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A CLUSTER-LIKE ALGORITHM FOR HIGH-PERFORMANCE MEDIA RETRIEVAL

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ABSTRACT

Tremendous growth of media applications including content-based retrieval with queries 'ad exemplum' often aligns problems of partitions matching to the front of the research issues. Already non-trivial media clustering is now put on a new semantic level of data interpretation. And though for last years researches have actively explored this area, the fundamental problem of high-performance metrical matching still remains unsolved. To speedup content based search an algorithm of preliminary distance matrix processing is proposed.

Index Terms - media retrieval, distance matrix, number of matches

1. INTRODUCTION

Recently, multimedia applications are undergoing explosive growth due to the monotonic increase in the available processing power and bandwidth. A prerequisite for the efficient multimedia information processing and interpretation is a careful analysis of the media types properties. Video, sound, images and text data require different processing algorithms yet for a really successful retrieval system it is more and more required to maintain the seamless different physical nature data integration. One promising solution that enables multimedia data search grounds on the concept of content-based search and retrieval. There are two substantial open issues in the field of media retrieval: semantic gap between low-level features extracted by computer and high-level concepts which human operates, and also high retrieval speed independent of the database volume. Therefore, there arises a problem of how to preprocess database content in order to speedup a search. So, from many performance characteristics of indexing methods we concentrated on those which measure the number of similarity evaluations at the search stage since calculations between multimedia sets are often time-consuming. To develop high performance search engines one usually can rely on metric space based approaches.

Existent metric indexing methods roughly may be classified into two groups: viz pivot-based and compact partitioning. In the first case a number of reference objects (so-called pivots) are chosen, and distances from some part of non-pivot objects to pivots are calculated and stored. The most popular approaches are full-matrix index AESA, sparse matrix LAESA and VP-tree [1]. Compact partitioning indexing algorithms like M-tree, D-index [2] form a sort of clusters around predefined reference objects. We propose a novel cluster-like algorithm of indexing in a metric space. This algorithm transforms a preliminary calculated distance matrix into a block-diagonal form what ensures the guaranteed min-max matches number at the retrieval stage with given value of required similarity. Contrariwise, the medians of each block can be chosen as pivots or vantage points to find approximate matches when the retrieved data does not necessarily have to be extremely similar example.

2. A CLUSTER-LIKE ALGORITHM

Retrieval system 'ad exemplum' extracts the content of the query and compares it with that of each database datum during querying. The result of this query can return one or more database representatives that are the most similar ones to the query example. For given metric and search radius as a basic criterion we have used the number of matches between the query and database elements. In other words, the problem lies in the preliminary clustering of the database with the search aiming to find the closest cluster and if necessary to continue searching inside the chosen cluster.

The problem statement may be formulated as follows. Let $\mathrm{X} = \{x_1, x_2, ..., x_N\}$ be a media (specifically, image) collection in which content-based retrieval is carried out. Suppose that the set U ($\mathrm{X} \subseteq \mathrm{U}$) defines problem-oriented field of image understanding. Result of ε- search with the query $y \in \mathrm{U}$ is any element (all elements) $x_i \in \mathrm{X}$ if $\rho(y, x_i) \le \varepsilon$ for given so-called search radius $\varepsilon \ge 0$ (here $\rho(\circ,\circ)$ is a metric). Let us introduce a notation $\rho_{i,j} = \rho(x_i, x_j)$ for elements of distance matrix $d(\mathrm{X})$ and consider some arbitrary subset of database elements for which $\rho_{i,j} \le \delta$. These objects can be used as a δ- search result, yet under that a formalization of all such groupings search procedures for some given criterion is necessary. As a basic

criterion we shall use the number of matches between the query and database elements. In other words, the problem lies in the preliminary clustering of the database with the search aiming to find the closest cluster and if necessary to continue searching inside the chosen cluster. Here the basic feature of clustering is matches number minimization. Let us consider the clustering procedure.

We shall call symmetrical l-range matrix as a Δ_l^k-block of distance matrix $d(\mathrm{X})$

$$\Delta_l^k[d(\mathrm{X})] = \begin{pmatrix} 0 & \rho_{k,k+1} & \cdots & \rho_{k,k+l-1} \\ \rho_{k+1,k} & 0 & \cdots & \rho_{k+1,k+l-1} \\ \cdots & \cdots & \cdots & \cdots \\ \rho_{k+l-1,k} & \rho_{k+l-1,k+1} & \cdots & 0 \end{pmatrix}$$

which is the result of rows and columns transposition with indices $\{i_1, i_2,..., i_l\}$ such that

$$\forall i', i'' \in \{i_1, i_2,..., i_l\} \Rightarrow \rho_{i',i''} \le \delta .$$

In addition we shall consider Δ_l^k-block of matrix $d(\mathrm{X})$ as maximal if

$$\nexists r \in \{1,2,...,n\} \setminus \{i_1,i_2,...,i_l\} : \rho_{r,i'} \le \delta \forall i' \in \{i_1,i_2,...,i_l\}.$$

There may exist some elements which can belong to two or more different Δ_l^k-blocks of matrix $d(\mathrm{X})$. It is obvious that two variants are possible: these elements are included into all possible blocks or they are included into those blocks for which sum of elements is minimal what meets compactness criterion (2).

As Δ-representation we shall call a block-diagonal type of matrix $d(\mathrm{X})$

$$\Delta[d(\mathrm{X})] = \begin{pmatrix} \Delta_{l_1}^{k_1} & & & 0 \\ & \Delta_{l_2}^{k_2} & & 0 \\ 0 & & \cdots & 0 \\ & 0 & 0 & \Delta_{l_m}^{k_m} \end{pmatrix}$$

where $k_1 = 1,\ k_i = \sum_{j=1}^{i-1} l_j + 1,\ \sum_{j=1}^{m} l_j \ge n$.

It is clear that under δ- search the Δ-representation with the minimal number of blocks will be the best one in respect to the number of matches. In other words forming Δ-representation of matrix under given δ should provide

$$\min_{\Delta_l^k \in d(\mathrm{X})} m . \quad (1)$$

In case when we have several maximal Δ_l^k-blocks one can considered a criterion

$$\min_{\Delta_l^k \in d(\mathrm{X})} \sum_{i,j \in \{i_1, i_2,..., i_l\}} \rho_{i,j} \quad (2)$$

which does not change the goal function (1) value, but allows to get more sufficient database clustering.

Introduce the procedure of forming the maximal Δ_j^i-block of matrix $d(\mathrm{X})$ on set $\{p_1, p_2,..., p_r\} \subseteq$ $\subseteq \{1, 2,..., \mathrm{N}\}$. We find a row α^* such that for all $q \in \{p_1, p_2,..., p_r\}$

$$\alpha^* = arg \max_{\alpha \in \{p_1, p_2,..., p_r\}} \{card\{\rho_{\alpha,q}\} : \rho_{\alpha,q} \le \delta\} . \quad (3)$$

Denote by $\{\alpha_1,...,\alpha^*,..., \alpha_\beta\}$ indices found in (3). If there exists more than one of such indices kit we shall randomly chose one of them. Two cases are possible:

$$\forall \alpha', \alpha'' \in \{\alpha_1,...,\alpha^*,..., \alpha_\beta\} \Rightarrow \rho_{\alpha',\alpha''} \le \delta , \quad (4)$$

$$\exists \alpha', \alpha'' \in \{\alpha_1,...,\alpha^*,..., \alpha_\beta\} \text{ such that } \rho_{\alpha',\alpha''} > \delta . \quad (5)$$

Implication (4) denotes that choice of α^* provides forming of maximal $\Delta_{\beta+1}^i$-block of matrix $d(\mathrm{X})$ on set $\{p_1, p_2,..., p_r\}$. Thus having redefined the search domain

$$\{p_1, p_2,..., p_r\} \leftarrow \{p_1, p_2,..., p_r\} \setminus \{\alpha_1, \alpha_2 ,..., \alpha_\beta\} \quad (6)$$

we can move on to forming the next maximal Δ_j^i-block starting from (3) if $\{p_1, p_2,..., p_r\} \ne \varnothing$.

Note that situation described in (5) is much more complicated, but it can be brought to (4) by iterative elimination of block outliers. Here again two situations are possible: equality of the eliminated elements amount on this step or their disparity.

Under disparity we sequentially eliminate α'_γ, $(\gamma = 1,...,\Gamma,\ \{\alpha'_0\}=\varnothing, \Gamma: \nexists \alpha', \alpha' \in \{\alpha_1,...,\alpha_\beta\} \Rightarrow \rho_{\alpha',\alpha''} > \delta$, $\{\alpha_1,..., \alpha_\beta\} \leftarrow \{\alpha_1,..., \alpha_\beta\} \setminus \{\alpha'_{\gamma-1}\}$) such that

$$\alpha'_\gamma = arg \max_{s \in \{\alpha_1,..., \alpha_\beta\}} \{card\{\rho_{q,s}\} : \rho_{q,s} > \delta,\ q \in \{\alpha_1,..., \alpha_\beta\}\}$$

until (4) is fulfilled.

If cardinality of indexing set reduced in this way still exceeds the number of compact elements of next distance matrix row according to (3) criterion, then the next block is obtained. Elsewise having α'_γ temporary eliminated from $\{p_1, p_2,..., p_r\}$, we repeat considered steps till the next Δ_j^i-block is obtained. After that all deleted rows are brought back for further analysis. On figure 1,) a geometrical interpretation of this case is shown. Fig. 1, b) illustrates the result of Δ_j^i-blocks forming.

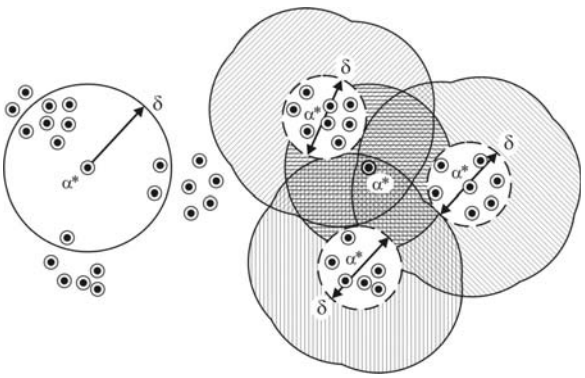

Figure 1. To the explanation of Δ_j^i-blocks forming

Consider choice of α^* when having multiple rows in (3). Emphasize that for (4) we have exactly β rows and α^* choice is not crucial as either all these

elements will be simultaneously assigned to one Δ_j^i -block (see fig. 1) or there are several blocks with the same cardinality and they all will be obtained sequentially. If (5) holds then choice α^* is also arbitrary since up to numeration all maximal blocks will be sequentially formed by reduction till cases (4).

Further eliminating from consideration set of indices $\{1, 2,..., k_1\}$ we get matrix of $(n-k_1)\times(n-k_1)$ dimension. Repeating the procedure for every new distance matrix firstly we get required representation in result, secondly by virtue of blocks maximality on each step (with accuracy up to enumeration) it provides fulfillment of (1).

3. RESULTS AND DISCUSSION

For the image processing a large variety of metrics is used as a similarity measure. Along with traditional metrics many approaches were exploited for introducing some distances which would take into consideration specific character of visual information. Working with templates leads to development of new metrics in some manner satisfying image interpretation tasks. Consider the metric using region content of images. This content can be induced by any segmentation.

Let Ω be an arbitrary measurable set with measure $\mu(\Omega)<\infty$, i.e. for any $A\subset\Omega$ exists some number $\mu(A)$ which is the measure (length, area, volume, mass distribution, probability distribution, cardinality, etc.). Let also $\mathcal{P}_\Omega$ be a power set in which all subsets are measurable. Introduce the set $\Pi_\Omega\subset\mathcal{P}_\Omega$ of finite (regarding the number of cosets) partitions of set Ω such that $\alpha\in\Pi_\Omega$, $\alpha=\{A_i\}_{i=1}^n$, $A_i\in\mathfrak{F}_\Omega$, $\Omega=\bigcup_{i=1}^n, A_i \forall i, j\in\{1,2,\ldots,n\}$: $: i\neq j \Rightarrow A_i\cap A_j=\varnothing$. The metric on Cartesian square $\Pi_\Omega\times\Pi_\Omega$ is

$$\rho(\alpha,\beta)=\sum_{i=1}^{n}\sum_{j=1}^{m}\mu(A_i\Delta B_j)\mu(A_i\cap B_j) \qquad (7)$$

where $A_i\Delta B_j=(A_i\backslash B_j)\cup(B_j\backslash A_i)$ is a symmetrical difference and $\beta\in\Pi_\Omega$, $\beta=\{B_j\}_{j=1}^m$ also. This result was initially proved by weak induction [3] for the case $\mu(A)=card\ A$ and then for arbitrary measurable set [4].

We applied developed indexing method with metric (7) to speedup region-based search of images. It should be noted, however, that there are still a lot of open issues here: selection of the δ value in order to construct more optimal in sense of matches number block-diagonal shapes of distance matrix, comparison with novel indexing methods like D-index. Finally, we think that our method could be effectively combined with existent indexing methods, for example, we can preprocess elements inside every Δ -block via another indexing method.

Finally, it should be noted that each block-diagonal submatrix corresponds to a cluster. Also it should be emphasized that simultaneous block-diagonalization may be continued and finally we get a hierarchical data organization which allows to construct nested media partitions, so that firstly one can seek a suitable class, then the most similar to the query subclass, and so on. The exhaustive search is fulfilled only on the lower level of hierarchy. Theoretic groundwork of optimizations for one-level clustering is given in [5] and for hierarchical one in [6]. Therefore, the basic feature of clustering is matches number minimization and maximal number of matches is equal to the sum of blocks at each hierarchy level and their maximal dimension at last level. As a result, the number of distance evaluations in worse-case conditions can be preserved.

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