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A Systematic approach for semantic gap reduction in CBMIR

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ABSTRACT

With the advancement of medical science, the number and types of various radiology images is also growing. It's not practically easy to find out special case history images form thousands of such images. It's rather easy to choose such images by content. We can find out similar images by query by example and finally we can put an algorithm to extract the content. By posing a distance vector algorithm we can choose images having similar features. For a medical practitioner it is very difficult to understand features of an image, he can rather use English type language to extract such images. Combining linguistic terms with the image features can easily eliminate this semantic gap.

Keywords— CBIR, fuzzy clustering, Linguistic terms, Semantic Gap

1.Introduction

Now a days a number of new technologies are there in medical field. Use of radiology images is very common to diagnose a disease. With the advancement of these images the need to archive these images also arises. But it's not possible to choose images form thousands of images to match with similar cases. Suppose a medical practitioner wants to match with similar cases of liver cysts of other patients, he has to find these from a large archive. So rather than finding such images by name we can match images by extracting the features of the images and by comparing with these features. Similar kind of cysts has similar type of features. So the doctor can find out similar case history. But there are number of problems that can arise. For example: How to extract image features of an image? Where to store these images? How to select similar type of images from thousands of images? How can medical practitioner understand low level terms?

1.1 The Concept of Content Based Image Retrieval

In content based Image Retrieval System, the media items extracted from the images and their values are sorted and are retrieved from the images stored in a database. These items are retrieved by posing a relevant query. First of all the features are indices are finally stored in a database. When a user poses a query, the features of the query images are also extracted and are compared with features of the images in database. These features are compared by some similarity measure or some distance vector. The retrieved images are ranked in order of their similarity. This chapter provides a short introduction to each of the steps mentioned above, which are also shown in Fig 1.1.

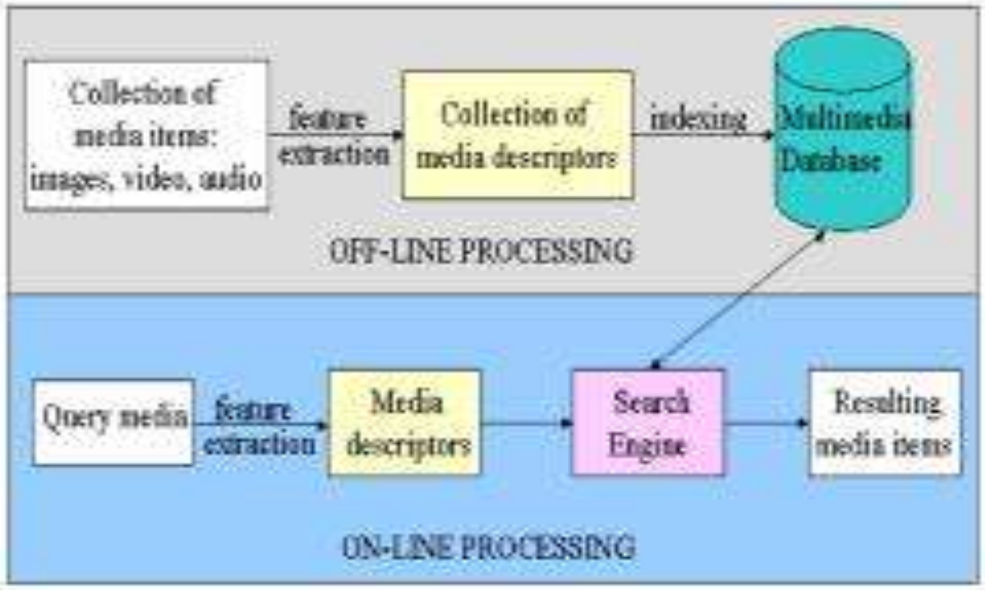

Figure 1.1 Block diagram of the content-based retrieval system

1.2 Challenges in CBMIR

CBIR techniques can be useful for doctors in assessing the medical images. It is very difficult to find out similar cases images from the huge medical image database. However by using CBIR technology the features of medical images can be extracted and compared with query images. Hence the doctor can find out the similar cases from the database in very fast and efficient manner. There are some issues that are still needed to be identified:

- As the medical database is growing in very fast speed and at a large scale, the fastest techniques of feature extraction are needed.
- The medical practitioners are unaware about engineering terms so there can be difficulty in understanding the low level features of the images. This gap in low level and high level terms is called Semantic gap.
- The inclusion of the large amounts of medical data into the retrieval process and case-based retrieval, different types of images must be classified.sao there is a need of various classification algorithms to be used in the medical feature database.

2. Concise Literature Review

Content Based Image retrieval has been used for the image retrieval for a long time now. Various techniques has been incorporated into this for the better retrieval for e.g. various distance calculating techniques, optimization techniques as well as semantic gap reducing techniques. The detailed literature reviews of CBIR are as follow:

Chiu et.al. [1] proposed a fuzzy CBIR system called LinStar texture i.e. linguistic star for textures. They proposed two major phases in their study i.e. Database creation and Query comparison. The proposed system removes two of the major problems of the CBIR i.e. semantic gap between low-level features i.e. numerical descriptors and high level Concepts i.e. textual description and Human perception subjectivity when images are perceived. MPEG-7 attends to standardize the interface of multimedia content description between low-level features and high-level semantic concepts. LinStar is a project which incorporates high-level textual concepts into CBIR system. In the proposed system, the fuzzy logic formulates the mapping of low-level numerical features into high-level textual concepts. In this approach, in database creation phase there are various steps involved for the purpose of mapping. In texture analysis, the texture of an image is analyzed. In this study a texture image is described as six Tamura features. These features characterize the low-level properties of an image. The six Tamura features are coarseness, contrast, line-likeness, regularity, roughness and directionality. In fuzzy clustering section, a fuzzy clustering algorithm was proposed to generate a term set and degrees of appearance for each Tamura feature can be interpreted as five linguistic terms. Linguistic terms contrast can be interpreted as "very low", "low", "medium on contrast" ,"high", and "very high". Coarseness can be interpreted as "very fine", "fine", "medium coarse", "coarse", and "very coarse". Similarly other Tamura features can also be interpreted. In query comparison phase a user can pose queries to retrieve desired images. These queries can be posed as visual examples or textual descriptions. In the textual queries, the linguistic terms are used by the users to pose a query. The query can be posed by logic composition. Logic operators include: AND ($\wedge$), OR ($\vee$), NOT ($\neg$) For example, consider an example "(fine $\vee$ regular) $\wedge$ very high on contrast". The final similarity was computed by min-max composition rules. For example, Min (max (μcrs, μreg), μcon). The user can also pose visual queries. The constraints have to be specified so that the images can be retrieved. The constraints may be "find the images of similar coarseness and contrast". The visual example query can be expressed as a logic composition of Tamura features. The similarity function for each Tamura feature value must be re-defined. All the partial similarity functions are calculated first and then the final similarity is computed by using min-max composition rules. In the proposed approach, Tamura features are effective in characterizing low-level statistical properties of textures. Linguistic terms are satisfactory for describing high-level textual concepts of the textures. So this system is proved to reduce the semantic gap between two levels.

Adnan Qayyum et al. [2] proposed a deep learning based framework for content based medical image retrieval by training a deep convolutional neural network for the classification task. Two strategies have been proposed for retrieval of medical images, one is by getting prediction about the class of query image by the trained network and then to search relevant images in that specific class. The second method is without incorporating the information about the class of the query image and therefore searching the whole database for relevant images. The proposed solution reduces the semantic gap by learning discriminative features directly from the images. Widely used metrics i.e., precision and recall were used to test the performance of the proposed framework for medical image retrieval.

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Mutasem K. Alsmadi [3] proposed an CBIR system using to retrieve images from databases by using MA. The proposed system extracted the query image features like color signature, shape and texture color. He uses MA based similarity measure to retrieve the relevant images. Incorporating GD algorithm with the GA increased the quality of solution (weight) through increasing the fitness number, which helped in enhancing the process of exploitation during the searching process. The execution results presented the success of the proposed method in retrieving the similar images from the images database.

Sk Mazharul Islam et al. [4] presents content-based image retrieval (CBIR) system with applications in one general purpose and two face image databases using two MPEG-7 image descriptors. The proposed method uses several sophisticated fuzzy-rough feature selection methods and combines the results of these methods to obtain a prominent feature subset for image representation for a particular query. Next, fuzzy-rough upper approximation of the target set (relevant list of images) with respect to the entire database that is represented by the prominent feature subset, is computed for retrieval and ranking. The information table on which every feature selection method works is small in size. Main reasons of performance boost of the proposed method are twofold. One is efficient feature subsets selection. The other reason is the fuzzy-indiscernibility relation based fuzzy-rough framework for computing upper-approximation which supports the approximate equality or similarity sense of CBIR. Fuzzy-rough upper approximation possibly adds more similar images in the relevant list from boundary region to expand the relevant list. The effectiveness of the proposed method is supported by the comparative results obtained from several single dimensionality reduction methods; several clustering based retrieval techniques and also tested for face image retrieval.

Wenbo Li et al.[5] proposed a new medical image retrieval model based on an iterative texture block coding tree. The corresponding methods for coarse-grained and fine grained similarity matching are also proposed. Moreover, a multi-level index structure is designed to enhance the retrieval efficiency. Experimental results show that, the methods are of high efficiency and appropriate tolerance on slight shifts, and achieve a relative better retrieval performance in comparison of other existing methods. Content-based medical image retrieval (CBMIR) has been widely studied for computer aided diagnosis. Accurate and comprehensive retrieval results are effective to facilitate diagnosis and treatment. Texture is one of the most important features used in CBMIR. Most of existing methods utilize the distances between matching point pairs for texture similarity measurement. However, the distance based similarity measurements are of low tolerance to slight texture shifts, which result in an excessive sensitivity. Furthermore, with the increase of the number of texture points, their time complexity is in explosive growth.

Deepanwita Datta et al.[6] proposed a graph-based key phrase extraction model that captures the relatedness between words in terms of both mutual information and relevance feedback. Most of the existing works have stressed on bridging the *semantic gap* by using textual and visual features, either in combination or individually. The way these text and image features are combined determines the efficacy of any retrieval. For the purpose, they had adopted Fisher-LDA to adjudge the appropriate weights for each modality. This provides us with an intelligent decision-making process favoring the feature set to be infused into the final query. Our proposed algorithm is shown to supersede the previously mentioned key-phrase extraction algorithms for query expansion significantly. A rigorous set of experiments performed on Image CLEF-2011 Wikipedia Retrieval task dataset validates our claim that capturing the semantic relation between words through Mutual Information

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followed by expansion of a textual query using relevance feedback can simultaneously enhance both text and image retrieval.

Chaoran Cui et al. [7] have investigated the challenge of incorporating semantic information into CBIR, and addressed the problem by introducing the hybrid textual-visual relevance learning. To alleviate the sparsity and unreliability of tags, they performed tag completion to fill the missing tags as well as correct noisy tags of images. To capture users' semantic cognition to images, they represented each image as a probability distribution over the permutations of tags. Textual relevance and visual relevance are effectively combined in a ranking aggregation way. Extensive experiments have been conducted on two benchmark datasets in comparison with the state-of-the-art methods.

Kulkarni et. al. [8] discussed a similar approach. In this approach, the Tamura features are extracted from the image and then converted to the natural language concepts with the help of a fuzzy clustering algorithm. The query in expressed as logic combination of natural language terms. The experiment was performed on Brodatz texture benchmark database.

3. Problem Statement

3.1 Feature Extraction

In the research we will extract these features by using GLCM or similar method. Grey level co-occurrence matrix (GLCM) technique is appropriate to use because most of the radiology images are grey. GLCM calculate that how often pairs of pixels with specific values occur in the image and what is their specified spatial relationship. GLCM creates a matrix and finally extract statistical measures form this matrix. GLCM can extract these types of features

(a)Contrast (b) Energy (c) Homogeneity (d) Entropy

CONTRAST: Contrast is the difference in luminance and/or color that makes an object distinguishable. It returns a measure of the intensity contrast between a pixel and its neighbor over the whole image.

The Contrast feature is calculated as: $\sum_i \sum_j (i-j)^2 P(i,j)$

Where: P = element i, j of the symmetrical GLCM

ENERGY: The energy feature is calculated as: $\sum_i \sum_j p^2(I,j)$

Where P = element i, j of the symmetrical GLCM

HOMOGENEITY: It returns a value that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal. Homogeneity feature is calculated as : $\sum_i \sum_j$

ENTROPY: Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image.

Entropy feature is calculated as: $\sum_i \sum_j p(i,j) \log P(i,j)$

Where: p =element i, j of the normalized symmetrical GLCM.

There are many other feature extraction and selection techniques which can be used such as Color auto-correlogram, Color moments, HSV histogram features, Stationary Wavelet transform (SWT) moments, Gabor wavelet transform, Binarized Statistical Image Features (BSIF) for the feature extraction in the CBIR system.

3.2 Indexing

We will extract the features and store these in image database for further use. Before storing into the database we can create a matrix to store these features.

3.3 Classification

Rather than by choosing from all type of radiology images, we can pose query by example first. By this method we can select similar images for e.g. images of liver only. From these images we can choose images having similar features by posing the query. We will apply a hybrid classification algorithm to classify image features on the database to retrieve exact set of the images that will increase the performance of the proposed system and meets the user's requirement

3.4 Linguistic terms

The last problem arises when medical practitioner is unable to understand low level features. To make his task easy we can use linguistic terms i.e. English like terms to find out similar images. To do this we have to choose different linguistic terms smooth, coarse, regular etc. A fuzzy clustering algorithm will be used to divide the features of the images into developed lexical phrases. If then else rules are used to create the range.

To solve this purpose we divide each feature into three linguistic terms. For e.g. homogeneity can be divided into three terms i.e low homogeneity, medium homogeneity and high homogeneity. We can impose these terms to the image database. The linguistic terms have relation with the low level features and this relation is shown in TABLE 1.

TEXTURE FEATURES	**LOW**	**MEDIUM**	**HIGH**
Homogeneity	Coarse	Regular	Smooth
Entropy	Smooth	Regular	Coarse
Contrast	Smooth	Regular	Coarse
Color shade	Smooth	Regular	Coarse

TABLE 1: Relation between various texture image features and linguistic terms

3.5 Performance testing

The proposed system will be evaluated on the various medical datasets (DICOM, CT and MRI) consisting of images of various modalities. To test the behavior of the proposed system will be evaluated with various performance parameters.

4. Research Objectives

- To extract and select the relevant features of DICOM images based on the feature extraction mechanism.
- To classify the images based on the hybrid classification technique so that the performance of the proposed system can be improved which in turn will improve the efficiency
- To evaluate the proposed system by using various parameters such as Recall, Precision, and Sensitivity.
- To use the linguistic terms to reduce the semantic gap

5. Conclusion

By Content Based Image Retrieval (CBIR) we can search and retrieve the images from a database on the basis of features that are extracted from the image themselves. In this paper, we have presented the research proposal plan to achieve an efficient CBIR using various classifiers. The focus is on medical images. Efforts will also be made to reduce the semantic gap. For this purpose, the Lexical terms will be created by using fuzzy clustering algorithm. DICOM images will be used for image retrieval

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