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Content-Based Image Retrieval Systems -Using 3D Shape Retrieval Methods with Medical Application

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Abstract: The lack of evaluations of the retrieval quality of systems becomes apparent along with the unavailability of large image databases free of charge with defined query topics and gold standards. However, some databases are available, from the NIH (National Institutes of Health), for example. Ideas for creating such image databases and evaluation methods are proposed. The last decade has witnessed great interest in research on content-based image retrieval. This has paved the way for a large number of new techniques and systems, and a growing interest in associated fields to support such systems. Likewise, digital imagery has expanded its horizon in many directions, resulting in an explosion in the volume of image data required to be organized. In this paper, we discuss some of the key contributions in the current decade related to image retrieval and automated image annotation. We also discuss some of the key challenges involved in the adaptation of existing image retrieval techniques to build useful systems that can handle real-world data. Recent developments in techniques for modeling, digitizing and visualizing 3D shapes has led to an explosion in the number of available 3D models on the Internet and in domain-specific databases. This has led to the development of 3D shape retrieval systems that, given a query object, retrieve similar 3D objects. For visualization, 3D shapes are often represented as a surface, in particular polygonal meshes, for example in VRML format. Often these models contain holes, intersecting polygons, are not manifold, and do not enclose a volume unambiguously. On the contrary, 3D volume models, such as solid models produced by CAD systems, or voxels models, enclose a volume properly. This paper surveys the literature on methods for content based 3D retrieval, taking into account the applicability to surface models as well as to volume models. The methods are evaluated with respect to several requirements of content based 3D shape retrieval, such as: (1) shape re-presentation requirements, (2) properties of dissimilarity measures, (3) efficiency, (4) discrimination abilities, (5) robustness.

Key words: *3D shape & Medical image retrieval, visual information retrieval, PCA, DICOM,* ADL's

I. INTRODUCTION TO IMAGE RETRIEVAL & 3D SHAPES RETRIEVAL

This section gives an introduction to content-based image retrieval systems (CBIRSs) and the technologies used in them. Image retrieval has been an extremely active research area over the last 10 years, but first review articles on access methods in image databases appeared already in the early 80s[1]. The following review articles from various years explain the state-of-the-art of the corresponding years and contain references to a large number of systems and descriptions of the technologies implemented. Insert [2] gives an extensive description of image archives, various indexing methods and common searching tasks, using mostly text-based searches on annotated images.

This article describes common problems such as the semantic gap or the sensory gap and gives links to a large number of articles describing the various techniques used in the domain.

The advancement of modeling, digitizing and visualizing techniques for 3D shapes has led to an increasing amount of 3D models, both on the Internet and in domain-specific databases. This has led to the development of the first experimental search engines for 3D shapes, such as the 3D model search engine at Princeton University, the 3D model retrieval system at the National Taiwan University, the Ogden IV system at the National Institute of Multimedia Education, Japan, the 3D retrieval engine at Utrecht University, and the 3D model similarity search engine at the University of Konstanz [3]. Laser scanning has been applied to obtain archives recording cultural heritage like the Digital Michelangelo Project and the Stanford Digital Formal Urbis Rome Project. Furthermore, archives containing domain-specific shape models are now accessible by the Internet.

A. Content-based image retrieval systems:

Most of these systems have a very similar architecture for browsing and archiving/indexing images comprising tools for the extraction of visual features, for the storage and efficient retrieval of these features, for distance measurements or similarity calculation and a type of Graphical User Interface (GUI).

Although early systems existed already in the beginning of the 1980s [4], the majority would recall systems such as IBM's QBIC (Query by Image Content) as the start of content-based image retrieval.

Most of the available systems are, however from academia. It would be hard to name or compare them all but some well-known examples include Candid, Photo book and Nitra that all use simple color and texture characteristics to describe the image content. Using higher level information, such as segmented parts of the image for queries, was introduced by the Blob world system. Picture Hunter on the other hand is an image browser that helps the user to find an exact image in the database by showing to the user images on screen that maximizes the information gain in each feedback step. A system that is available free of charge is the GNU Image Finding Tool (GIFT). Some systems are available as demonstration versions on the web such as Viper, WIPE or Compass.

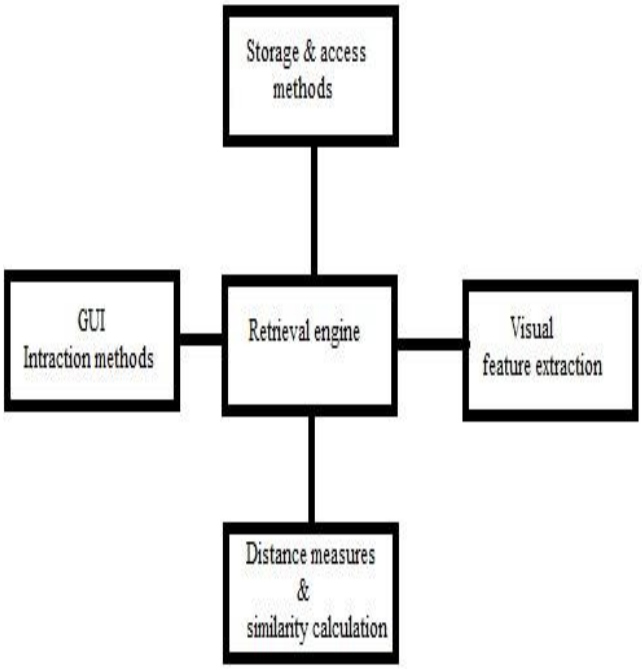

Figure.1: The principle components of all content based image retrieval systems.

B. Visual features used:

Visual features were classified in into primitive features [5] such as color or shape, logical features such as identity of objects shown and abstract features such as significance of scenes depicted. Still, all currently available systems only use primitive features unless manual annotation is coupled with the visual features as in.

a. Colour:

In stock photography (large, varied databases for being used by artists, advertisers and journalists), color has been the most effective feature and almost all systems employ colors. Although most of the images are in the RGB (Red, Green, and blue) color space, this space is only rarely used for indexing and querying as it does not correspond well to the human color [6] perception.

b. Texture:

These texture measures try to capture the characteristics of the image or image parts with respect to changes in certain directions and the scale of the changes. Partly due to the imprecise understanding and definition of what exactly visual texture actually is, texture measures have an even larger variety than color measures

c. Local and global features:

Both, color and texture features can be used on a global image level or on a local level on parts of the image. The easiest way to use regional features is to use blocks of fixed size and location, so called partitioning of the image.

d. Segmentation and shape features:

In image retrieval, several systems attempt to perform an automatic segmentation of the images in the collection for feature extraction [7]. To have an effective segmentation of images using varied image databases the segmentation process has to be done based on the color and texture properties of the image regions.

C. Comparison techniques used:

Basically all systems use the assumption of equivalence of an image and its representation in feature space. These systems often use measurement systems such as the easily understandable Euclidean vector space model [8] for measuring distances between a query image and possible results representing all images as feature vectors in an n-dimensional vector space. This is done, although metrics have been shown to not correspond well to human visual perception. Several other distance measures do exist for the vector space model such as the city-block distance; the Mahalanobis distance or a simple histogram intersection. Still, the use of high-dimensional feature spaces has shown to cause problems and great care needs to be taken with the choice of distance measurement to be chosen in order to retrieve meaningful results.

a. Storage and access methods:

These methods often need to use dimension reduction techniques or pruning methods to allow for an efficient and quick access to the data. Some indexing techniques such as the KD-trees are described in Principal Component Analysis (PCA) for feature space reduction is used in. This technique is also called Karhunen - Loeve Transform (KLT).

II. USE OF IMAGE RETRIEVAL IN MEDICAL APPLICATIONS

The management and the access to these large image repositories become increasingly complex. Most access to these systems is based on the patient identification or study characteristics (modality, study description) as it is also defined in the DICOM standard. Imaging systems and image archives have often been described as an important economic and clinical factor in the hospital environment. Several methods from the computer vision and image processing fields already have been proposed for the use in medicine more than ten years ago. Several radiological teaching files exist and radiology reports have also been proposed in a multimedia form in.

An interface of a typical content-based retrieval system is shown in Figure 2.

A. The need for content-based medical image retrieval:

The goals of medical information systems have often been defined to deliver the needed information at the right time, the right place to the right persons in order to improve the quality and efficiency of care processes [9]. Such a goal will most likely need more than a query by patient name, series ID or study ID for images.

For the clinical decision-making process it can be beneficial or even important to find other images of the same modality, the same anatomic region of the same disease. Although part of this information is normally contained in the DICOM headers and many imaging devices are DICOM-compliant at this time, there are still some problems. DICOM headers have proven to contain a fairly high rate of errors, for example for the field anatomical region, error rates of 16% has been reported. This can hinder the correct retrieval of all wanted images.

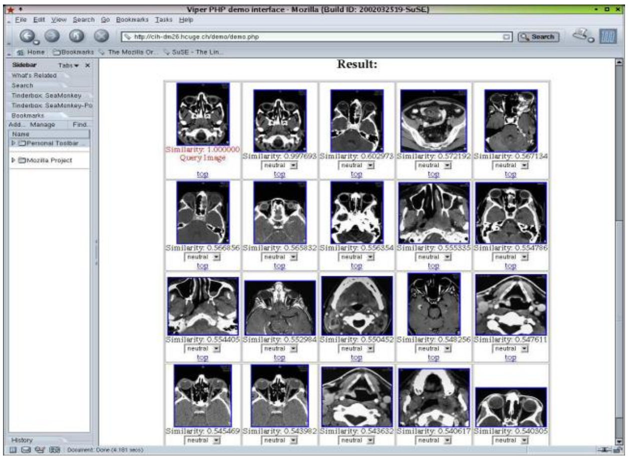

Figure 2: A screenshot of a typical image retrieval system showing retrieved images similar to an example in a web browser interface.

a. *3D shape retrieval aspects:*

In this section we discuss several issues related to 3D shape retrieval.

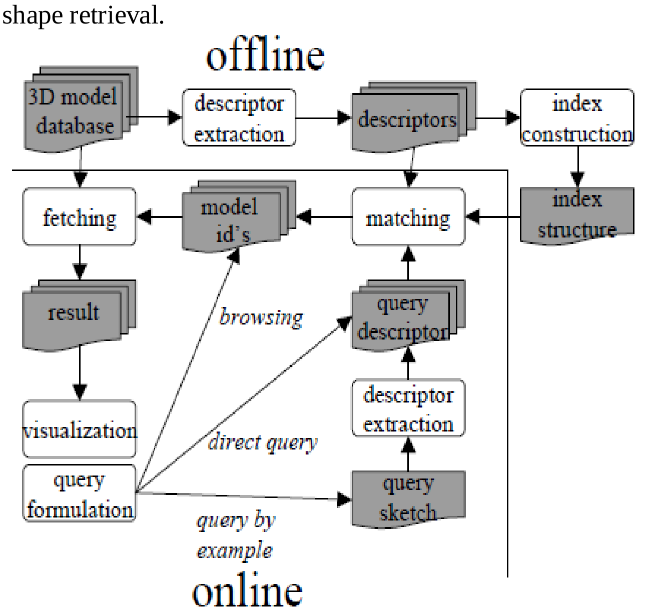

Figure 3: Conceptual framework for shape retrieval

b. *3D shape retrieval frameworks:*

At a conceptual level, a typical 3D shape retrieval framework as illustrated by fig. 3, consists of a database with an index structure created offline and an online query engine. Each 3D model has to be identified with a shape descriptor, providing a compact overall description of the shape. To efficiently search a large collection online, an indexing data structure and searching algorithm should be available. The online query engine computes the query descriptor, and models similar to the query model are retrieved by matching descriptors to the query descriptor from the index structure of the database. The similarity between two descriptors is quantified by a dissimilarity measure. Three approaches can be distinguished to provide a query object: (1) browsing to select a new query object from the obtained results, (2) a direct query by providing a query descriptor, (3) query by example by providing an existing 3D model or by creating a 3D shape query from scratch using a 3D tool or sketching 2D projections of the 3D model. Finally, the retrieved models can be visualized.

B. *Measuring similarity:*

In order to measure how similar two objects are, it is necessary to compute distances between pairs of descriptors using a dissimilarity measure. Although the term similarity is often used, dissimilarity corresponds to the notion of distance: small distances means small dissimilarity, and large similarity. A dissimilarity measure can be formalized by a function defined on pairs of descriptors indicating the degree of their resemblance. Transformation invariance has to be satisfied, if the comparison and the extraction process of shape descriptors have to be independent of the place, orientation and scale of the object in its Cartesian coordinate system [10].

C. *Pose normalization:*

In the absence of prior knowledge, 3D models have arbitrary scale, orientation and position in the 3D space. Because not all dissimilarity measures are invariant under rotation and translation, it may be necessary to place the 3D models into a canonical coordinate system. This should be the same for a translated, rotated or scaled copy of the model. The PCA algorithm for pose estimation is fairly simple and efficient. However, if the Eigen values are equal, principal axes may switch, without affecting the Eigen-values. Similar Eigen values may imply an almost symmetrical mass distribution around an axis (e.g. nearly cylindrical shapes) or around the centre of mass (e.g. nearly spherical shapes).

III. SHAPE MATCHING METHODS

In this section we discuss 3D shape matching methods. We divide shape matching methods in three broad categories:

a) Feature based methods,
b) Graph based methods and
c) Other methods.

Fig. 4 illustrates a more detailed categorization of shape matching methods. Note, that the classes of these methods are not completely disjoined. For instance, a graph-based shape descriptor, in some way, describes also the global feature distribution. By this point of view the taxonomy should be a graph.

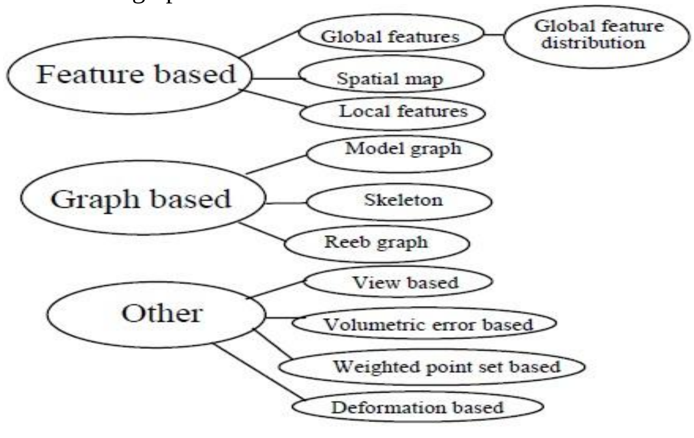

Figure4. Taxonomy of shape matching methods.

A. *Feature based methods:*

In the context of 3D shape matching, features denote geometric and topological properties of 3D shapes. So 3D shapes can be discriminated by measuring and comparing their features. Feature based methods can be divided into four categories according to the type of shape features used:

a) Global features,
b) Global feature distributions,
c) Spatial maps, &
d) Local features.

Feature based methods from the first three categories represent features of a shape using a single descriptor consisting of a *d*-dimensional vector of values, where the dimension *d* is fixed for all shapes.

B. Comparison methods and feature space reductions:

Most systems do not give many details on the distance measurements or comparison methods used which most likely implies an Euclidian vector space model using either a simple Euclidean distance (L2) or something close such as city block distance or L1. To efficiently work with these distances even in large databases, the dimensionality is often reduced.

This can be done with methods such as Principal Component Analysis (PCA) or Minimum Description Length (MDL) [11] that try to reduce the dimensionality while staying as discriminative as possible. In principle, redundant information is removed but this can also remove small but important changes from the feature space. Techniques such as KD-trees and R-trees are also used in medicine for efficient access to such a large feature spaces.

C. Image databases used for evaluation:

Those systems that do perform evaluation often only use screenshots of example results to queries. A single example result does not reveal a great deal about the real performance of the system and is not objective as the best possible query result can be chosen arbitrarily by the authors. This problematic in retrieval system evaluation is described in detail in. Most other system evaluations show measures with a limited power for comparison. In, the [12] precision of the four highest ranked images is used which does not reveal much about the number of actually relevant items and gives very limited information about the system. Measures the number of times a differently scaled or rotated image retrieves the original which is also not very close to medical image retrieval reality.

D. Graph based methods:

In general, the feature based methods discussed in the previous section take into account only the pure geometry of the shape. In contrast, graph based methods attempt to extract a geometric meaning from a 3D shape using a graph showing how shape components are linked together. Graph based methods can be divided into three broad categories according to the type of graph used:

a) Model graphs,
b) Reeb graphs, and
c) Skeletons.

For an extensive discussion of Reeb graphs and skeletons we refer the reader to the paper of Biasotti et al. [13].

Efficient computation of existing graph metrics for general graphs is not possible: computing the edit distance is NP-hard and computing the maximal common sub-graph is even NP-complete.

a. Model graph based similarity:

The model graph based approaches are especially relevant for the CAD/CAM community, but are difficult to apply for models of natural shapes like humans and animals [14]. Approaches between media and various data can be eased. On the other hand, anonym zed image archives can be made available for medical students for educational purposes. Content-based techniques allow browsing databases and then comparisons of diagnoses of visually similar cases. Especially for Internet-based teaching, this can offer new possibilities.

b. Skeleton based similarity:

Sundar et al. [15] use as a shape descriptor a skeletal graph that encodes geometric and topological information. After voxelization of a shape, the skeletal points are obtained by a distance transform-based thinning algorithm developed by Galvanic using a thinness parameter. The skeletal points are connected in an undirected acyclic shape graph by applying the Minimum Spanning Tree algorithm. Decreasing the thinness results in denser skeletal graphs. So, by using different values of the thinness parameter they obtain a hierarchical graph structure. Each node in the graph represents a segment of the original skeleton. With each node a geometrical signature vector is associated encoding the radial distribution about the segment. Also, with each node of the graph a topological signature vector is associated encoding the topology of the sub-trees rooted at the node. This topological signature vector is defined recursively over the sub-graphs of the node using eigenvalues of their adjacency matrices.

IV. APPLICATIONS

An important focus for ADL's collection is on information supporting basic science, including the Earth and Social Sciences. The image datasets (will) include digital elevation models (DEMs), digital raster graphics (DRGs), scanned aerial photo-graphs, Land sat images, seismic datasets, Sierra Nevada Ecologic Project datasets, and Mojave Ecologic Project datasets.(Figure5)

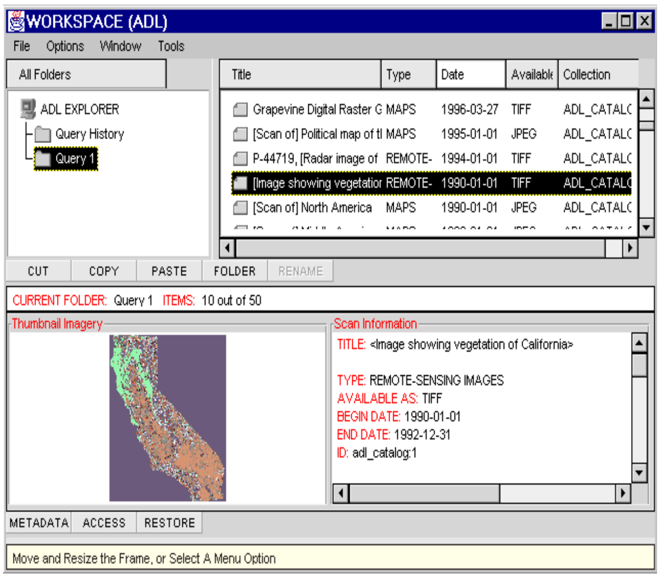

Figure 5

V. OVERVIEW AND CONCLUSIONS

In this section we summarize our discussion on shape matching methods from the previous section and indicate directions for further research. Feature based methods, categorized into

a) Global features,
b) Global feature distributions,
c) Spatial maps and
d) Local features,

Characterize shapes by their feature values. The shape matching methods from the first three categories represent the feature values by a vector in a high ***d***-dimensional vector space. Since the feature values are typically computed by sampling 3D shapes, no restrictions on the kind of shape model are imposed and in general the descriptor computation is fast. Because a feature vector is a point in a fixed ***d***-dimensional space, two models can be compared fast by computing their distance in this space. Also, indexing is straightforward and retrieval can be implemented efficiently by nearest neighbour search. In general these methods are robust, because they are based on sampling. For most features, normalization is required e.g. using the PCA or rotation invariant shape descriptors should be obtained.

The discriminative abilities of Osaka's method have been improved by further refinements of distribution methods as well as by several methods based on spatial maps. If details of shapes are not taken into account, these methods distinguish shapes very well. Details may be taken into account using higher order moments, but this has not been verified by experiments.

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VII. REFERENCES

[1]. S.-K. Chang, T. Kunii, Pictorial data-base applications, IEEE Computer 14 (11) (1981)13-21.

[2]. P. G. B. Enser, Pictorial information retrieval, Journal of Documentation 51 (2) (1995) 126-170.

[3]. 3D model similarity search engine, http://merkur01.inf.uni-konstanz.de/CCCC/.

[4]. N.-S. Chang, K.-S. Fu, Query-by-pictorial-example, IEEE Transactions on Software Engineering SE 6 No 6 (1980) 519-524.

[5]. J. P. Eakins, M. E. Graham, content-based image retrieval, Tech. Rep. JTAP-039, JISCTechnology Application Program, Newcastle upon Tyne (2000).

[6]. D. M. Squire, W. M • uller, H. M • uller, T. Pun, Content-based query of image databases: in-17spirations from text retrieval, Pattern Recognition Letters (Selected Papers from The 11th Scandinavian Conference on Image Analysis SCIA '99) 21 (13-14) (2000) 1193-1198, b.K. Ersboll, P. Johansen, Eds.

[7]. C. Carson, M. Thomas, S. Belongie, J. M. Hellerstein, J. Malik, Blobworld: A system for region-based image indexing and retrieval, in: D. P. Huijsmans, A. W. M. Smeulders (Eds.), Third International Conference On Visual Information Systems (VISUAL' 99), no. 1614 in Lecture Notes in Computer Science, Springer-Verlag, Amsterdam, The Netherlands, 1999, pp. 509-516. 519-524.

[8]. W. Niblack, R. Barber, W. Equitz, M. D.Flickner, E. H. Glasman, D. Petkovic, P. Yanker, C. Faloutsos, G. Taubin, QBIC project: querying images by content, using color, texture, and shape, in: W. Niblack (Ed.), Storage and Retrieval for Image and Video Databases, Vol. 1908 of SPIE Proceedings, 1993, pp. 173-187.

[9]. M. Flickner, H. Sawhney, W. Niblack, J. Ashley, Q. Huang, B. Dom, M. Gorkani, J. Hafner, D. Lee, D. Petkovic, D. Steele,P. Yanker, Query by Image and Video Content:The QBIC system, IEEE Computer 28 (9) (1995) 23-32.

[10]. J. Barros, J. French, W. Martin, P. Kelly, and M. Cannon. Using the triangle inequality to reduce the number of comparisons required for similarity-based retrieval. In *Proc. of SPIE*, volume 267, pages 392–403, 1996.

[11]. D. Dori, Cognitive image retrieval, in: A. Sanfeliu, J. J. Villanueva, M. Vanrell, R. Alc_ezar, J.-O. Eklundh, Y. Aloimonos (Eds.), Proceedings of the 15th International Conference on Pattern Recognition (ICPR 2000), IEEE, Barcelona, Spain, 2000, pp. 42-45.

[12]. S. M. Rahman, Design & Management of Multimedia Information Systems: Opportunities & Challenges, Idea Group Publishing, London, 2001.

[13]. S. Biasotti, S. Marini, M. Mortara, and G. Patan´e. An overview of properties and efficacy of topological skeletons in shape modelling. In *SMI 2003*, pages 245–254, 2003.

[14]. K. Lou, S. Janyanti, N. Iyer, Y. Kalyanaraman, S. Prabha kar , and K. Ramani. A reconfigurable 3D engineering shape search system part II: database indexing, retrieval and clustering. In *DETC'03*, 2003.

[15]. P. Min, J. A. Halderman, M. Kazhdan, and T. A. Funkhouser. Early experiences with a 3D model search engine. In *Web3D Symposium*, pages 7–18, March 2003.