept operators. |
| Output: | \( IS \) // Set of semantic predicate implications. |
| Variables: | Implication\_Operator, Implication\_Value |

Begin

For each \( P_i \) in \( P \)

For each \( P_{i+1} \) in \( P \)

\[ \text{Implication\_Operator} = \text{Operator\_Implication}(\theta_i, \theta_{i+1}, O_{KB}) \]

If (\( \theta_i, \theta_{i+1} \in \{ \theta_c \text{ any}, \theta_c \text{ some}, \theta_c \text{ all}, \theta_c \text{ ln} \} \)) // Set operators

\[ \text{Implication\_Value} = \text{Value\_Set\_Implication}(V_i, V_{i+1}, V_{KB}) \]

Else // Mono-valued operators

\[ \text{Implication\_Value} = \text{Value\_Implication}(V_i, V_{i+1}, V_{KB}) \]

End If

If (Implication\_Operator == 2) // \( \theta_i \Leftrightarrow \theta_{i+1} \)

If (Implication\_Value == 2) // \( V_i \Leftrightarrow V_j \)

\[ IS = IS \cup (P_i \Leftrightarrow P_j) \]

Else If (Implication\_Value == 1) // \( V_i \Rightarrow V_j \)

\[ IS = IS \cup (P_i \Rightarrow P_j) \]

Else If (Implication\_Value == -1) // \( V_j \Rightarrow V_i \)

\[ IS = IS \cup (P_j \Rightarrow P_i) \]

End If

Else If (Implication\_Operator == 1) // \( \theta_i \Rightarrow \theta_j \)

If (Implication\_Value == 2 or Implication\_Value == 1) // \( \theta_i \Rightarrow \theta_j \)

\[ IS = IS \cup (P_i \Rightarrow P_j) \]

End If

Else If (Implication\_Operator == -1) // \( \theta_j \Rightarrow \theta_i \)

If (Implication\_Value == 2 or Implication\_Value == -1) // \( V_j \Rightarrow V_i \)

\[ IS = IS \cup (P_j \Rightarrow P_i) \]

End If

End For

End For

End

Figure 7. Algorithm SPI for identifying the semantic implications between predicates

### 5.4. Algorithm Complexity

The computational complexity of our Semantic Predicate Implication (SPI) is estimated on the basis of the worst case scenario. Suppose \( n_c \) represents the number of concepts in the concept knowledge base considered, \( d \) the maximum depth in the concept knowledge base considered, \( n_{pv} \) the number of user predicates with single values, \( n_{pv} \) the number of predicates with value sets, and \( n_v \) the maximum number of values contained in a value set. SPI algorithm is of time complexity \( O(n_{pv}^2 \times n_c \times d + n_{pv} \times n_v \times n_c \times d) \) since:

- The neighborhood of a concept is generated in \( O(n_c \times d) \) time, which comes down to the complexity of algorithm Value\_Implication.
- The neighborhood of an operator is generated in constant time: \( O(1) \), which comes down to the time complexity of algorithm Operator\_Implication. Therefore, identifying implications for predicates with simple values is of time complexity \( O(n_{pv}^2 \times n_c \times d) \).
- The Value\_Set\_Implication algorithm is of complexity \( O(n_v \times n_c \times d) \).
Subsequently, identifying semantic implications for predicates with value sets is of time complexity $O(n_{pred}^2 \times n_v \times n_c \times d)$.

6. Implementation and Experimental Tests

6.1. Prototype

To validate our approach, we have implemented a C# prototype entitled “Multimedia Semantic Implication Identifier” (MSI2) encompassing:

- A relational database, storing multimedia objects via Oracle 9i DBMS,
- Relational tables for storing the reference value knowledge base $V_{KB}$ and the operator knowledge base $O_{KB}$. Note that $O_{KB}$ is constant (cf. Figure 2),
- An interface allowing users to formulate multimedia queries.

In Figure 8, we show how the prototype accepts a set of input multimedia queries. Automatic processes subsequently calculate query access frequencies, identify corresponding predicates, and compute for each multimedia type (cf. Definition 2) its Predicate Usage Matrix (PUM) and its Predicate Affinity Matrix (PAM), introduced in [Navathe et al. 1995], [Belatreche et al. 1997] (cf. Figure 8). The PAM is used to underline the affinity between predicates, implication being a special kind of affinity [Navathe et al. 1995], [Belatreche et al. 1997]. The PUM and PAM make up the inputs to the primary horizontal partitioning algorithm: Make_Partition [Navathe et al. 1995] or Com_Min [Ozsu and Valduriez 1991].

6.2 Simulation Example

Among the various experiments conducted, we present here a simple simulation example comparing predicate affinities (PAM) obtained with the inclusion of our multimedia semantic implication rules, and analyzing the corresponding fragments. In the following example, multimedia type “Video”, designating movies (i.e. audio-visual data), is selected for PUM and PAM calculations. In this experiment, a 100 node knowledge base, extracted from WordNet provided the reference for predicate value implications (part of the knowledge base is depicted in Figure 1). Let $Q = \{Q_i = 0 \text{ to } 5\}$ be a set of user queries searching for video objects and $P = \{P_i = 0 \text{ to } 11\}$ be the set of predicates used by $Q$ (Figure 8). Given the PUM, the PAM attained after applying our semantic implication algorithms in shown in Figure 8. Note that the traditional PAM matrix will lack our semantic implications, identified here by implication signs, and only contains null affinities instead (it is omitted due to the lack of space).

Recall that following [Navathe et al. 1995] [Belatreche et al. 1997], the PAM is a square and symmetric matrix where each value $\text{aff}(P_i, P_j)$ can be numerical or non numerical. Numerical affinity represents the sum of the frequencies of queries which access simultaneously $P_i$ and $P_j$. Non numerical affinity\(^1\) underlines the implication relation between predicates $P_i$ and $P_j$. Note that “numerical” predicates, yielding traditional implications (for example $P_1$: $x < 2 \Rightarrow P_2$: $x < 4$), were excluded for the sake of simplicity and clearness. Hence, the traditional PAM should be restricted to numerical affinities whereas the updated PAM should reflect both numerical and non numerical (semantic implication) affinities:

- Predicates $P_3$ (Event = "Football match") and $P_7$ (Event = "Hokey match") imply $P_6$ (Event = "Sport game")
- $P_1$ (Location = "Rome”), $P_{10}$ (Location = "Paris") and $P_{12}$ (Location = "Champs Elysees") imply $P_6$ (Location like "%Europe") having:
  - $\Rightarrow$ like % (cf. Figure 2).
  - Rome, Paris, Champs Elysees $\Rightarrow$ Europe.
- Predicate $P_{12}$ (Location = "Champs Elysees") implies $P_{10}$ (Location = "Paris").

\(^1\) Non numerical affinity can also designate the “close” usage of two predicates $P_i$ and $P_j$, in that both $P_i$ and $P_j$ are used jointly with a predicate $P_k[15]$. Nonetheless, we disregard this kind of affinity for the sake of clearness.
Predicate $P_4$ (Keywords $\neq$ all ("Night", "Freeway", "Speed")) implies $P_2$ (Keywords $\neq$ "Night"):
- $\neq$ all $\Rightarrow \neq$ (cf. Figure 2).
- (Night, Freeway, Speed) $\Rightarrow$ Night.

Predicate $P_9$ (Event = "Car crash") implies $P_3$ (Event like "_Accident") having:
- $=$ $\Rightarrow$ like _ (cf. Figure 2).
- Car crash $\Rightarrow$ Accident

Predicate $P_{11}$ (Keywords = Some ("Night", "Freeway", "Speed")) implies $P_{13}$ (Keywords in ("Highway", "Night")) having:
- $=$ Some $\Rightarrow$ in (cf. Figure 2).
- (Night, Freeway, Speed) $\Rightarrow$ (Highway, Night)

The primary horizontal fragmentation algorithm *Make-Partition* [Navathe et al. 1995], applied on the uPAM matrix obtained above, generates the predicate clusters shown in Figure 9. These clusters are further refined following a post-processing procedure developed in [Belatreche et al. 1997], based on the semantic implications identified in the uPAM, to yield the final horizontal minterm fragments shown in Figure 9. As a matter of fact, since $P_4 \Rightarrow P_2$, $P_9 \Rightarrow P_3$, $P_{13} \Rightarrow P_{10}$ and $P_{11} \Rightarrow P_{14}$, then $P_4$, $P_9$, $P_{13}$ and $P_{11}$ should be removed from the corresponding clusters [Belatreche et al. 1997], consequently yielding the minterms shown below.
Recall that ignoring implications can lead, in multimedia applications, to higher computation costs when creating fragments, bigger fragments which are very restrictive for multimedia storage, and retrieval, as well as data duplication on several sites. For instance, in the current example, applying Make_Partition without considering the semantic implications between predicates (PAM lacking all semantic implications, which are replaced by null values) yields the following minterm fragments: $F_1(P_0 \land P_1 \land P_2)$, $F_2(P_1 \land P_2 \land P_3)$, $F_3(P_0 \land P_1 \land P_4)$, $F_4(P_2 \land P_5 \land P_6)$, $F_5(P_2 \land P_7 \land P_8)$, $F_6(P_1 \land P_2 \land P_9)$, $F_7(P_0 \land P_10 \land P_11)$, $F_8(P_12 \land P_13 \land P_14)$, $F_9(Else)$. On can clearly recognize the higher number of minterms, in comparison with those identified using the semantic implications (i.e., uPAM in Figure 8), which obviously underlines higher computation costs when creating the multimedia partitions. In addition, the obtained fragments induce data duplication among each other, e.g., between $F_1$ and $F_3$, as well as $F_2$ and $F_6$, which is detrimental to data fragmentation.

6.2. Timing Analysis

We have shown that the complexity of our approach (SPI and underlying algorithms) simplifies to $O(n_{pred}^2 \times n_v \times n_c \times d)$. It is quadratic in the size of user predicates ($n_{pred}$), and varies with value set cardinalities ($n_v$), as well as the size of the value knowledge base $V_{KB}$ considered ($n_c \times d$). We have verified those results experimentally. Timing analysis is presented in Figure 10. The experiments were carried out on Pentium 4 PC (with processing speed of 3.0 GHz, 504 MB of RAM). Note that in these experiments, a set of 1200 semantic predicates was generated in a random fashion, value-set cardinalities (varying between 2 and 20 per value set, cf. Figure 10) being under strict user control. Multiple value knowledge bases, extracted from WordNet, with varying depth (from 6 to 16 levels, cf. Figure 10.b) and number of concepts (from 100 to 132000 nodes, cf. Figure 9.b) were also considered. One can see from the result that the time to compute semantic implications grows in a polynomial fashion with the number of predicates.

![Figure 10. Timing results regarding the number of predicates, value set cardinalities, and $V_{KB}$ size](image)

Recall that the reference value knowledge base $V_{KB}$ and operator knowledge base $O_{KB}$ are stored in a relational database and are queried for each value and operator in the concerned predicates when identifying implication. Thus, querying the $V_{KB}$ knowledge base for each predicate value requires extra time (database access time) and hence contributes to increasing time complexity. Therefore, we believe that system performance would improve if the reference $V_{KB}$ knowledge base could fit in primary memory.

7. Conclusion

Fragmentation techniques are used in distributed system design to reduce accesses to irrelevant data, thus enhancing system performance [Ezeife and Barker 1995]. In this study, we address primary horizontal fragmentation in multimedia databases. In particular, we emphasize semantic-based predicates implication which are required in current fragmentation algorithms, in order to partition multimedia data efficiently. Our approach is complementary to that
developed in [Saad et al. 2006], targeting implications between low-level multimedia predicates (applied on complex feature vectors such as dominant color, texture, etc.) as a prerequisite to performing multimedia fragmentation. We propose a set of algorithms for identifying implications between semantic predicates, based on operator and value implications. Operator implications are identified utilizing a specific operator knowledge base developed in our study. Value implications are discovered following domain-oriented or generic value concept knowledge bases such as WordNet [WordNet 2005]. We developed a prototype to test our approach. Timing results show that our method is of polynomial complexity.

We are currently conducting fragmentation experiments on real multimedia data so as to analyze our approach’s efficiency with respect to traditional methods. Future directions include studying derived horizontal fragmentation and vertical fragmentation of multimedia data, taking into account semantic and low-level multimedia features. We also plan on releasing a public version of our prototype.

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