International Journal of Current Research and Modern Education (IJCRME)
ISSN (Online): 2455 - 5428
(www.rdmodernresearch.com) Volume I, Issue I, 2016

CONTENT BASED IMAGE RETRIEVAL BY CONTINUOUS FEATURE SELECTION

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Abstract:

Graph BASED ranking models have been deeply studied and widely applied in information retrieval area. But the problem of applying a novel and efficient graph-based model for content based image retrieval (CBIR), especially for out-of-sample retrieval on large scale databases is still being researched. Traditional image retrieval systems are based on keyword search, such as Google and Yahoo image search. In these systems, a user keyword (query) is matched with the context around an image including the title, manual annotation, web document, etc. These systems don't utilize information from images. However these systems suffer many problems, such as shortage of the text information and inconsistency of the meaning of the text and image. Content-based image retrieval is a considerable choice to overcome these difficulties. CBIR has drawn a great attention in the past two decades. Different from traditional keyword search systems, CBIR systems utilize the low-level features, including global features (e.g., color moment, edge histogram etc.) amount of researches have been performed for designing more informative low-level features to represent images, or better metrics (e.g., DPF [6]) to measure the perceptual similarity, but their performance is restricted by many conditions and is sensitive to the data. Relevance feedback is a useful tool for interactive CBIR. User's high level perception is captured by dynamically updated weights based on the user's feedback. Most traditional methods focus on the data features too much but they ignore the underlying structure information, which is of great importance for semantic discovery,

Introduction:

Especially when the label information is unknown. Many databases have underlying cluster or manifold structure. Under such circumstances, the assumption of label consistency is reasonable. It means that those nearby data points, or points belong to the same cluster or manifold, are very likely to share the same semantic label. This phenomenon is extremely important to explore the semantic relevance when the label information is unknown.

A good CBIR system should consider images' low-level features as well as the intrinsic structure of the image database. Manifold Ranking (MR) a famous graph-based ranking model, ranks data samples with respect to the intrinsic geometrical structure collectively revealed by a large number of data. It is exactly in line with our consideration. MR has been widely applied in many applications, and shown to have excellent performance and feasibility on a variety of data types, such as the text image and video. By taking the underlying structure into account, manifold ranking assigns each data sample a relative ranking score, instead of an absolute pair wise similarity as traditional ways. The score is treated as a similarity metric defined on the manifold, which is more meaningful to capturing the semantic relevance degree. He et al firstly applied MR to CBIR, and significantly improved image retrieval performance compared with state-of-the-art algorithms. However, manifold ranking has its own drawbacks to handle large scale databases – it has expensive computational cost, both in graph construction and ranking computation stages. Particularly, it is unknown how to hand leans out-of-sample query (a new sample) efficiently under the existing framework. It is unacceptable to recompute the model for a new query. That means, original manifold ranking is inadequate for a real world CBIR system, in which the user provided query is always an out-of-sample.

The original manifold ranking is extended to propose a novel framework named Efficient Manifold Ranking (EMR). We try to address the shortcomings of manifold ranking from two perspectives: the first is scalable graph construction; and the second is efficient computation, especially for out-of-sample retrieval. Specifically, we build an anchor graph on the database instead of the traditional k-nearest neighbor graph, and design a new form of adjacency matrix utilized to speed up the ranking computation. The model has two separate stages: an offline stage for building (or learning) the ranking model and an online stage for handling a new query. With EMR, we can handle a database with 1 million images and do the online retrieval in a short time. To the best of knowledge, no previous manifold ranking based algorithm has run out-of-sample retrieval on a database in this scale.

Module Description:

The MODULES are as the following

- ✓ Training module
- ✓ Feature extraction
- ✓ Learning and Classification
- ✓ Output results

Training Module:

Here the training medical images are uploaded. The preprocessing is done here. It reduces any problems and noise in the uploaded images. The preprocessed output is stored for the next steps i.e. feature extraction. For analysis of images, one of the issues is the effective identification of features in the images and the other one is extracting them. One of the difficult tasks knows the image domain and obtaining a priori knowledge of what information is required from the image. This is one of the reasons the Image Mining process cannot be completely automated. A current technique in image retrieval and classification (two of the dominant tasks in Image Mining) concentrates on content-based techniques.

The processing in our system consists of three steps. In the gathering stage, the system automatically gathers images related to given class keywords from the Web. In the learning stage, it extracts image features from gathered images and associates them with each class.

Feature Extraction:

Two types of feature extractors were employed to perform the experiments:

- ✓ A texture-based extractor and
- ✓ A shape-based extractor.

The texture-based descriptor used was based on the Haralick descriptors [4], obtained from co-occurrence matrix that have been largely used to a texture-based image representation.

The features obtained from the Haar like descriptors employed in our experiments are variance, entropy, energy, homogeneity, 3rd order moment, inverse variance and step. All these descriptors were combined in a single feature vector, generating a feature vector composed of 140 elements. The shape-based extractor employed the improved EM/MPM algorithm proposed. The images are firstly segmented using a technique that combines a Markov Random Field and a Gaussian Mixture Model.

The segmentation of images is accomplished according to a fixed number of different texture regions, where six features are extracted for each region: the mass m (or size); the centroid (xo and yo); the average gray level (µ), the fractal dimension (D); and the linear coefficient (b) used to estimate D. In our experiments we segmented the images in five regions. The shape-based extractor produced feature vectors composed of 30 elements.

In the gathering stage, an image-gathering module gathers images from the Web related to the class keywords. Note that our image-gathering module is not called image ``search'' but image ``gathering'', since it has the following properties:

- ✓ It does not search for images over the whole Web directly,
- ✓ It does not make an index of the Web images in advance, and
- ✓ It makes use of search results of commercial keyword-based search engines for the class keywords.

These systems search for images based on the query keywords first, and then a user selects query images from their search results. These three systems carry out their search in such an interactive manner. Our module is different from those in that our system only needs one-time input of query keywords due to automatic image selection mechanism.

Learning and Classification:

In the system, image classification is performed by image-feature-based search. First, in the learning stage, an image-learning module extracts image features from gathered images and associates image features with the classes represented by the class keywords. Next, in the classification stage, we classify an unknown image into one of the classes by comparing image features.

In our method of image classification, image features of not only a target object but also non-target objects such as the background are used as a clue of classification, since non-target objects usually have strong relation to a target object. For example, a cow usually exists with a grass field and/or a fence in a farm, and a lion usually exists in a savanna or a zoo.

Although the number of combinations of a target object and non-target objects is large, we think that we can deal with this largeness by gathering a large amount of image from the Web and by using them for learning. Here, we do not set up "reject", and then all test images are classified into any class.

Output Results:

We made six kinds of classification experiments from no.1 to no.6 for 10 kinds of gathered images, 10 kinds of gathered images with only correct ones (selected by hand), 10 kinds of images selected from the commercial image database (Corel Image Gallery), 20 kinds of gathered images, 20 kinds of images with only correct ones, and 50 kinds of images, respectively.

In the experiments, we exploited three kinds of image features, which are color signatures, region signatures using the *k*-means clustering method, and region signatures using the JSEG segmentation algorithm. The gathered images from the human anatomy for 10 kinds of class keywords related to animals shown in Table 1. The total number of gathered image was 4582, and the precision(pri.) by subjective evaluation was 68.2%, which is defined to be *NOK/(NOK+NNG)*, where *NOK*, *NNG* are the number of relevant images and the number of irrelevant images to their keywords. It describes only the results by color signatures for the individual classes, since most of the results by color signatures are superior to the results by region signatures using *k*-means and JSEG. In the tables, ``(r1)'' and ``(r2)'' mean region signatures using the *k*-means clustering and region signatures using the JSEG region segmentation method, respectively.

The recall(rec.) is defined to be MOK/Mtest, the precision (pri.) is defined to be MOK/(MOK+MNG) and F-measure(F) is the harmonic mean of the recall and the precision, where MOK, MNG, and Mtest are the number of correctly classified images, the number of incorrectly classified images, and the number of test images for each class, respectively. All values are represented in percentage terms. In the experiment no.1, we obtained 34.3 as the F-measure value by color signatures.

Existing System:

The recent wide spread of digital imaging devices, we can easily obtain digital images of various kinds of real world scenes. It is hard to apply conventional image recognition methods to such generic recognition. Most of their applicable targets are restricted. Whilst this review is primarily focused on techniques for the storage and retrieval of electronic images, it is useful to reflect on the traditional practices of picture and other manual collections of images and videos. Image collections of various types are maintained by a wide range of organization, of all sizes and in a variety of sectors. Traditionally, images will be stored in their original analogue form, in wallets, files or folders, which in turn will be arranged on shelves, in drawers or in cabinets. The level of indexing associated with manual image collections will be closely related to the importance of the collection, the way it is used, and the time and resources allocated to the task. Knowledge of the collection usually rests with the librarians, archivists, curators or others responsible for its upkeep and, less often, the actual users. When manual collections are digitised, decisions have to be made about the associated metadata and often it may not be feasible, due to lack of resources, to upgrade the content of the catalogue or textual record associated with each image.

The need for efficient storage and retrieval of images has been recognized by managers of large image collections such as picture libraries and design archives for many years. The normal technique used is to assign descriptive metadata in the form of keywords, subject headings or classification codes to each image when it is first added to the collection, and to use these descriptors as retrieval keys at search time.

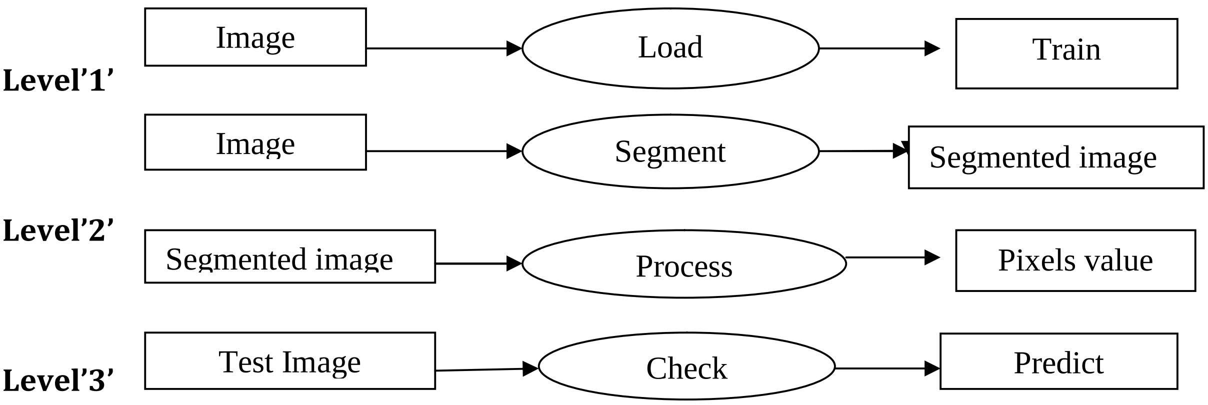
Drawbacks:

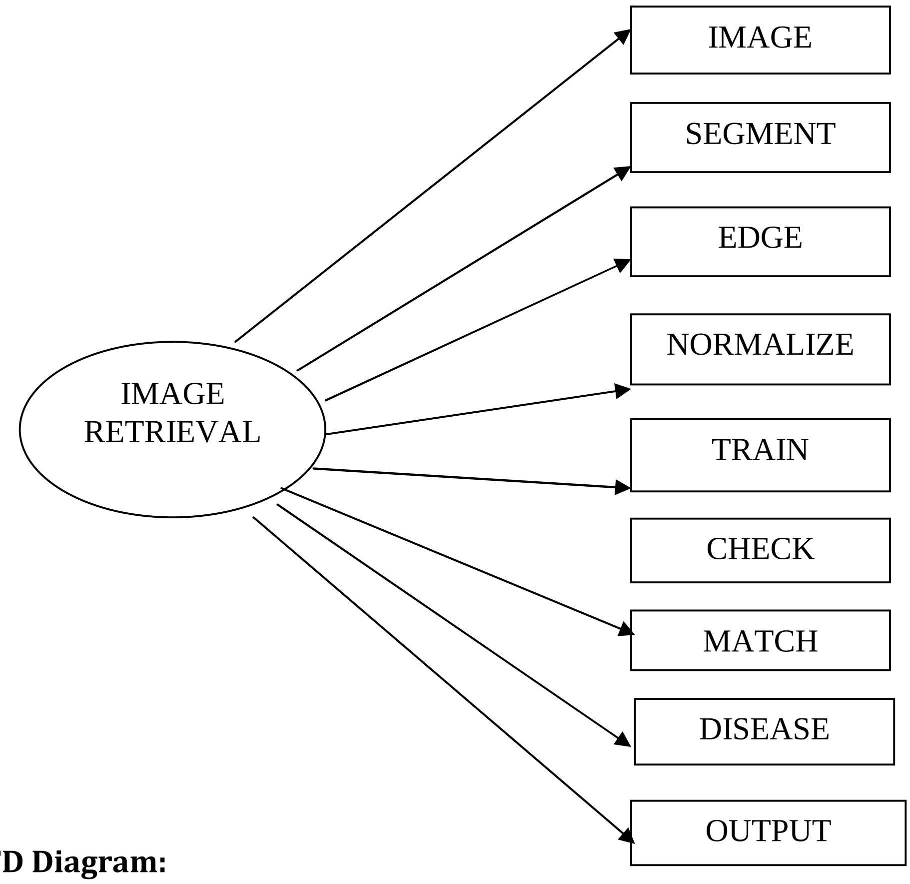
- ✓ Operate with low-level characteristics processing color regions, shapes, texture, and they do not provide the analysis of image semantics.
- ✓ Computing similarity between wavelet coefficients of querying and preprocessed images.
- ✓ Creating keywords for a large number of images is time consuming.
- ✓ The keywords are inherently subjective and not unique.
- ✓ Cannot be applied to large datasets.

Proposed System:

The proposed method utilizes images gathered from the Web for learning of a generic image classification system instead of commercial image collections. This research is Web image mining for generic image classification. Web images are taken by a large number of people for various kinds of purpose. The ability to retrieve by shape is perhaps the most obvious requirement at the primitive level. Unlike texture, shape is a fairly well-defined concept – and there is considerable evidence that natural objects are primarily recognized by their shape. A number of features characteristic of object shape (but independent of size or orientation) are computed for every object identified within each stored image. Queries are then answered by computing the same set of features for the query image, and retrieving those stored images whose features most closely match those of the query. Two main types of shape feature are commonly used – global features such as aspect ratio, circularity and moment invariably.

Shape matching of three-dimensional objects is a more challenging task – particularly where only a single 2-D view of the object in question is available. While no general solution to this problem is possible, some useful inroads have been made into the problem of identifying at least some instances of a given object from different viewpoints. One approach has been to build up a set of plausible 3-D models from the available 2-D image, and match them with other models in the database.



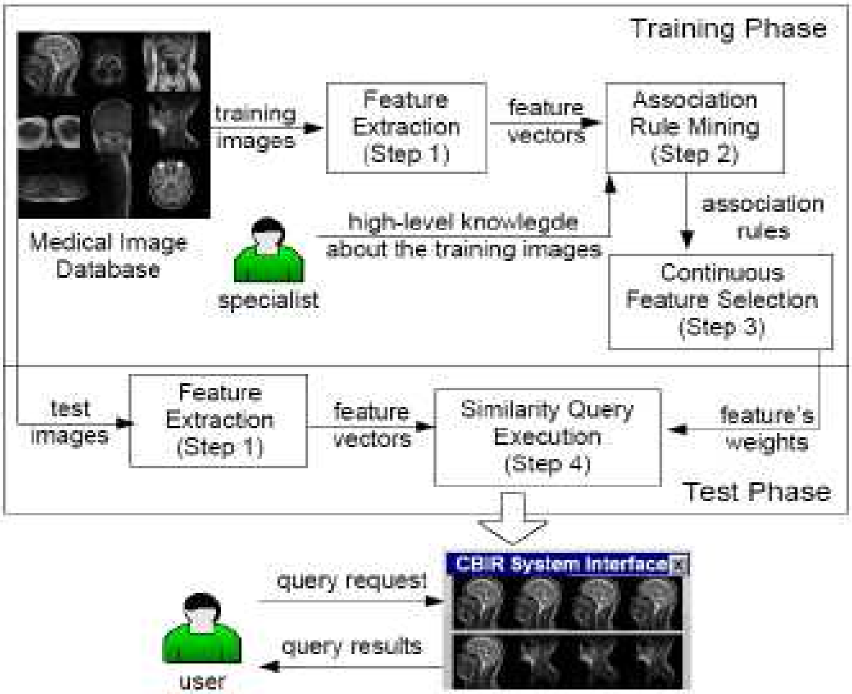


DFD Diagram:

System Architecture:

An architecture description is a formal description of a system, organized in a way that supports reasoning about the structural properties of the system. It defines the system components or building blocks and provides plan from which products can be procured, and systems developed, that will work together to implement the overall system.

System Architecture:



Implementation is the stage of the project when the theoretical design is turned into a working system. Implementation is the phase where the software goes for the actual functioning. System implementation is the process of making the newly designed system fully operational. The system is implemented after careful testing.

The method applies statistical association rules to find patterns relating low-level image features to high-level knowledge about the images, and it uses the patterns mined to determine the weight of the features. The feature weighting through the statistical association rules reduces the semantic gap that exists between low-level features and the high-level user interpretation of images, improving the precision of the content-based queries.

Moreover, the proposed method performs dimensionality reduction of image features avoiding the "dimensionality curse" problem. Experiments show that the proposed method improves the precision of the query results up to 38%, indicating that statistical association rules can be successfully employed to perform continuous feature selection in medical image databases.

The number of combinations of a target object and non-target objects is the large; we think that we can deal with this largeness by gathering a large amount of image from the Web and by using them for learning. Here, we do not set up "reject", and then all test images are classified into any class.

System Maintenance:

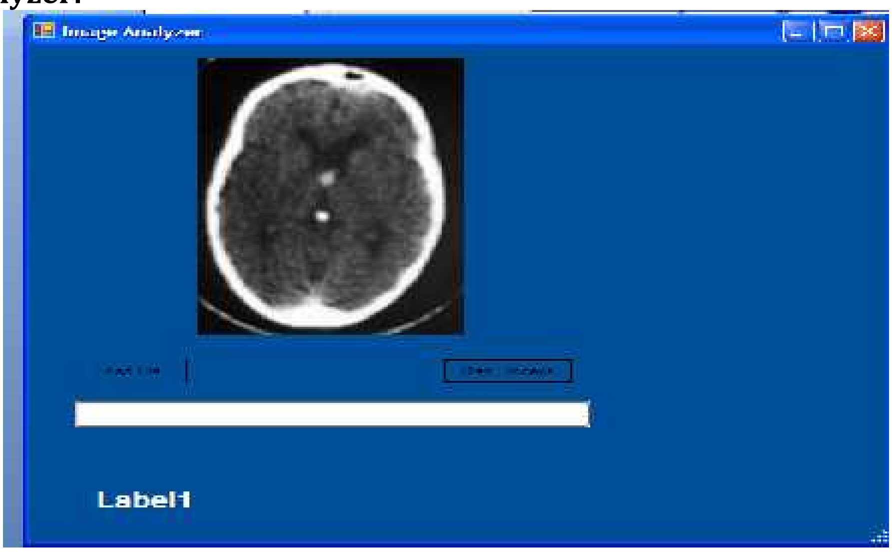
System Development is the process of defining, testing and implementing a new software application or program. It could include the internal development of customized systems. The systems development life cycle (SDLC), also referred to as the application development life-cycle, is a term used in systems engineering, information systems and software engineering to describe a process for planning, creating, testing, and deploying an information system. The systems development life-cycle concept applies to a range of hardware and software configurations, as a system can be composed of hardware only, software only, or a combination of both. Within the computer subculture known as the demo scene, a non-interactive multimedia presentation is called a demo (or demonstration).

Demo groups create demos to demonstrate their abilities in programming, music, drawing, and 3D modeling. The key difference between a classical animation and a demo is that the display of a demo is computed in real time, making computing power considerations the biggest challenge. Demos are mostly composed of 3D animations mixed with 2D effects and full screen effects.

Login:

Home Page:

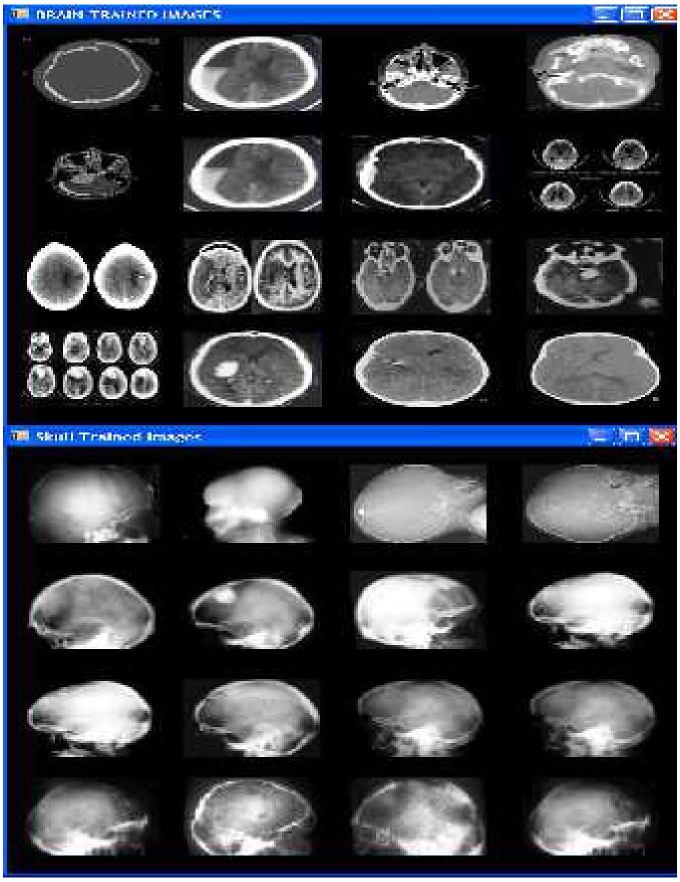
Image Analyzer:



Example of Image Analysis:

Scan Image Comparator:

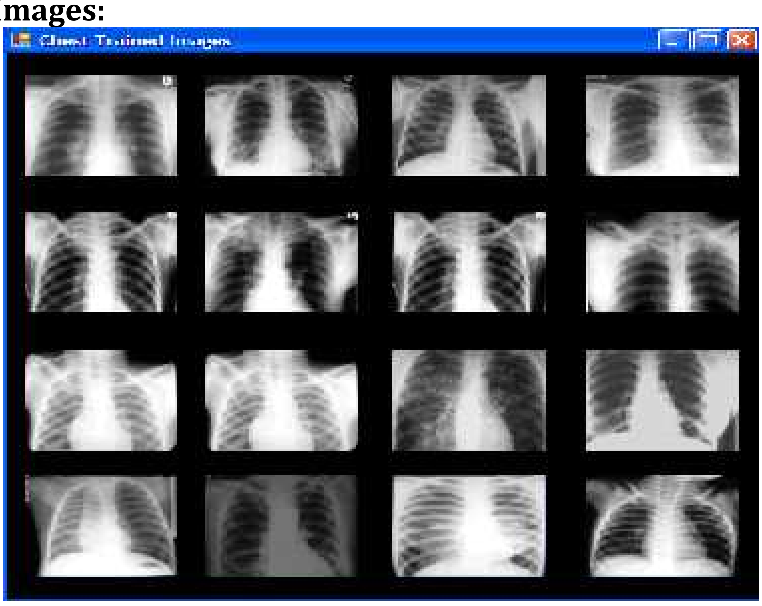
Trained Images:



Hand Trained Images:

Spinal Chord Trained Images

Chest Trained Images:



Conclusion:

The proposed method employs statistical association rules to reduce the semantic gap inherent in the EMR systems. Our approach can also be employed to perform dimensionality reduction, minimizing the "dimensionality curse" problem. The experiments performed show that the proposed method improves the precision of the query results up to 38%, always outperforming the precision obtained by the original features, while decreasing the memory and processing costs. These results testify that statistical association rules can be successfully employed to perform continuous feature selection in medical image databases, weighting the features in similarity query executions.

Future Enhancement:

Future work includes verifying the results of applying our technique using other distance functions and incorporating other mining techniques. In future we segmented the images in many regions. The shape-based extractor produced feature vectors composed of 30 elements.

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