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A Medical Images Based Retrieval System using Soft Computing Techniques

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***Abstract*—**Content-Based Image Retrieval (CBIR) has been one on the most vivid research areas in the field of computer vision over the last 10 years. Many programs and tools have been developed to formulate and execute queries based on the visual or audio content and to help browsing large multimedia repositories. Still, no general breakthrough has been achieved with respect to large varied databases with documents of difering sorts and with varying characteristics. Answers to many questions with respect to speed, semantic descriptors or objective image interpretations are still unanswered. In the medical field, images, and especially digital images, are produced in ever increasing quantities and used for diagnostics and therapy. In several articles, content based access to medical images for supporting clinical decision making has been proposed that would ease the management of clinical data and scenarios for the integration of content-based access methods into Picture Archiving and Communication Systems (PACS) have been created. This paper gives an overview of soft computing techniques. New research directions are being defined that can prove to be useful. Still, there are very few systems that seem to be used in clinical practice. It needs to be stated as well that the goal is not, in general, to replace text based retrieval methods as they exist at the moment.

***Keywords*—**CBIR, GA, Rough sets, CBMIR

I. Introduction

MANY contemporary scholars have been very much devoted to the design of image databases, as similarity retrieval is important for applications such as medical imaging, office automation, digital library, computer aided design, and multimedia publications. The coarse feature descriptor is used at the first stage to quickly screen out non-promising images; the fine feature descriptor is subsequently employed to find the truly matched images. Proposed Soft Computing based Feature Extraction Techniques of medical image analysis, an image is viewed as a set of Points. That assumption ushers in either a rough set or near set, fuzzy logic, Genetic algorithm (GA) approach to medical image used for analysis & feature extraction.

There are a number of practical outcomes of the near set approach, e.g., feature selection, objective evaluation of image segmentations, and image classification.

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There are a number of practical outcomes of the near set approach, e.g., feature selection, objective evaluation of image segmentations, image classification, object recognition in images, granular computing, and various forms of machine learning [1,2,3,4]. We review and discuss some representative methods to provide inspiring examples to illustrate how these techniques can be applied to solve medical imaging problems and how medical images can be analyzed, processed, and characterized by soft computing. And their applications are like Intelligent Medical Imaging Systems, Computational Anatomic Atlases, Surface and Volume Registration, Medical Image Analysis, Feature Extraction and Pattern Recognition, Image-Guided Surgery/ Therapy, Functional/ Molecular/ Metabolic Image Analysis, Medical Image Databases, Multidimensional Data Visualization, Multimodal Image Analysis

II. Early work

In contrast with early years, we have witnessed a major shift from global feature representations for images, such as color histograms and global shape descriptors, to local features and descriptors, such as salient points, region-based features, spatial model features, and robust local shape characterizations shown in Fig.1. It is not hard to imagine this shift to have been triggered by a realization that the image domain is too deep for global features to reduce the semantic gap. Local features often correspond with more meaningful image components, such as rigid objects and entities, which make association of semantics with image portions.

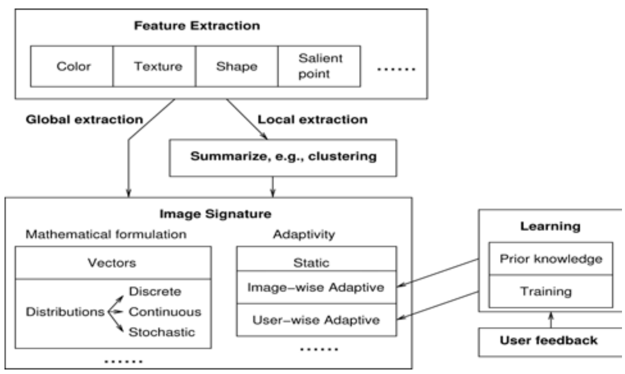

Fig. 1 An overview of different features in image.

The availability of 3D and stereo image data, whenever obtainable, should be exploited to extract features more coherent to the human vision system. In summary, reducing the sensorial gap in tandem with the semantic gap should continue be a goal for the future. As shown in Fig.1 similarity computation can be performed with feature vectors, region-based signatures, or summarized local features. The main advantage of a single vector representing an image is that algebraic and geometric operations can be performed efficiently and in a principled fashion shown in figure 2.

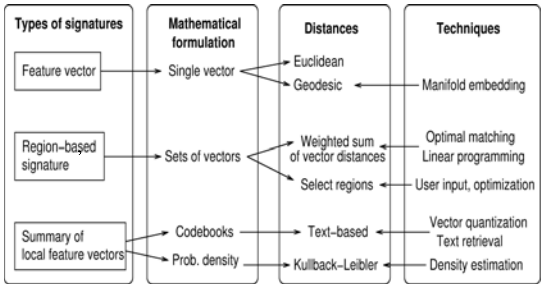

Fig. 2 Different types of image similarity measure, their mathematical formulations, and techniques for computing them.

However, many such representations lack the necessary detail to represent complex image semantics. For example a picture of two cups on a plate by a windowsill cannot easily be mapped to a finite vector representation, simply because the space of component semantics is extremely large, in practice. Instead, if a concatenation of region descriptors is used to represent a picture, it is more feasible to map the component semantics (e.g., cup, window) to image regions. On the other hand, extracting semantically coherent regions is in itself very challenging. Probabilistic representations can potentially provide an alternative, allowing rich descriptions with limited parameterization. The early years of research showed us the benefits as well as the limitations of feature vector representations [5,6]. They also paved the way for the new breed of region-based methods, which have now become more standard than ever before. The idea of region-based image querying also gained prominence in the last few years. Many new salient-feature-based spatial models were introduced, particularly for recognizing objects within images, building mostly on early and pre-2000 work. The idea that image similarity is better characterized by geodesic distances over a nonlinear manifold embedded in the feature space has improved upon earlier notions of a linear embedding of images. A number of systems have also been introduced for public usage in recent years. The future of image similarity measures lies in many different avenues.

The subjectivity in similarity needs to be incorporated more rigorously into image similarity measures, to achieve what can be called personalized image search. This can also potentially incorporate ideas beyond the semantics, such as aesthetics and personal preferences in style and content. Extensions of the idea of nonlinear image manifolds to incorporate the whole spectrum of natural images, and to allow adaptability for personalization, are avenues to consider. While development of useful systems continues to remain critical, the ever-elusive problem of reducing the semantic gap needs concerted attention. Various image types and the systems shown in Table1.

TABLE I VARIOUS IMAGE TYPES AND SYSTEMS THAT USING THESE IMAGES

Images used	Names of the systems
HRCTs of the lung	ASSERT
Functional PET	FICBDS
Spine X-rays	CBIR2, MIRS
Pathologic images	IDEM, I-Browse, Pathfinder, PathMaster
CTs of the head	MIMS
Mammographies	APKS
Images from biology	BioImage, BIRN
Dermatology	MELDOQ, MEDS
Breast cancer	biopsies BASS
	MedGIFT, ImageEngine

III. SOFT COMPUTING TECHNIQUE

The ability of rough sets to handle images: Rough sets provide reasonable structures for the overlap boundary given domain knowledge. The case study for images of the heart on cardiovascular magnetic resonance (MR) images also extends to handling multiple types of knowledge including: myocardial motion, location and signal intensity. A study concerned with distinguishing different picture types of the central nervous system is introduced in [7]. Research involving color images appears in [8]. The basic idea of a histon is to build a histogram on top of the histograms of the primary color components red, green, and blue. The authors show that the base histogram correlates with the lower approximation, whereas the encrustation correlates with the upper approximation. The problem of a machine vision application where an object is imaged by a camera system is considered in [9]. The object space can be modeled as a finite subset of the Euclidean space when the objects image is captured via an imaging system. Rough sets can bound such sets and provide a mechanism for modeling the spatial uncertainty in the image of the object. This work introduced a rough sets approach for building pattern matching systems that can be applicable with a wide range of images in medical sciences.

A. Rough Sets in Medical Image Segmentation

The basic idea behind segmentation-based rough sets is that while some cases may be clearly labeled as being in a set X (called the positive region in rough sets theory), and some cases may be clearly labeled as not being in set X (called the negative region), limited information prevents us from labeling all possible cases clearly. The remaining cases cannot be distinguished and lie in what is known as the boundary region.

Among many difficulties in segmenting MRI data, the partial volume effect arises in volumetric images when more than one tissue type occurs in a voxel. In such cases, the voxel intensity depends not only on the imaging sequence and tissue properties, but also on the proportions of each tissue type present in the voxel. Widz et al. [10] discussed the partial volume effect problem in the segmentation of magnetic resonance imaging data that entails assigning tissue class labels to voxels. They employ rough sets to automatically identify the partial volume effect, which occurs most often with low resolution imaging.

An interesting strategy for color image segmentation using rough set theory has been presented in [11]. A new concept of encrustation of the histogram, called histon, has been proposed for the visualization of multi-dimensional color information in an integrated fashion and its applicability in boundary region analysis has been shown. The histon correlates with the upper approximation of a set such that all elements belonging to this set are clarified as possibly belonging to the same segment or segments showing similar color value.

B. Retrieval using Fuzzy Logic

The fused data is used in the retrieval process. The most frequently used similarity function is the KNN (K Nearest Neighbor) [13]. The similarity degree can be computed in various manners. In [12], we summarize the similarity functions most relevant to our study. The similarity formulas from this table have been applied for the fused values from the concepts from a document inside the database and the query document. It must be stated that a document in this case represents the concepts from the text and the image that have been fused and are stored as dictionaries. The aim of these formulas is to find the documents that have the most concepts in common with the query document, giving a higher similarity degree such that they are retrieved in a correct order.

C. Symbolic AI

We use a knowledge-based approach to develop a retrieval engine than can reason with concepts abstracted over multiple media forms. In contrast to the usual deductive approach (e.g. [14, 15]), we model retrieval as a problem of abduction. Abduction is a reasoning model for constructing an appropriate explanation for a set of observed patterns. Concepts are abstract entities and cannot be directly observed in the documents. However, they manifest themselves as some observable patterns in the media components of the documents. In our model of reasoning, we identify the documents that can account for the expected media patterns as the candidates for retrieval. Our framework is general enough to combine data from content analysis of multiple media forms as well as meta-data, such as annotations, that may be associated with the documents.

We note that the very nature of a concept defies principle of logical deduction for their identification. In the first place, concepts are abstract and are defined only through the observation models as examples. Further, a combination of media patterns may not be unique to a media object. For example, the shape of a minarette is very similar to that of a chimney, and there is a possibility of confusion between the two. Thus, the observations provide, at best, plausible explanations to the media objects caused by a concept. We follow an abductive model of reasoning in our retrieval system. We believe a document to pertain to a concept when the observed media-patterns corroborate the hypothesis.

Such reasoning often requires some underlying assumptions. For example, a long and narrow vertical structure can be interpreted to be a minarette and not a chimney, assuming that the image pertains to a construction of historic importance. We use classification knowledge to derive such assumptions. The documents are pre-classified to some broad, possibly overlapping subject classes with the help of associated meta-data. Classification knowledge helps in optimising processing of a query also. It suggests a set of documents or repositories, where the requested concepts are most likely to appear. Without this knowledge, we would need to schedule the pattern recognition routines on every document in the repositories. Such a proposition could be prohibitively costly for any non-trivial collection. The classification cannot, however, be the sole basis for retrieval since the perspective of a pre-classification may not account for all types of queries that a system might require to process [16, 17].We can formalise the principle of abduction used for retrieval as follows. If a concept C implies a set of media patterns {M}, then C can be abduced from {M} in presence of some set of assumptions {A}, i.e. $if\ C > \{M\}, then\{M\} \wedge \{A\} \geq C$

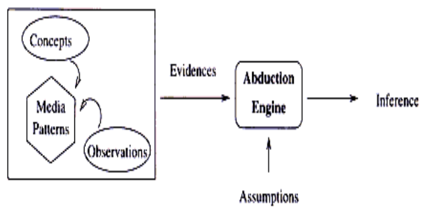

Fig. 3 Symbolic AI

Figure 4 explains the basic model of an abductive engine used for retrieval. Our model of abductive reasoning relies on fusion of information from multiple sources. This necessitates operation of reasoning process at multiple levels of abstraction. At each level of abstraction, we need a different form of knowledge for reasoning. At the lowest level, we achieve media abstraction using the recognition functions. Recognition functions encapsulates structural knowledge about the media form. They can cope up with the heterogeneity of the media forms and format and can identify combinations of complex media-objects in spite of local variations. We use conceptual knowledge for deriving the search specification from the conceptual terms in the queries. Domain expertise establishes the relationships across the concepts in the domain of discourse[18, 19]. It defines the observation model for the concepts in terms of media specific objects and their properties. We model retrieval as a problem of distributed AI to exploit the possibility of a distributed knowledgebase. Besides, a distributed model can conveniently cope up with multiple user locations and distributed information sources. We implement the retrieval system with a multi-agent architecture. An agent is a software entity that has its own independent set of beliefs, capabilities, choices and commitments. It functions autonomously in an environment in which other processes take place and other agents possibly exist [20].

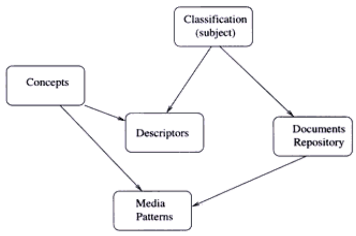

Fig. 4 Basic model of an abductive engine

In a multi-agent system, problem solving is achieved through coordination of autonomous and possibly heterogeneous set of agents.

D. Evolutionary Computing Methods for Spectral Retrieval

A methodology for processing spectral images to retrieve information on underlying physical, chemical, and/or biological phenomena is based on evolutionary and related computational methods implemented in software. In a typical case, the solution (the information that one seeks to retrieve) consists of parameters of a mathematical model that represents one or more of the phenomena of interest. The methodology was developed for the initial purpose of retrieving the desired information from spectral image data acquired by remote-sensing instruments aimed at planets (including the Earth). Examples of information desired in such applications include trace gas concentrations, temperature profiles, surface types, day/night fractions, cloud/aerosol fractions, seasons, and viewing angles[21, 22]. The evolutionary computing methods (ECM) used in this methodology are Genetic Algorithms and Simulated Annealing, both of which are well-established optimization techniques and have also been described in previous NASA Tech Briefs articles.

IV. Challenges and Future Directions for Feature Extraction

We have described a feature extraction algorithm which is robust to illumination changes and can capture the geometric relationships present in the images. As a future improvement, it would be interesting to use the hierarchy tree as an aid to deciding which classes are most similar, and to use features specially extracted to distinguish between them.

Rough set theory encompasses an extensive group of methods that have been applied in the medical domain and that are used for the discovery of data dependencies, importance of features, patterns in sample data, and feature space dimensionality reduction. From what has been presented in the literature, it is obvious that the rough set approach provides a promising means of solving a number of medical imaging problems. It should be observed that rough set or near set by themselves or in combination with other computational intelligence technologies work remarkably well in separating medical images into approximation regions that facilitate automated image segmentation and object recognition. The challenge now is to develop near set-based methods that offer an approach to classifying perceptual objects by means of features. It is fairly apparent that near set methods can be useful in object recognition, especially in solving medical imaging problems. The near set approach to object description, feature selection, and automatic image segmentation based on the partition of an image into equivalence classes offer a practical as well as straightforward approach to classifying images. It is in the domain of medical image segmentation that the near set approach holds the greatest promise for medical imaging. A combination of various computational intelligence technologies in pattern recognition and, in particular, medical imaging problems has become one of the most promising avenues in image processing research[23, 24]. From the perspective of rough sets, further explorations into possible hybridizations of rough sets with other technologies are necessary to build a more complete picture of rough or near set-based applications in medical imaging. What can be said at this point is that the rough set and near set approaches pave the way for new and interesting avenues of research in medical imaging and represent an important challenge for researchers.

V. Soft Computing Based framework for content-based image retrieval

The effectiveness of content-based image retrieval (CBIR) systems can be improved by combining image features or by weighting image similarities, as computed from multiple feature vectors. However, feature combination do not make sense always and the combined similarity function can be more complex than weight-based functions to better satisfy the users' expectations. We address this problem by presenting a Genetic Programming framework to the design of combined similarity functions. Our method allows nonlinear combination of image similarities and is validated through several experiments, where the images are retrieved based on the shape of their objects. Experimental results demonstrate that the GP framework is suitable for the design of effective combinations functions[25,26].

A. Feature extraction algorithm

Encodes image properties into a feature vector and a similarity function computes the similarity between two images as a function of the distance between their feature vectors. An image database can be indexed by using multiple pairs of feature extraction algorithms and similarity functions. We call each pair a database descriptor, because they tell how the images are distributed in the distance space. By replacing the similarity function, for example, we can make groups of relevant images more or less compact, and increase or decrease their separation [27]. These descriptors are commonly chosen in a domain-dependent fashion, and, generally, are combined in order to meet users' needs. The importance of considering the pair, feature extraction algorithm and similarity function, as a descriptor should be better understood. In CBIR systems, it is common to find solutions that combine image features irrespective of the similarity functions [3, 28]. However, these techniques do not make sense, for example, when the image content is a shape and the properties are curvature values along it and color/texture properties inside it. The similarity function usually has a crucial role in making the descriptor as invariant as possible to changes in image scale and rotation. This is true even when we consider only shape descriptors. It does not make sense, for example, to combine multiscale fractal dimensions [2] with bean angle statistics (BAS) [4] irrespective of their similarity functions. The importance of the similarity function coupled with the feature extraction algorithm is illustrated in Fig. 1.[29,30] Precision–recall curves were computed from an MPEG-7 part B database [5] for four different descriptors. They provide different combinations of feature extraction algorithms that encode BAS [4] and segment salience's (SS) [6], with Euclidean metric and matching by optimum correspondent subsequence (OCS) [7] as similarity functions. We are not mixing properties, only replacing similarity functions, to show their role in the effectiveness of each descriptor. Both SS and BAS have been proposed with OCS. Fig.5 shows that the configurations which use OCS yield the best effectiveness.

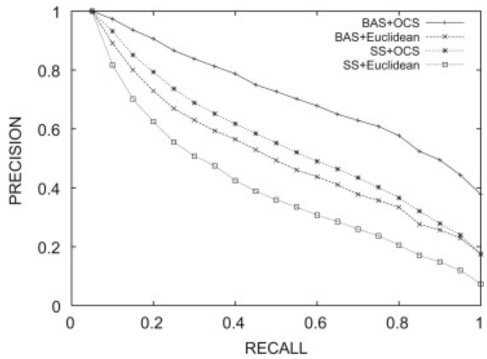

Fig. 5 Precision–recall curves for BAS and SS descriptors in MPEG-7 database using two different similarity functions.

VI. Why Soft Computing is better than Support vector Machine

At a higher level, we really wish to combine descriptors encoding several properties in order to address the semantic gap problem: it is not easy for a user to map her/his visual perception of an image into low level features. Without mixing distinct properties in a same feature vector, this combination could be done by weighting the similarity values resulting from different descriptors [3], [31] and [32]. However, more complex functions than a linear combination are likely to provide more flexibility in matching the results with the users' expectations. We address the problem by presenting a genetic programming (GP) framework to the design of combined similarity functions. Our solution relies on the creation of a composite descriptor, which is simply the combination of pre-defined descriptors using the GP technique. We employ GP to combine the similarity values obtained from each descriptor, creating a more effective fused similarity function. As far as we know, this approach is original and opens a new and productive field for investigation (considering, for example, different applications, descriptors, and GP parameters).

VII. Advantage of Soft Computing over Support vector Machine (SVM)

Our motivation to choose GP stems from its success in many other machine learning applications [11], [12] and [13]. Some works, for example, show that GP can provide better results for pattern recognition than classical techniques, such as Support Vector Machines [14]. Different from previous approaches based on genetic algorithms (GAs), which learn the weights of the linear combination function [15], our framework allows nonlinear combination of descriptors. It is validated through several experiments with two image collections under a wide range of conditions, where the images are retrieved based on the shape of their objects.

VIII. Future Of Soft Computing For CBMIR

We have outlined some applications of soft computing agent. For example, multi-agent cooperates with soft computing to optimize the decision support system and routing task, which considers some human preference and is better than habitual method. And mobile soft computing agent performs very well in custom dependent production and internet browsing. It has many advantages in its realization. Furthermore, soft computing agent today is being applied in a range of areas including information retrieval, image processing, engineering, process control, data mining, decision making, internet and others [26]. We have known that soft computing, which has been widely used as we have mentioned in the above passage, can obtain a reasonable decision in complex, uncertain and ill-defined environment, and the agent can perform a specific task on behalf of a person or an organization [32]. The SCA taking advantages of soft computing and agent will be a new trend, especially in the situations which are filled with uncertain, imprecise and complex problems.Vision in general and images in particular have always played an important and essential role in human life. In the past they were, today they are, and in the future they will continue to be one of our most important information carriers. Nowadays, the field of image processing also has numerous commercial, scientific, industrial and military applications. All these applications result from the interaction between fundamental scientific research on the one hand, and the development of new and high-standard technology on the other hand. In order to cope with the variety of image processing challenges, several techniques have been introduced and developed, quite often with great success. Among the different techniques that are currently in use, we also encounter soft computing techniques. Soft computing is an emerging field that consists of complementary elements of fuzzy logic, rough sets, neural computing, evolutionary computation, machine learning and probabilistic reasoning. SCIP working group is an informal organization that aims to establish and intensify international cooperation between researchers in the area of soft computing in image processing. It currently has over 170 members ,from 40 countries. One of the means to achieve the goals is the organization of special sessions at international conferences. High-quality special issues of internationally established journals hold the key to further improve the dissemination of the recent advances in the field. Consequently, it is expected that this work will serve as a fertile ground for creative discussion to researchers working in this field.

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