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Automatic Image Annotation-A Proposed Method

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***Abstract*— Medical images play a central role in patient diagnosis, therapy, surgical planning, medical reference, and medical training. With the advent of digital imaging modalities, as well as images digitized from conventional devices, collections of medical images are increasingly being held in digital form. It becomes increasingly expensive to manually annotate medical images. Consequently, automatic medical image annotation becomes important. This paper reviews annotation of medical records.**

***Keywords*— Image parsing, Ontological modeling, Semantic image annotation**

1. INTRODUCTION

Health care information technologies produce the increasing number of medical images in different imaging modalities, like radiography (CR), Computer tomography (CT), magnetic resonance (MR), ultrasound (US), nuclear medicine (NM). Management of medical data volume is complicated, and there is a gap in understanding the visual content of the image. Most of the medical image inspection techniques are based on tacit knowledge of experts. Semantic annotations facilitate the gathering of information from medical experts and can be used to represent the visual knowledge. These data are useful for creation a computer-based assistant, collecting information about the medical inspection process, same as to query and retrieve image from medical record databases. Automated or semi-automated content-based image retrieval (CBIR) systems based on low-level features have demonstrated poor performance when applied to databases with a broad spectrum of imaging modalities, anatomies, and pathologies. The search by particular textual description, or by fusing the results of visual and textual techniques, is more precise compared to the search by the image content. Such method provides better means to organize and search an image database.

During the past years, Content Based Image Retrieval (CBIR) has gained much for its potential application in multimedia management. In the current stage, an effective search engine is needed for huge database. "Content-based" means that the search analyses, the contents of the image rather than the metadata such as keywords, descriptions or tags associated with the image. The term "content" might be referred as color, shape, texture, or any other information that can be derived from the image itself. It is also known as Query By Image Content (QBIC) or Content- Based Visual Information Retrieval (CBVIR). The CBIR system have used in varies applications such as Medical diagnosis, Crime prevention, Fashion and interior design, Architectural and engineering, Journalism and advertising, Education and training, Cultural heritage, Home entertainment, Geographical information and remote sensing system and web searching.

Due to the large number of the images without text information, content-based medical image retrieval (CBMIR) [1-3] has received increased attention. We call the semantic similarity defined between different appearances of the same object the intra-object similarity and the semantic similarity defined between different objects the inter-object similarity. A semantic similarity in this paper refers to both intra object and inter-object semantic similarities. Each image in the database contains only one object. The semantic similarity between two images is the semantic similarity between the objects contained by the images. For example, the semantic similarity between an elbow image in coronal view and an elbow image in sagittal view is intra-object similarity while the semantic similarity between a hand image and an upper-arm image is inter object similarity. Compared with the general medical image retrieval problems, the problem addressed here has the following properties:

1. The images in the retrieval database can be annotated into one of the pre-defined labels, which are denoted as the ground truth labels of the images. Due to the ground trothing complexity, only a small portion of the whole image collections have their ground truth labels available.
2. Given a specific query, the correctly retrieved images should have the same ground truth label, which may not necessarily equal to the ground truth label of the query image provided that the query image and the retrieved images share a sufficient semantic similarity. This means that a user may query the database with an image that is close to but not exactly what he/she expects.

Review Works

ECOC [4-5] is used to solve an H-class (H >> 2) classification problem using multiple 2-class classifiers, which are called individual classifiers. The procedure to select the individual classifiers is called coding. The labels of the original H-class classification problem are called overall labels. The labels of the individual classifiers are called individual labels. If we represent the individual labels of one sample as a vector, which is called the code of the sample, all the training samples with the same overall label should have the same code.

Automatic Image Annotation (AIA) is a process assigning the information or data to an image. It is done with the caption or the keyword of the image. Machine learning techniques are commonly used for the image classification and image feature analysis such as segmentation and so on. In this image annotation method, a general term is usually quoted called 'blob'. A blob is a part of an image with a vocabulary meaning. The image is separated into blobs based on the region or cluster and the corresponding blobs are labeled with a vocabulary. In the medical imaging, image annotation helps the doctor to find out the description of an image. For example, in the case of spine x-ray image each section could be annotated and it would be useful for the diagnostic to examine the case based on the image description [5]. Phash (Perceptual Hash) is a fingerprint of an audio and video file formed from several characters from its content. Phash is a robust algorithm mostly used for similarity identification. Phash is a hashing function which could be used in Crypto-hashing, Digital Watermarking and Digital Signal Processing. There are four types of phash algorithm used: 1. DCT (Discrete Cosine Transform) based Hash, 2. Marr- Hildreth Operator based Hash, 3. Radial Variance Based Hash, 4. Block Mean Value based Hash. In this paper, we discuss on Average Perceptual Hashing Algorithm which is similar like Block Mean Value based Hashing Algorithm [6].

Automatic medical image categorization is also done using CBIR and data mining. The research article says that, the accuracy of the image categorization examined with best ten matches is 97.7%. Texture measure is done using image feature techniques. Image similarity is evaluated based on the distance or score compared with images in the database. The automatic classifier process is processed using k-nearest-neighbor which fixes the distance measures and also the classifier prefers the exact category for an input image based on votes over the k-references near to featured distance measures. The best recognition rate is 43.9% for the DCT-based features. The system categorized with 6335 images in which there are 80 categories and also evaluations are done for 54, 57 and 70 categories of radiology images. Within in ten good matches the accuracy of the system is noted as 98.0 percentages [7].

Proposed System

Diagnosis and treatment planning for patients can be significantly improved by comparing with clinical images of other patients with similar anatomical and pathological characteristics. This requires the images to be annotated using common vocabulary from clinical ontologies. Current approaches to such annotation are typically manual, consuming extensive clinician time, and cannot be scaled to large amounts of imaging data in hospitals. On the other hand, automated image analysis while being very scalable do not leverage standardized semantics and thus can't be used across specific applications.

The clinicians today deeply rely on images for screening, diagnosis, treatment planning and follow up. Due to the huge amount of medical images acquired at the hospitals, new technologies for image search are needed. Current systems only support indexing these images by keywords which cannot be searched and retrieved for their content. The vision of THESEUS-MEDICO is to provide Web 3.0 technologies to perform semantic search in medical image databases taking formal knowledge from ontologies and the image content into account. A potential scenario could be to list all images from patients with lymphoma, which have not been staged yet. Classical search will fail in this scenario, while semantic search could provide the clinician with a ranked list of images, showing enlarged lymph nodes and an involvement of spleen lesions. With the reasoning facilities of the ontology, search queries can also be expanded [1], such that the search for 'lymphatic system' results in images labeled with 'spleen', 'thymus' or 'lymph node'. With standards such as DICOM SR (structured reports), some commercial systems already started to use ontologies, mostly SNOMED, to label medical images. However, this makes structured reporting necessary, which is not accepted by clinicians yet due to higher efforts compared to conventional natural language reporting and missing automatic tools. The hybrid solution proposed in MEDICO consists of an image parsing system which automatically detects landmarks, segments organs, and maps them to ontological concepts and a context-sensitive annotation tool for the clinician.\

The training sets consist of predefined medical keyword and sets of images. In our study, 1926 images were provided by medical research centre. All the images are in PNG format of various dimensions. The images are classified into several categories such as Skull, Bone Joint, Hand- Wrist, Chest-Abdomen, Breast, Foot and Spine. The images are categorized based on a unique id as an image file name. The MEDICO system shows a 3-tier

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server architecture and it is shown in figure 1.

Currently, the server makes use of three services for semantic annotation:
1. The Image Parsing System automatically detects anatomical structures in CT volumes and maps them to concept labels coming from the Medico Ontology.

2. The Context Support Service implements spatial reasoning which enables the filtering of concepts for the interactive semantic reporting on the basis of image-based contextual information.

3. The Navigation Support Service links the Anatomy Browser with the Medico Ontology.

The client applications as well as the Image Parsing System use the Annotation Database and Data Repository for persisting meta data needed by semantic queries. The Data Repository stores large data such as surface meshes which represent organs, image masks, and annotated textual reports. These data are referenced by the Annotation Database. The objective of the image parsing system is to automatically annotate anatomical structures in medical images.

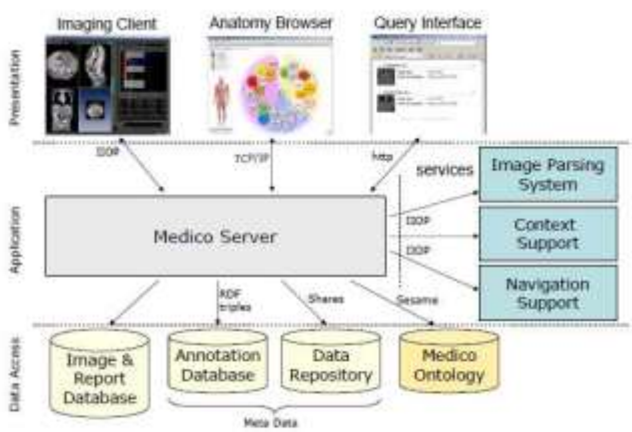

Figure 1. Overall architecture of the MEDICO system.

The process chain of the image parsing system consists of two main parts: the Discriminative Anatomical Network (DAN) and the database-guided segmentation module. It is illustrated in Figure 2.

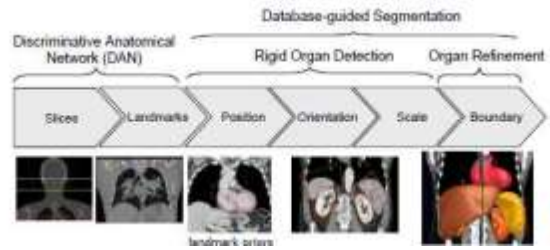

Figure 2. The process chain of the integrated image parsing system.

The purpose of the DAN is to give an estimate about the scale of the patient, the portion of the volume visible, and to detect a set of landmarks. To obtain a fast and robust system, the landmarks are connected in a graph (network). Information regarding the location of each landmark is propagated through the graph, which not only speeds up detection, but also increases detection accuracy. The database-guided segmentation module uses the output of the DAN for the detection of the position, the orientation, and scale of the organs visible in the given volume portion. By the use of boundary classifiers the organs are subsequently delineated. The precision of the organ segmentation within the image parsing system was evaluated with cross-validation using a mesh-to-mesh error metric. The basic process is given below:

Input:
The training sets consist of predefined medical keyword and sets of images. All the images are in PNG format of various dimensions.

Process
The input PNG image is stored in a temporary directory of the web server and image processing techniques are applied to the user query-image namely grayscale conversion and resizing. Grayscale conversion is done at this process. After the color conversion, the image is resized to a define size. It is done for segmentation of images. It is shown in figure 3.

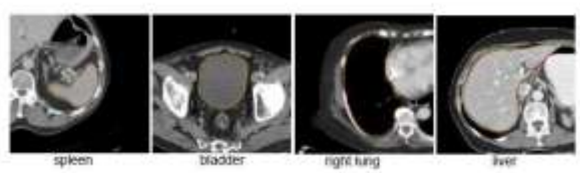

Figure 3. High quality segmentations of some selected organs.

Based on the color pixels of a feature extracted image hash value is generated. Perceptual hashing generation

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method is used and the hash value is represents in binary and hexadecimal format.
The query-image hash string is compared with the training set images. Similarity is measure in the basis of hamming distance score. Based on the score the similar images are retrieved. If the hamming distance score is too far when compared to query-image hash string then it is neglected.
The results are shown to user which contains the similar images and the corresponding hamming distance score. The system gives an option to examine the precision and recall by selecting the matched and unmatched image for all retrieved images via select box so that query result is evaluated.
Perceptual hashing is a robust algorithm widely used for content identification. In our system, we used block-mean perceptual hashing algorithm where the algorithm takes the color pixels of an image to generate the hash value. The study says P-hash is reliable and fastest algorithm. In this methodology, similar like Block-Mean value Perceptual hashing image color mean value hashing technique is used. Where the hash string is generated using the color of an images. Pixel color average is taken as mean value based on the average rate the hash string is formed. The image is scaled to defined small size.
The original annotated keywords are used for automatic annotation. The keywords are classified and categorized based on the image id. Each category has a unique id and in the case of images, it is categorized based on the id. The automatic annotation works depend upon the retrieved images and its id with corresponding categorized keyword.

Output:
The system is using different process in which input image is examined and result is obtained
based on id.

CONCLUSIONS

We conclude that Perceptual hashing algorithm has very high robustness and in the CBIR it would be useful. This novel approach could be used in Medical diagnostic centre or Research Medical Hospitals for case-based reasoning.

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