Similarity Matrix Compression for Efficient Signature Quadratic Form Distance Computation

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ABSTRACT

Determining similarities among multimedia objects is a fundamental task in many content-based retrieval, analysis, mining, and exploration applications. Among state-of-the-art similarity measures, the Signature Quadratic Form Distance has shown good applicability and high quality in comparing flexible feature representations. In order to improve the efficiency of the Signature Quadratic Form Distance, we propose the similarity matrix compression approach which aims at compressing the distance's inherent similarity matrix. We theoretically show how to reduce the complexity of distance computations and benchmark computation time improvements. As a result, we improve the efficiency of a single distance computation by a factor up to 9.

Categories and Subject Descriptors

H.2.4 [**Systems**]: Multimedia databases, Query processing; H.3.3 [**Information Search and Retrieval**]: Retrieval models, Search process

General Terms

Theory, Experimentation, Performance

Keywords

Signature Quadratic Form Distance, Similarity Matrix Compression, Content-Based Multimedia Retrieval, Similarity Search, Efficient Query Processing

1. INTRODUCTION

Content-based multimedia retrieval [6, 9, 13, 15, 17] is a widespread interdisciplinary field attracting both academia and industry. Retrieving multimedia objects sharing the most similar contents with regard to the query object is frequently performed by computing distance values among the objects' feature representations. This fundamental task has to be performed effectively and efficiently in order to satisfy users aiming at retrieving the most relevant objects in low query response times.

In particular for multimedia data where similarity measures have to cope with adaptable content representations, the *Signature Quadratic Form Distance* [2, 5] has shown good applicability and high quality in comparing flexible feature representations, so-called *feature signatures*, with each other leading to high retrieval performance [3]. By adapting the cross-dimension concept of the traditional *Quadratic Form Distance* [8, 16], this adaptive similarity measure is not only defined for the comparison of feature histograms exhibiting the same length and structure but also for feature signatures of different size and structure.

Although it is shown that the Signature Quadratic Form Distance is a generalization of the Quadratic Form Distance [5], approximation techniques for efficient query processing [1, 10, 12, 16] applicable to the traditional Quadratic Form Distance are generally not applicable to the Signature Quadratic Form Distance [4]. Thus, the present paper introduces the *similarity matrix compression* approach in order to reduce the computational effort spent for the computation of the Signature Quadratic Form Distance. By making use of feature signatures partially sharing the same inherent information, we compress the distance's similarity matrix and show how to compute the Signature Quadratic Form Distance thereon. Our approach improves the efficiency of a single distance computation by a factor up to 9 and is thus applicable for efficient query processing in voluminous multimedia databases.

The organization of the present paper is as follows: in Section 2, we review the feature extraction process and the Signature Quadratic Form Distance on feature signatures. Additionally, we argue the inapplicability of existing techniques. Section 3 is devoted to the similarity matrix compression approach which is evaluated in Section 4. We conclude our work in Section 5 with an brief outlook on future work.

2. RELATED WORK AND BACKGROUND

In this section, we first study the feature extraction process and the resulting feature representation forms of multimedia data, *feature histograms* [8, 11] and *feature signatures* [3, 14]. Then, we present the Signature Quadratic Form Distance defined to compare feature histograms as well as feature signatures. Last, we briefly discuss efficient query processing techniques existing for the Quadratic Form Distance and argue their inapplicability to the Signature Quadratic Form Distance.

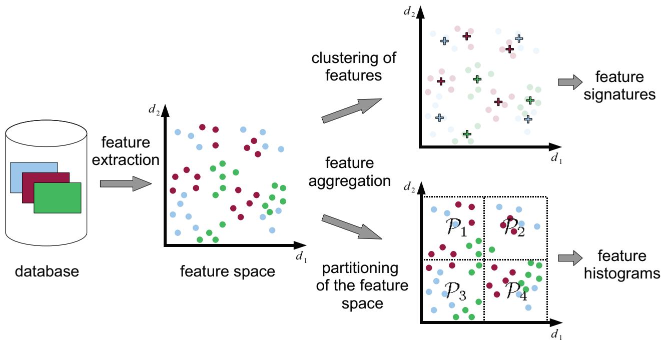

Figure 1: The feature extraction process in two steps: the objects' properties are extracted and mapped in some feature space and then represented in a more compact form.

The goal of the feature extraction process is to digitize and store the data objects' inherent properties in a compact way. Figure 1 illustrates the two main steps of the feature extraction process.

In the first step of the process, *feature extraction*, each data object is mapped onto a set of features in an appropriate feature space $\mathcal{FS}$ which comprises various dimensions, such as position, color, or texture. In this way, the content of each data object is exhibited via its feature distribution in the feature space. The features in the figure belonging to the same data object are shown via the same color, i.e. the blue, red, and green data objects are expressed by the blue, red, and green points in the feature space, respectively. More details about features for content-based multimedia retrieval can for instance be found in the work of Deselaers et al. [7] and Veltkamp et al. [18].

The second step of the process, *feature aggregation*, aggregates the extracted data objects' feature distributions via global partitioning of the feature space or clustering of features for each data object individually, as can be seen on the right-hand side in Figure 1. For each data object o, a single *feature histogram* of form $h^o = (h^{o_1}, \ldots, h^{o_n})$ can be generated where each entry $h^{o_i} \in \mathcal{R}^{\geq 0}$ of the feature histogram corresponds to the number of features located in the corresponding global partition $\mathcal{P}_i$. Thus a global partitioning of n partitions will lead to n-dimensional feature histograms. In the figure, we illustrate the aggregation of features according to four global partitions $\mathcal{P}_1, \ldots, \mathcal{P}_4$, which are fixed for all database objects. In contrast to feature histograms, each *feature signature* aggregates its data object features by individual clustering. As can be seen in the figure, the resulting feature signatures consist of clusters of the objects' features with the corresponding weights and centroids, visualized by pluses with different colors for each data object. The resulting feature signatures of the red and blue objects contain four centroids while the green object's feature signature comprises three centroids. In this way, each data object is represented by a single feature signature which is formally defined below.

Figure 2: An example image and the corresponding feature signature visualization.

Definition 1. *Feature Signature*
Given a feature space $\mathcal{FS}$ and a clustering $\mathcal{C} = \mathcal{C}_1, \ldots, \mathcal{C}_n$ of the features $f_1, \ldots, f_k \in \mathcal{FS}$ of object o, the feature signature S^o is defined as a set of tuples from $\mathcal{FS} \times \mathcal{R}^+$ as follows:

$$S^o = \{\langle c^{o_i}, w^{o_i} \rangle, i = 1, \ldots, n\},$$

where $c^{o_i} = \frac{\sum_{f \in \mathcal{C}_i} f}{|\mathcal{C}_i|}$ and $w^{o_i} = \frac{|\mathcal{C}_i|}{k}$ represent the centroid and weight, respectively.

According to Definition 1, a feature signature S^o is a set of centroids $c^{o_i} \in \mathcal{FS}$ with the corresponding weights $w^{o_i} \in \mathcal{R}^+$ of the clusters $\mathcal{C}_i$. As the clustering per individual data object is not restricted to predefined partitions in the feature space, a feature signature represents the feature distribution of its data object more meaningfully than a feature histogram. Due to the individual clustering of features, feature signatures furthermore achieve a better balance between expressiveness and efficiency than feature histograms. Moreover, each feature histogram can be expressed as a corresponding feature signature by substituting the clustering with global partitioning.

An example image and its feature signature visualization are given in Figure 2 where the feature signature of the image is visualized from a five dimensional feature space (two position and three color dimensions) in a two-dimensional position space. Each circle and its radius correspond to a cluster and the weight of the cluster, respectively. The figure indicates that the corresponding feature signature approximates the visual content of an image very well. In this example, the sky, beach, and plants can be matched to their pairs of centroids and weights, accordingly.

Based on the previously defined feature representation forms, namely feature histograms and feature signatures, we will continue with presenting the Signature Quadratic Form Distance [2, 5], an adaptive similarity measure for content-based multimedia retrieval [3]. As this distance generalizes the traditional Quadratic Form Distance [8, 16], we give the latter's definition and explanation first.

Definition 2. *Quadratic Form Distance*
Given two feature histograms h^q and h^p and a similarity matrix $A \in \mathcal{R}^{|h^q| \times |h^p|}$, the Quadratic Form Distance QFD_A between h^q and h^p is defined as:

$$QFD_A(h^q, h^p) = \sqrt{(h^q - h^p) \cdot A \cdot (h^q - h^p)^T}.$$

The similarity matrix A of a Quadratic Form Distance QFD_A realizes the cross-dimension concept by modeling similarities among all dimensions of the feature histograms. While the Quadratic Form Distance given in Defintion 2 is limited to compare feature histograms of the same size and structure, the Signature Quadratic Form Distance is able to compare flexible feature signatures of different size and structure with each other. For this purpose, the cross-dimension concept of the Quadratic Form Distance is adapted to the Signature Quadratic Form Distance. The distance computation is shifted from comparing all dimensions of the feature histograms to comparing all centroids of the feature signatures. For this purpose, the Signature Quadratic Form Distance makes use of a similarity function f_s modeling the similarity between two centroids. The formal definition of the Signature Quadratic Form Distance is given below.

Definition 3. *Signature Quadratic Form Distance*
Given two feature signatures $S^q = \{\langle c^{q_i}, w^{q_i}\rangle | \; i = 1, \dots, n\}$ and $S^p = \{\langle c^{p_i}, w^{p_i}\rangle | \; i = 1, \dots, m\}$, and a similarity function $f_s(c_i, c_j) \mapsto \mathcal{R}$, the Signature Quadratic Form Distance $SQFD_{f_s}$ between S^q and S^p is defined as:

$$SQFD_{f_s}(S^q, S^p) = \sqrt{(w^q | - w^p) \cdot A_{f_s} \cdot (w^q | - w^p)^T},$$

where $A_{f_s} \in \mathcal{R}^{(n+m)\times(n+m)}$ is the similarity matrix arising from applying the similarity function f_s to the corresponding centroids, i.e. $a_{ij} = f_s(c_i, c_j)$. Furthermore, $w^q = (w^{q_1}, \dots, w^{q_n})$ and $w^p = (w^{p_1}, \dots, w^{p_m})$ form weight vectors, and $(w^q | - w^p) = (w^{q_1}, \dots, w^{q_n}, -w^{p_1}, \dots, -w^{p_m})$ denotes the concatenation of w^q and $-w^p$.

The similarity matrix A_{f_s} is dynamically determined for each comparison of two feature signatures and reflects similarities among all centroids of both feature signatures. $A_{f_s} = [a_{ij}]$ is computed by similarity functions [2, 5], such as $a_{ij} = e^{-L_2^2(c_i,c_j)/2}$. In this way, the Signature Quadratic Form Distance between two feature signatures S^q and S^p is computed by taking into account the centroids' weights and positions in the feature space.

The Signature Quadratic Form Distance is able to to determine a distance value between feature signatures and also feature histograms of any lengths and structure, by adapting the cross-dimension concept. Although it generalizes the Quadratic Form Distance, we argue for the inapplicability of existing efficient query processing techniques in the remainder of this section.

Over the last couple of years, numerous works addressing efficient query processing with the Quadratic Form Distance on feature histograms have been presented. Ellipsoid query processing using index structures [10, 16], reduction of dimensionality [12], and approximation techniques with sphere and box approximations [1] are some examples of these techniques. By examining these techniques, we have seen that they all rely on a fixed similarity matrix which means that the matrix will not change during a single query process. In the case of feature histograms, the entries of a similarity matrix model similarities among individual global partitions. This induces a fixed similarity matrix as the partitions typically do not change. In the feature signature case, the similarity matrix models similarities among centroids, which are based on an individual clustering, and thus changes from computation to computation. Thus, we have to apply the existing techniques for each distance computation individually, which is inapplicable in terms of efficiency. This briefly describes the inapplicability of existing techniques to the Signature Quadratic Form Distance in order to improve the efficiency of query processing. More details can be found in the work of Beecks et al. [4].

In the next section, we will present the *similarity matrix compression* approach in order to reduce the computational effort spent for single Signature Quadratic Form Distance computations.

3. SIMILARITY MATRIX COMPRESSION

In this section, we present the *similarity matrix compression* approach for the efficient query processing regarding the Signature Quadratic From Distance.

The idea of the proposed approach is to compress the similarity matrix of the Signature Quadratic Form Distance by making use of feature signatures partially sharing the same inherent information.

In order to formalize the compression in form of a specific Signature Quadratic Form Distance, we first define global and local components of feature signatures. Local components express individual information of a feature signature whereas global components capture the information shared among all feature signatures.

Without loss of generality, we define global and local components between *two* feature signatures in below. In this particular case, the global and local components of a feature signature only depend on the other feature signature. The definition can be easily extended to a larger set of feature signatures.

Definition 4. *Global and Local Components*
Given two feature signatures $S^q = \{\langle c^{q_i}, w^{q_i}\rangle, i = 1, \dots, n\}$ and $S^p = \{\langle c^{p_i}, w^{p_i}\rangle, i = 1, \dots, m\}$, we define the global components S^q_g and S^p_g and the local components S^q_l and S^p_l of the feature signatures S^q and S^p as follows:

$$\begin{aligned} S^q_g &:= \{\langle c, w\rangle \in S^q \mid \exists w' \in \mathcal{R}^+ : \langle c, w'\rangle \in S^p\}, \\ S^p_g &:= \{\langle c, w\rangle \in S^p \mid \exists w' \in \mathcal{R}^+ : \langle c, w'\rangle \in S^q\}, \\ S^q_l &:= S^q \backslash S^q_g, \\ S^p_l &:= S^p \backslash S^p_g. \end{aligned}$$

The global components S^q_g and S^p_g of the corresponding feature signatures contain the tuples from $\mathcal{FS} \times \mathcal{R}^+$ whose centroids appear in both feature signatures as *global centroids*. In contrast, the local components S^q_l and S^p_l comprise tuples whose centroids are contained in exactly one feature signature.

In other words, global and local components are themselves feature signatures reflecting shared and individual information, respectively. By rearranging the weights of these components, the sorted weight vectors, as given in the following definition, are implied.

Definition 5. *Sorted Weight Vectors*
Given two feature signatures $S^q = \{\langle c^{q_i}, w^{q_i}\rangle, i = 1, \ldots, n\}$ *and* $S^p = \{\langle c^{p_i}, w^{p_i}\rangle, i = 1, \ldots, m\}$ *with* $k \leq \min\{n, m\}$ *global centroids, i.e.* $|S^q_g| = |S^p_g| = k$*, we define the sorted weight vectors* $\widetilde{w}^q, \widetilde{w}^p$ *as follows:*

$$
\begin{aligned}
\widetilde{w}^q &:= (\widetilde{w}^q_g|\widetilde{w}^q_l) := (\widetilde{w}^{q_1}, \ldots, \widetilde{w}^{q_k}|\widetilde{w}^{q_{k+1}}, \ldots, \widetilde{w}^{q_n}),\\
\widetilde{w}^p &:= (\widetilde{w}^p_g|\widetilde{w}^p_l) := (\widetilde{w}^{p_1}, \ldots, \widetilde{w}^{p_k}|\widetilde{w}^{p_{k+1}}, \ldots, \widetilde{w}^{p_m}),
\end{aligned}
$$

under the following conditions:

$$
\begin{array}{ll}
(i) & \forall i\ 1 \leq i \leq k,\ \exists c.\\
& \langle c, \widetilde{w}^{q_i}\rangle \in S^q_g \wedge \langle c, \widetilde{w}^{p_i}\rangle \in S^p_g,\\
(ii) & \forall i\ k+1 \leq i \leq n,\ \exists c.\ \langle c, \widetilde{w}^{q_i}\rangle \in S^q_l,\\
(iii) & \forall i\ k+1 \leq i \leq m,\ \exists c.\ \langle c, \widetilde{w}^{p_i}\rangle \in S^p_l,\\
(iv) & \forall i,j\ 1 \leq i,j \leq n,\ i \neq j,\ \exists c, c'.\\
& \langle c, \widetilde{w}^{q_i}\rangle \in S^q \wedge \langle c', \widetilde{w}^{q_j}\rangle \in S^q \wedge c \neq c',\\
(iv) & \forall i,j\ 1 \leq i,j \leq m,\ i \neq j,\ \exists c, c'.\\
& \langle c, \widetilde{w}^{p_i}\rangle \in S^p \wedge \langle c', \widetilde{w}^{p_j}\rangle \in S^p \wedge c \neq c'.
\end{array}
$$

Sorting and thus aligning the feature signatures' weight vectors w^q and w^p (see Definition 3 in Section 2) according to the global and local components given in Definition 4, we defined the sorted weight vectors $\widetilde{w}^q$ and $\widetilde{w}^p$ which are necessary for the similarity matrix compression. It can be shown that the computation of the Signature Quadratic Form Distance yields the same distance value whether the weight vectors w^q, w^p or the sorted weight vectors $\widetilde{w}^q, \widetilde{w}^p$ are used, i.e. the computed distance value of the Signature Quadratic Form Distance is independent of the centroids order in which they appear in the feature signatures.

Based on the definitions of global and local components (Definition 4) and sorted weight vectors of feature signatures (Definition 5), we formalize the similarity matrix compression approach in the remainder of this section. For this purpose, we illustrate the similarity matrix compression approach by visualizing the structure of the similarity matrices without compression and with compression in Figure 3. We denote the original uncompressed similarity matrix depicted on the left-hand side by A, instead of A_{f_s}, and the compressed similarity matrix depicted on the right-hand side by A'. The structures of both similarity matrices are given by the corresponding global and local centroids denoted as c^q_g, c^p_g, c^q_l, and c^p_l. While the original uncompressed similarity matrix exhibits a 4×4 block structure, the compressed one will be reduced to a similarity matrix comprising a 3×3 block structure.

Considering the structure of the original uncompressed similarity matrix A, the goal of the similarity matrix compression is to compress the blocks marked green and orange as they contain the same similarity information which is implied by the global centroids. In this way, the similarity matrix A is compressed to a smaller similarity matrix A' comprising the same similarity information as A. This compression can be used to simplify the computation of the Signature Quadratic Form Distance in order to speed up the computation, as shown in the following theorem.

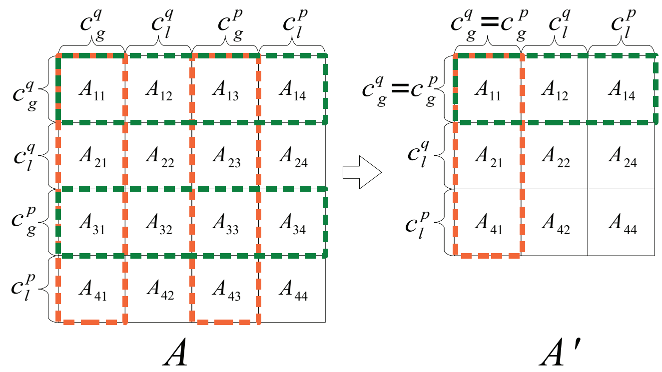

Figure 3: Similarity matrix compression: the original uncompressed similarity matrix A and the compressed similarity matrix A'.

Theorem 1. *Similarity Matrix Compression*
Given two feature signatures $S^q = \{\langle c^{q_i}, w^{q_i}\rangle, i = 1, \ldots, n\}$ *and* $S^p = \{\langle c^{p_i}, w^{p_i}\rangle, i = 1, \ldots, m\}$*, it holds that*

$$
\begin{aligned}
&SQFD^2_A(S^q, S^p)\\
&\quad = (\widetilde{w}^q_g - \widetilde{w}^p_g|\widetilde{w}^q_l| - \widetilde{w}^p_l) \cdot A' \cdot (\widetilde{w}^q_g - \widetilde{w}^p_g|\widetilde{w}^q_l| - \widetilde{w}^p_l)^T,
\end{aligned}
$$

where $A \in \mathcal{R}^{(n+m)\times(n+m)}$ *and* $A' \in \mathcal{R}^{(n+m-k)\times(n+m-k)}$ *are the uncompressed and compressed similarity matrices as depicted in Figure 3.*

Proof.

$$
\begin{array}{ll}
& SQFD^2_A(S^q, S^p)\\
= & ((\widetilde{w}^q_g|\widetilde{w}^q_l)| - (\widetilde{w}^p_g|\widetilde{w}^p_l)) \cdot A \cdot ((\widetilde{w}^q_g|\widetilde{w}^q_l)| - (\widetilde{w}^p_g|\widetilde{w}^p_l))^T\\
= & \underbrace{\widetilde{w}^q_g A_{11} \widetilde{w}^{q\,T}_g - \widetilde{w}^q_g A_{13} \widetilde{w}^{p\,T}_g - \widetilde{w}^p_g A_{31} \widetilde{w}^{q\,T}_g + \widetilde{w}^p_g A_{33} \widetilde{w}^{p\,T}_g}_{A_{11}=A_{13}=A_{31}=A_{33} \Rightarrow (\widetilde{w}^q_g - \widetilde{w}^p_g)\cdot A_{11} \cdot (\widetilde{w}^q_g - \widetilde{w}^p_g)^T}\\
+ & \underbrace{\widetilde{w}^q_g A_{12} \widetilde{w}^{q\,T}_l - \widetilde{w}^p_g A_{32} \widetilde{w}^{q\,T}_l - \widetilde{w}^q_g A_{14} \widetilde{w}^{p\,T}_l + \widetilde{w}^p_g A_{34} \widetilde{w}^{p\,T}_l}_{A_{12}=A_{32}, A_{14}=A_{34} \Rightarrow (\widetilde{w}^q_g - \widetilde{w}^p_g)\cdot A_{12} \cdot \widetilde{w}^{q\,T}_l - (\widetilde{w}^q_g - \widetilde{w}^p_g)\cdot A_{14} \cdot \widetilde{w}^{p\,T}_l}\\
+ & \underbrace{\widetilde{w}^q_l A_{21} \widetilde{w}^{q\,T}_g - \widetilde{w}^q_l A_{23} \widetilde{w}^{p\,T}_g - \widetilde{w}^p_l A_{41} \widetilde{w}^{q\,T}_g + \widetilde{w}^p_l A_{43} \widetilde{w}^{p\,T}_g}_{A_{21}=A_{23}, A_{41}=A_{43} \Rightarrow \widetilde{w}^q_l \cdot A_{21} \cdot (\widetilde{w}^q_g - \widetilde{w}^p_g)^T - \widetilde{w}^p_l \cdot A_{41} \cdot (\widetilde{w}^q_g - \widetilde{w}^p_g)^T}\\
+ & \widetilde{w}^q_l A_{22} \widetilde{w}^{q\,T}_l - \widetilde{w}^q_l A_{24} \widetilde{w}^{p\,T}_l - \widetilde{w}^p_l A_{42} \widetilde{w}^{q\,T}_l + \widetilde{w}^p_l A_{44} \widetilde{w}^{p\,T}_l\\
= & (\widetilde{w}^q_g - \widetilde{w}^p_g) \cdot (A_{11}(\widetilde{w}^q_g - \widetilde{w}^p_g)^T + A_{12} \widetilde{w}^{q\,T}_l - A_{14} \widetilde{w}^{p\,T}_l)\\
+ & \widetilde{w}^q_l \cdot (A_{21}(\widetilde{w}^q_g - \widetilde{w}^p_g)^T + A_{22} \widetilde{w}^{q\,T}_l - A_{24} \widetilde{w}^{p\,T}_l)\\
+ & \widetilde{w}^p_l \cdot (A_{41}(\widetilde{w}^q_g - \widetilde{w}^p_g)^T + A_{42} \widetilde{w}^{q\,T}_l - A_{44} \widetilde{w}^{p\,T}_l)\\
= & (\widetilde{w}^q_g - \widetilde{w}^p_g|\widetilde{w}^q_l| - \widetilde{w}^p_l) \cdot A' \cdot (\widetilde{w}^q_g - \widetilde{w}^p_g|\widetilde{w}^q_l| - \widetilde{w}^p_l)^T.
\end{array}
$$

□

According to Theorem 1, the computation of the Signature Quadratic Form Distance is carried out via the compressed similarity matrix A' comprising 9 blocks which can be seen in Figure 3 on the right-hand side.

Let us now examine these blocks of the compressed similarity matrix A' and the resulting Signature Quadratic Form Distance computation shown in Theorem 1 in terms of efficient query processing. The query processing is carried

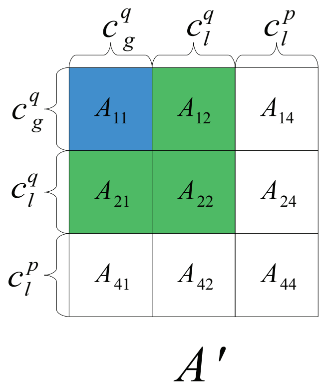

Figure 4: Precomputing the blocks of the compressed similarity matrix A': the blue block can be computed before the query is issued, while the green blocks can be computed once the query is issued.

out by computing the Signature Quadratic Form Distance between the query feature signature S^q and each database object's feature signature S^p and ranking the database objects according to increasing distance values to the query.

On the premise that the global centroids c_g^q and c_g^p of the global components S_g^q and S_g^p of a specific database are known in advance and that the query process makes use of a predetermined similarity function, we can precompute the entries of the corresponding similarity matrix block A_{11} before a query is given.

At query time the entries of the similarity matrix blocks A_{12}, A_{21}, and A_{22} can be computed. They contain similarity information about the query feature signature's local components and thus solely rely on the query feature signature. Furthermore, the remaining similarity matrix blocks A_{14}, A_{24}, A_{41}, A_{42}, and A_{44} have to be computed for each distance computation since these blocks can only be computed by taking into account the local centroids of database objects' feature signatures.

We depict the precomputation possibilities of a compressed similarity matrix in Figure 4 where the computation of the similarity matrix' entries of block A_{11} is indicated by the blue color. These entries can be computed in advance, without knowing the query. The green colored blocks indicate blocks of the similarity matrix which can be computed once the query is issued.

To sum up, we have introduced the similarity matrix compression approach compressing a similarity matrix of the Signature Quadratic Form Distance, which comprises a 4×4 block structure, to a smaller similarity matrix comprising a 3×3 block structure. We have shown in Theorem 1 that the Signature Quadratic Form Distance can be efficiently computed using the compressed similarity matrix. Additionally, we briefly described which blocks of the compressed similarity matrix can be precomputed in order to improve the efficiency of the query process even more. In the following section, we evaluate the similarity matrix compression approach in terms of efficiency.

Table 1: Average computation time values in milliseconds needed to compute the Signature Quadratic Form Distance by using similarity matrix compression *with precomputation*.

	size of feature signatures				
c_g(%)	100	200	400	800	s_f
80	3.14	12.71	50.78	206.05	9.0
60	6.95	27.67	110.45	445.04	4.1
40	11.24	44.93	179.43	720.15	2.6
20	16.09	64.49	257.65	1033.54	1.8
0	28.81	114.96	459.89	1844.17	

Table 2: Average computation time values in milliseconds needed to compute the Signature Quadratic Form Distance by using similarity matrix compression *without precomputation*.

	size of feature signatures				
c_g(%)	100	200	400	800	s_f
80	10.37	41.86	166.12	663.7	2.8
60	14.21	56.54	228.09	905.16	2.0
40	18.35	73.76	297.93	1181.04	1.6
20	23.25	93.39	374.31	1493.24	1.2
0	28.81	114.96	459.89	1844.17	

4. EXPERIMENTAL EVALUATION

In this section, we evaluate our approach in terms of efficient query processing by measuring the computation time needed to compare two feature signatures using the Signature Quadratic Form Distance.

For this purpose, we generated feature signatures with different size, i.e. with different number of centroids and weights, where we assumed 7-dimensional centroids reflecting position, color, and texture information. We varied the number of centroids of the feature signatures to be compared between 100 and 800, and the ratio c_g of global centroids between 0% and 80%.

In our experiments, we computed the Signature Quadratic Form Distance using the similarity function $a_{ij} = e^{-L_2(c_i,c_j)/2}$ where L_2 denotes the Euclidean distance. We ran all experiments on a 2.4GHz Intel Core 2 Duo machine and implemented our approach in JAVA 1.6.

The results of the computation time values averaged over 100 Signature Quadratic Form Distance computations are shown in Table 1 and Table 2. The first table reports the measured computation time values by applying the similarity matrix compression approach and all the possible precomputations as described in the previous section. The computation time values, given in milliseconds, indicate that the efficiency of the proposed similarity matrix compression approach depends on the ratio of global centroids c_g, i.e. the size of the global components S_g^q and S_g^p. The larger the size of global components, the higher the efficiency of our approach. Consequently, the highest speed-up factor s_f of 9 was reached when we set the ratio c_g of global centroids to 80%.

Table 2 gives the computation time values by using the similarity matrix compression approach without precomputation. As a result, the time needed to compute the Signature Quadratic Form Distance increases and the highest speed-up factor s_f of 2.8 was also reached by setting the ratio c_g of global centroids to 80%.

To sum up, we have shown that the proposed similarity matrix approach reduces the computation time of the Signature Quadratic Form Distance. Combining the similarity matrix compression with the possible precomputations, we reach a speed-up factor of 9. Thus our approach can successfully be applied to rank multimedia databases efficiently.

5. CONCLUSIONS

In this paper, we presented the similarity matrix compression approach for improving the efficiency of Signature Quadratic Form Distance computations. The experimental results indicate that a speed-up factor of 9 is obtained when our approach is applied to the Signature Quadratic Form Distance.

As future work, we plan to involve users in the evaluation process of the similarity matrix compression approach on different image, video, and audio databases. Furthermore, we plan to study the effectiveness of the proposed approach in different content-based retrieval applications.

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