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Soft Computing based Retrieval System for Medical Applications

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***Abstract*—**With increasing data in medical databases, medical data retrieval is growing in popularity. Some of this analysis including inducing propositional rules from databases using many soft techniques, and then using these rules in an expert system. Diagnostic rules and information on features are extracted from clinical databases on diseases of congenital anomaly. This paper explain the latest soft computing techniques and some of the adaptive techniques 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. These approaches pave the way for new and interesting avenues of research in medical imaging and represent an important challenge for researchers.

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

I. Introduction

CONTENT-based image retrieval (CBIR) the retrieval of images on the basis of features automatically derived from the images themselves - is now a thriving field for research and development, with reports of new techniques appearing almost daily. As the field has matured, the nature of the problems faced by researchers and developers has inevitably changed. Much early research, [1, 2, 3] was concerned primarily with establishing the feasibility of retrieving images from large collections using automatically-derived features. More recent research [4,5,6] for recent comprehensive reviews has concentrated on identifying improved techniques for CBIR, including new types of feature, representation method and matching technique. Now the feasibility of the underlying technology has been demonstrated, effort can be devoted to the crucial question of how to design and build systems that successfully meet real user needs. Most current CBIR techniques are geared towards retrieval by some aspect of image appearance, depending on the automatic extraction and comparison of image features judged most likely to convey that appearance.

The features most often used include color [7,8], texture [9,10], shape [11,12], spatial layout [13], based on genetic algorithm(GA) and rough sets [14] [15].

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In fact the CBIR packages making use of such techniques are commonly available. Using these techniques the features become very powerful as they take into the consideration, the relative spatial grouping of the local features become very robust towards small amount of noise and towards natural difference in radiograph images originating under different conditions and/ or from different persons. This is not because the need for such systems is lacking, there is ample evidence of user demand for better image data management in fields as diverse as crime prevention, photo-journalism, fashion design, trademark registration, and medical diagnosis [16,17]. It is because there is a mismatch between the capabilities of the technology and the needs of users. The vast majority of users do not want to retrieve images simply on the basis of similarity of appearance. They need to be able to locate pictures of a particular type (or individual instance) of object, phenomenon, or event [18] and have a useful distinction [16] between retrieval by primitive image feature. (such as color, texture or shape)and semantic feature (such as the type of object or event depicted by the image). Eakins [19] has taken this distinction further, identifying three distinct levels of image query. Although the volume of research into user needs is not large, the results of those studies which have been conducted to date (e.g. [18]) suggest strongly that very few users need level 1 retrieval. The majority of image queries received by picture libraries are at level 2, though a significant number (particularly in specialist art libraries) are at level 3. The overwhelming majority of CBIR systems, both commercial and experimental, offer nothing but level 1 retrieval. A few experimental systems now operate at level 2, but none at all at level 3.

What are the prospects of bridging what has been referred to as the semantic gap [16], and delivering the image retrieval capabilities that users really want? This paper aims to answer this question by reviewing current research into semantic image retrieval, with particular emphasis on the contribution which techniques from related fields such as artificial intelligence (AI)are making to developments in this area. CBIR may have its roots in the field of classical image analysis; it relies on many standard image analysis techniques, such as convolution, edge detection, pixel intensity histogramming, and power spectrum analysis. But a successful solution to the problems of semantic image retrieval (if one exists at all) may well require a significant paradigm shift, involving techniques originally developed in other fields. CBIR has already benefited greatly from insights derived from related fields. A prime example of this process is the technique of relevance feedback [20], originally developed for text retrieval, where users indicate the relevance of each item of output received, and the system amends its search strategy accordingly. Relevance feedback is showing considerable promise in the image retrieval area, largely because users can rapidly judge the relevance of a retrieved image within seconds. It has now been successfully implemented in several experimental CBIR systems [21,22]. Other examples where CBIR has benefited from insights from related fields include relatively efficient direct access via multidimensional indexing, from the database management field [23], and retrieval by subjective appearance, drawing on Gestalt psychology [24]. AI, defined by Luger and Stubblefield [25] as `the study of the mechanisms underlying intelligent behavior though the construction and evaluation of artifacts that enact those mechanisms, appears a particularly promising source of ideas for advancing the art of semantic image retrieval. It aims to develop techniques which allow a machine to generate solutions & interact with the environment and learn from past experience; generate output matching that of a human expert; in other words, to exhibit intelligent behavior, defined by Newell and Simon [26] as `behavior appropriate to the ends of the system and adaptive to the demands of the environmental. Most observers would agree that assessing the contents of a set of images in order to decide their relevance to a query was indeed a task requiring intelligence in this sense. In the context of image retrieval, the end of the system is the identification of a set of images from a collection which meets a user's perhaps subjective and poorly-formulated need, and adaptive to the demands of the environment implies that the system should offer flexibility in allowing different modes of user interaction, and learn from user feedback.

II. The Need for Soft Computing retrievals

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. The earlier study was concerned with distinguishing different picture types of the central nervous system. Research involving color images appears in many works. Researchers used the primary measure as a visualization of multi-dimensional color information. The basic idea was to build a histogram on top of the histograms of the primary color components of red, green, and blue. The concept of region of interest (ROI) is commonly used in medical imaging. A ROI is a selected subset of samples within an image identified for a particular purpose. For instance the endocardial border may be defined on the basis of image formation for the purpose of assessing cardiac function.

The problem of a machine vision application where an object is imaged by a camera system is considered earlier. 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 set approach for building pattern matching systems that can be applicable with a wide range of images in medical sciences.

Identifying even a relatively simple artifact such as a chair is a rather more complex process. Since chairs come in a wide variety of colors, textures and shapes, primitive image features are unlikely to suffice on their own. The problem of recognizing a chair is not perceptually more difficult than that of recognizing a banana. The difference lies in the degree of interpretation necessary. Recognition of an object as a chair requires reference to some higher-level model, defining spatial, structural and perhaps other constraints. Such a model needs to be susceptible to modification, to include the possibility that new designs of chair may appear in the future (not a problem one would expect to encounter with bananas!). Humans build up and refine such a model automatically from past experience: for machines, the process is less straightforward. The need to gain such experience directly is one reason why Brooks has advocated designing robots in humanoid form.

Identifying complex human artifacts is still more problematic. Experienced engineers can readily recognize a pressure-limiting valve in an engineering drawing, even though its actual shape may vary considerably - presumably because their training enables them to draw reasonable inferences from the appearance and layout of key components, as well as the nature of any larger structures in which they appear. But even a highly intelligent human would find such a task impossible without the requisite engineering training. The need to update one's mental model of a specialist device of this kind is likely to be even greater than for an everyday object such as a chair, since new designs are likely to appear at frequent intervals. Yet another layer of complexity is encountered when trying to interpret scenes depicting specific types of event. To recognize a photograph as that of a child's birthday party demands not only the identification of objects which might be present in such scenes (young human figures, balloons, lighted candles), but a further level of reasoning about the relationship of these objects to each other and the extent to which these conform to prior expectations of what occurs at such events. Again, the ability to update such mental models in the light of changing circumstances is crucial. The issues surrounding human recognition and classification of images have been extensively studied by Rosch. These findings give some indication of the likely success of semantic image retrieval techniques which rely on automatic derivation of object or scene labels from visual features of the image. Such techniques are most likely to succeed for objects within an image which correspond to basic classes (such as banana or horse)whose members share a strong visual similarity. For such objects it should be possible to construct or learn suitable object models permitting recognition of typical examples of each class. For other types of object (such as bird or tree), a similar approach based on visual similarity of subclasses (probably, though not necessarily, based on existing taxonomic divisions such as sparrow, parrot or eagle) may prove more effective. For object classes where many defining attributes are non-visual (such as chair or pump), however, this approach appears doomed to failure - though the fact that humans can recognize such objects from visual cues alone suggests that the problem is in principle soluble. To develop a complete understanding of image contents at the semantic level is a formidable task, well beyond the capabilities of any current machine. Fortunately, such a complete level of understanding is not an essential prerequisite for successful semantic image retrieval, as several researchers in the field have pointed out earlier. Empirically, a retrieval system can be regarded as successful if it has the ability to classify a sufficiently high proportion of objects sought by users accurately enough for its retrieval output to satisfy a searcher's needs. In many contexts (including photo-journalism), this means that quite low classification accuracy may be acceptable, provided the searcher can in fact find a usable picture. An analogous situation holds in text retrieval, where effective retrieval systems have been around for years, despite continuing difficulties with automatic text understanding. Unfortunately it is not yet clear what level of image understanding is in fact required for successful classification and retrieval. The only way to resolve this question appears to lie in the development and evaluation of semantic image retrieval techniques.

III. The Techniques of Soft Computing

The computational intelligence and medical imaging are discussed in this section. The fuzzy sets theory, neural networks, and evolutionary computation type of approaches are characterized on the basis of their ability to effectively model complex phenomena and provide solutions. The medical imaging techniques are gaining ground due to newly developed imaging modalities and improvement of device capabilities. Combining computational intelligence approaches with medical imaging is undoubtedly a challenging and promising research field. Neural Networks is: Evolutionary Computing; Rough Sets; Fuzzy Logic; Symbolic AI

A. Evolutionary Computing

There is increasing interest in the use of Image Retrieval techniques to aid diagnosis by identifying the region of abnormalities from bio-medical images. Such images usually have higher resolution than general-purpose pictures. The system uses concept based pixel descriptors, which combines the human perception of color and texture into a single vector. The region extracted using the feature vectors represented in the form of pixel descriptor are fed as input to a neural network, which is trained for classification of images using genetic algorithm. The technique has been implemented on the database of biomedical images.

B. Evolutionary Computing Methods

The methodology for processing spectral images to retrieve information on underlying physical, chemical, and/or biological phenomena is based on evolutionary computational methods implemented in software. 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. 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. The well-established optimization evolutionary computing methods (ECM) used in this methodology are Genetic Algorithms and Simulated Annealing. These are embedded in a conceptual framework, represented in the architecture of the implementing software, that enables automatic retrieval of spectral and angular data and analysis of the retrieved solutions for uniqueness.

C. Rough Sets

Rough set theory is being used for extraction of rules from databases where the advantage of creation of readable if-then rules. Such rules have a potential to reveal previously undiscovered patterns in the data. Unlike other computational intelligence techniques, rough set analysis requires no external parameters and uses only the information presented in the given data. One of the nice features of rough set theory is that it can tell whether the data is complete or not based on the data itself. On the other hand, if the data is complete, rough sets are able to determine whether there are any redundancies in the data and find the minimum data needed for classification. This property of rough sets is very important for applications where domain knowledge is very limited or data collection is expensive/laborious because it makes sure the data collected is just sufficient to build a good classification model without sacrificing the accuracy or wasting time and effort to gather extra information about the objects.

D. Fuzzy Logic

One important challenge in modern CBMIR approaches is represented by the semantic gap related to the complexity of the medical knowledge. Among the methods that are able to close this gap in CBMIR, the use of medical thesauri/ontologies has interesting perspectives due to the possibility of accessing on-line updated relevant webservices and to extract real-time medical semantic structured information. The most of the proposed methods are evaluated on the Cross Language Evaluation Forum’s (CLEF) medical image retrieval benchmark, by focusing also on a more homogeneous component medical image database: the Pathology Education Instructional Resource (PEIR) to obtain four square matrices.

E. Symbolic AI

This is a knowledge-based approach to develop a retrieval engine than can reason with concepts abstracted over multiple media forms. Abduction is a reasoning model for constructing an appropriate explanation for a set of observed patterns. The 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.

IV. 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. 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. 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.

Analysis of the earlier works as reviewed above suggests the following conjectures. Although none is readily quantifiable, or susceptible to mathematical proof, they should all be empirically testable in the same sense.

However, these have often been applied to peripheral aspects of the problem in hand, and there appears to be considerable scope for the more systematic application of AI techniques and concepts. Adaptive learning is perhaps the prime example here. The potential of techniques such as case-based reasoning, explanation-based learning , reasoning by analogy and conceptual clustering to provide systematic learning capabilities for image retrieval systems remains largely untapped. The opportunities for developing truly intelligent image retrieval systems by combining techniques from the fields of image processing and artificial intelligence are considerable.

V. WHY SOFT COMPUTING IS BETTER THAN SVM

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. 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).

A. *Advantage of Soft Computing over SVM*

Our motivation to choose GP stems from its success in many other machine learning applications. Some works, for example, show that GP can provide better results for pattern recognition than classical techniques, such as Support Vector Machines. Different from previous approaches based on genetic algorithms (GAs), which learn the weights of the linear combination function, 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. These algorithms demonstrate the effectiveness of the soft computing according to various evaluation criteria. Given that it is not based on feature combination, the framework is also suitable for information retrieval from multimodal queries, as for example by text, image, and audio.

B. *Background*

i) Genetic programming

GAs and GP [40] belong to a set of artificial intelligence problem-solving techniques based on the principles of biological inheritance and evolution. Each potential solution is called an individual (i.e., a chromosome) in a population. Both GA and GP work by iteratively applying genetic transformations, such as crossover and mutation, to a population of individuals to create more diverse and better performing individuals in subsequent generations. A fitness function is available to assign a fitness value for each individual.

The main difference between GA and GP relies on their internal representation—or data structure—of an individual. In general, GA applications represent each individual as a fixed-length bit string, like (1101110…) or a fixed-length sequence of real numbers (1.2,2.4,4,…). In GP, on the other hand, more complex data structures are used (e.g., trees, linked lists, or stacks. Fig.1 shows an example of a tree representation of a GP individual.

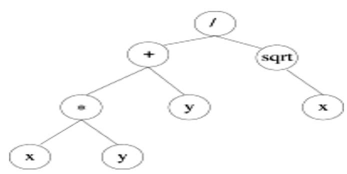

Fig. 1. A sample tree representation

Furthermore, the length of a GP data structure is not fixed, although it may be constrained by implementation to be within a certain size limit. Because of their intrinsic parallel search mechanism and powerful global exploration capability in a high-dimensional space, both GA and GP have been used to solve a wide range of hard optimization problems that oftentimes have no known optimum solutions.

ii) GP components

In order to apply GP to solve a given problem, several key components of a GP system need to be defined.

GP searches for good combination functions by evolving a population along several generations. Population individuals are modified by applying genetic transformations, such as reproduction, mutation, and crossover. The reproduction operator selects the best individuals and copies them to the next generation. The two main variation operators in GP are mutation and crossover. Mutation can be defined as random manipulation that operates on only one individual. This operator selects a point in the GP tree randomly and replaces the existing subtree at that point with a new randomly generated subtree [18]. The crossover operator combines the genetic material of two parents by swapping a subtree of one parent with a part of the other (see 2).

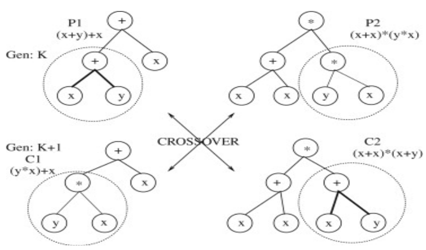

Fig. 2 A graphical illustration of the crossover operation

C. CBIR model

In this section, we formalize how a CBIR system can be modeled.

Definition 1

An *image* $\hat{I}$ is a pair (D_I, $\vec{I}$), where:

- $D_I \subset \mathbb{Z}^2$ is a finite set of *pixels*, and
- $\vec{I} : D_I \rightarrow \mathbb{D}'$ is a function that assigns to each pixel p in D_I a vector $\vec{I}(p)$ of values in some arbitrary space $\mathbb{D}'$ (for example, $\mathbb{D}' = \mathbb{R}^3$ when a color in the RGB system is assigned pixel).

Definition 2

A *simple descriptor* (briefly, *descriptor*) D is defined as a pair (ε_D,δ_D), where:

- $\varepsilon_D : \hat{I} \rightarrow \mathbb{R}^n$ is a function, which extracts a *feature vector* $\vec{v}_{\hat{I}}$ from an *image* $\hat{I}$.
- $\delta_D : \mathbb{R}^n \times \mathbb{R}^n \rightarrow \mathbb{R}$ is a *similarity function* that computes the similarity between two images by taking into account the distance between their corresponding *feature vectors*

.

Definition 3

A *feature vector* $\vec{v}_{\hat{I}}$ of an image $\hat{I}$ is a point in $\mathbb{R}^n$ space: $\vec{v}_{\hat{I}} = (v_1, v_2, \ldots, v_n)$, where n is the dimension of the vector. Examples of possible feature vectors are the color histogram [19], the multiscale fractal curve, and the set of Fourier coefficients. They encode image properties, such as color, shape, and texture. Note that different types of feature vectors may require different similarity functions. Fig. 3(a) illustrates the use of a simple descriptor D to compute the similarity between two images $\hat{I}_A$ and $\hat{I}_B$. First, the extraction algorithm ε_D is used to compute the feature vectors $\vec{v}_{\hat{I}_A}$ and $\vec{v}_{\hat{I}_B}$ associated with the images. Next, the similarity function δ_D is used to determine the similarity value d between the images.

Definition 4

A *composite descriptor* $\hat{D}$ is a pair $(\mathcal{D}, \delta_{\mathcal{D}})$ (see Fig. 3(C)), where:

- $\mathcal{D} = \{D_1, D_2, \ldots, D_k\}$ is a set of k pre-defined simple descriptors.
- $\delta_{\mathcal{D}}$ is a similarity function which combines the similarity values obtained from each descriptor $D_i \in \mathcal{D}$, i=1,2,…,k.

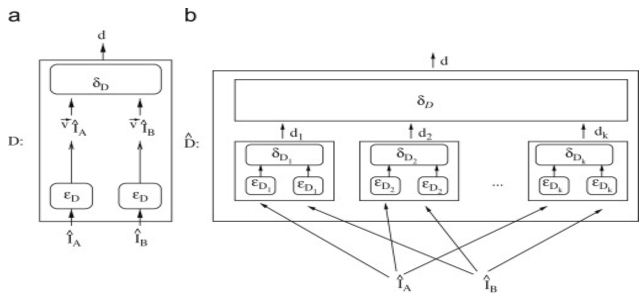

Fig. 3 (a) The use of a simple descriptor D for computing the similarity between images. (b) Composite descriptor.

VI. GP FRAMEWORK FOR CBIR

Here framework uses GP to combine simple descriptors. This decision stemmed from three reasons: (i) the large size of the search space for combination functions; (ii) previous success of using GP in information retrieval; and (iii) no prior work on applying GP to image retrieval.

The corresponding CBIR system can be characterized as follows. For a given large image database and a given user-defined query pattern (e.g., a query image), the system retrieves a list of images from the database which are most "similar" to the query pattern, according to a set of image properties. These properties may take into account the shape, color, and/or texture of the image objects, and are represented by simple descriptors. These simple descriptors are combined using a composite descriptor , where is a mathematical expression uniquely represented as an expression tree, whose non-leaf nodes are numerical operators and the leaf node set is composed of the similarity values di, i=1,2,…,k. Fig. 4 shows a possible combination (obtained through the GP framework) of the similarity values d1, d2, and d3 of three simple descriptors.

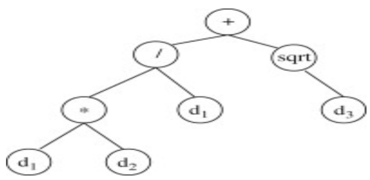

Fig. 4 Example of a GP-based similarity function represented in a tree.

The overall retrieval framework can be divided into two different approaches based on whether or not it considers the use of validation sets in the similarity function discovery process. Overtraining can occur when the learned or evolved model fits the particulars of the training data overly well and consequently does not generalize to new unseen examples

A. GP framework without validation sets

Algorithm 1 illustrates the GP-based retrieval framework without considering validation sets. Initially, the population starts with individuals created randomly (step 4). This population evolves generation by generation through genetic operations (step 5). A fitness function is used to assign the fitness value for each individual (step 5.1.1). This value is used to select the best individuals (step 5.2). Next, genetic operators are applied to this population aiming to create more diverse and better performing individuals (step 5.4). The last step consists in determining the best individual to be applied to the test set (step 6). The commonest choice is the individual with the best performance in the training set (e.g., the first tree of the last generation).

Algorithm 1

(1) Let T be a training set

(2) Let S be a set of pairs (i, fitnessi), where i and fitnessi are an individual and its fitness, respectively.

(3) S←

(4) P← Initial random population of individuals (“ similarity trees”)

(5) For each generation g of Ng generations do

(5.1) For each individual i P do

(5.1.1) fitnessi←fitness(i,T)

(5.2) Record the top Ntop individuals and values in Sg

(5.3) S←S Sg

(5.4) . Create a new population P by:

(5.4.1) Reproduction

(5.4.2) Crossover

(5.4.3) Mutation

(6) Apply the “best individual” in S on a test set.

B. GP framework with validation sets

The last step presented in the GP framework consists in determining the best individual to be applied to the test set. Since the natural choice would be the individual with best performance in the training set, it might not generalize due to over-fitting during the learning phase. In order to alleviate this problem, the best individuals over the generations are applied to a validation set. In that way, it is possible to select the individual that presents the best average performance in both sets: training and validation. Algorithm 2 presents the GP framework for image retrieval that considers the use of validation sets.

Note that, since the average does not ensure that the selected individual has a similar performance in both sets, it would be interesting to consider the standard deviation to correct such a bias. Formally, we apply the method described to determine the best individual: let be the average performance of individual i in the training and validation sets, and σ(fi) be the corresponding standard deviation. The best individual is given by (1).

Algorithm 2

(1) Let T be a training set

(2) Let V be a validation set S←

(3) Let S be a set of pairs (i,fitnessi), where i and fitnessi are an individual and its fitness, respectively.

(4) S←

(5) P← Initial random population of individuals (“ similarity trees”)

(6) For each generation g of Ng generations do

(6.1) For each individual i P do

(6.1.1) fitnessi←fitness(i,T)

(6.2) Record the top Ntop individuals and their values in Sg

(6.3) S←S Sg

(6.4) . Create a new population P by:

(6.4.1) Reproduction

(6.4.2) Crossover

(6.4.3) Mutation

(7) F←

(8) For each individual i S do

(8.1) F←F {(i,fitness(i,V))};

(9) BestIndividual←SelectionMethod(F,S)

(10) Apply the “best individual” on a test set of images

The main difference between Algorithms 1 and 2 relies on the use of a validation set to identify appropriate individuals to be used on the test set. The individual selection method used in Algorithm 2 (step 8) considers the performance of individuals in the training set (stored in the set S) and in the validation set (stored in the set F), and individual that satisfies Equation.

VII. CONCLUSIONS

We have proposed an abductive framework of reasoning for retrieval of multimedia documents. The proposed method can retrieve documents based on concepts abstracted over multiple media forms. We use conceptual and media knowledge to derive combinations of media patterns that can be used to identify the concepts presented in a query and are invariant over media specific variations. The documents that provide plausible explanations to the expected media patterns are selected for retrieval. The method of partitioning the knowledge base required for retrieval is a unique feature of the approach. It has resulted in modelling retrieval as a problem of distributed techniques using well-defined functional units of knowledge. In nut-shell, many successful algorithms applied in medical imaging have been reported in the literature and the applications of rough sets & genetic programming in medical image processing have to be analyzed individually. Rough sets & genetic programming are the new challenges to deal with the issues that cannot be addressed by traditional image processing algorithms or by other classification techniques. By introducing rough sets, algorithms developed for medical imaging and pattern recognition often become more intelligent and robust that provides a human-interpretable, low cost, exact enough solution, as compared to traditional techniques. and their applications to medical imaging including object representation, image segmentation, classification and feature extraction. Finally, the main purpose here is to present to the rough sets and GA techniques for medical imaging research communities for the state of the art approach in both applications. Consequently, it is expected that this work will serve as a fertile ground for creative discussions to researchers working in this field.

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