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Content based medical image retrieval using dictionary learning

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ABSTRACT

In this paper, a clustering method using dictionary learning is proposed to group large medical databases. An approach grouping similar images into clusters that are sparsely represented by the dictionaries and learning dictionaries simultaneously via *K*-SVD is proposed. A query image is matched with the existing dictionaries to identify the dictionary with the sparsest representation using an Orthogonal Matching Pursuit (OMP) algorithm. Then images in the cluster associated with this dictionary are compared using a similarity measure to retrieve images similar to the query image. The main features of the method are that it requires no training data and works well on the medical databases which are not restricted to specific context. The performance of the proposed method is examined on IRMA test image database. The experimental results demonstrate the efficacy of the proposed method in the retrieval of medical images.

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1. Introduction

The problem of searching for similar images in a large image repository based on content is called Content Based Image Retrieval (CBIR) [1]. The traditional Text Based Image Retrieval (TBIR) approach has many practical limitations [2] like the images in the collection being annotated manually, which becomes more difficult as the size of the image collection increases. Another important limitation is the inadequacy in representing the image content. CBIR approaches are proposed to overcome the limitations of text based image retrieval.

As more and more hospitals purchase *picture archiving and communication systems* (PACS), the medical imagery world wide is increasingly acquired, transferred and stored digitally [3]. The increasing dependence on modern medical diagnostic techniques like radiology, histopathology and computerized tomography has led to an explosion in the number of medical images stored in hospitals. Digital image retrieval technique is crucial in the emerging field of medical image databases for clinical decision making process. It can retrieve images of similar nature (like same modality and disease) and characteristics. The images of various modalities are becoming an important source of anatomical and functional information for the diagnosis of diseases, medical research and education [4]. In a typical CBIR system in medical domain, subtle differences between images cannot be considered irrelevant. Consequently, a Content Based Medical Image Retrieval (CBMIR) system having a kind of invariance (with respect to any transformation) is of value [5,6].

The major limitations associated with existing medical CBIR are (1) in most cases, physicians have to browse through a large number of images for identifying similar images, which takes lot of time. (2) Most of the existing tools for searching medical images use text based retrieval techniques. The text based image retrieval suffers from several limitations [7] such as the need for manual annotation. Thus, the existing medical image search and retrieval techniques are not very efficient in terms of time and accuracy. Another important issue in medical CBIR is to find images with similar anatomical regions and diseases. For example, in the case of brain tumor images, the tumor can be at any of the different stages and an image of the tumor in a state could be in any orientation [6,32]. So, there is a need for invariant medical image retrieval technique to find images of a similar (same stage) tumor.

Of late, sparse representation received a lot of attention from the signal and image processing communities. Sparse coding involves the representation of an image as a linear combination of some atoms in a dictionary [12]. It is a powerful tool for efficiently processing data in nontraditional ways. This is mainly due to the fact that signals and images of interest admit sparse representation

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in some dictionary, which may be identified based on the properties of signals at hand. Recently, dictionaries learnt from the data were found to have potential for several applications. Several interesting dictionary learning methods like *K*-SVD [8] and Method of Optimal Directions (MOD) [13] were developed to provide each member of database with sparse representation. The emerging filed of compressed sensing has a potential for exploiting sparsity present in medical images. This work is an attempt towards proposing a new CBMIR technique that relies on sparsity based concepts.

In particular, we propose a dictionary based clustering algorithm for grouping the images in medical databases. This clustering technique increases the retrieval speed and improves the accuracy of the results. The dictionary based methods rely on the premise that two signals belonging to the same cluster have decomposition in terms of similar atoms (columns) of a dictionary. Making use of this property, we match the input query with the appropriate cluster. The selection of features for adequately representing the class specific information is an important step in CBIR. For this, we divide the image into four sub-images of equal size. In addition, we consider another sub-image which is of same size as other four sub-images to capture the rich information available at the center of medical images. We then partition each sub-image into concentric circular regions around the center, and consider the mean and variance of pixel intensities in each region as components in the feature vector. Some image retrieval methods were proposed in the literature which made use of SVM [9–11]. It is to be emphasized here that K-SVD and SVM based methods are different in the sense that K-SVD is a dictionary learning approach banking on the concept of sparsity, which is not the case with SVM. While SVM requires some training data, the way we use K-SVD in the present work does not require any labeled data. The present CBMIR technique centers around images produced in radiology. As color and shape features are of less importance in medical domain [3], we use texture features in the present work.

The work done in this paper has the objective of categorizing (and retrieving) radiological images consisting of different organs, modality, views. We demonstrate the usefulness of our approach through extensive experimental results. For a given *N*, the number of clusters, we design *N* dictionaries to represent the clusters. We associate an image of database to a dictionary based on the sparsity criterion. Given a query image, we invoke the concept of sparsity to identify appropriate cluster, wherein we search for relevant images. The rest of the paper is organized as follows: Sections 2 and 3 give brief accounts of a survey of related works and dictionary learning. Section 4 presents the proposed content based medical image retrieval using dictionary learning method. Experiments of CBMIR application are discussed in detail in Section 5. Finally, Section 6 concludes this paper.

2. Related work

Chu et al. [16] described a knowledge based image retrieval of computed tomography (CT) and magnetic resonance imaging (MRI) images. In this approach, the brain lesions were automatically segmented and represented through a knowledge based semantic model. Cai et al. [17] proposed a CBIR system for functional dynamic positron emission tomography (PET) images of the human brain, where clusters of tissue time activity from the temporal domain were used in the computation of similarity measure for retrieval. In [18], the delineations of the regions of interest were manually performed on the key frame from the stack of high resolution CT images. These were used as features to represent the entire image.

In the Bag-Of-Words (BOW) [5] framework, the image patches were sampled densely or sparsely by "interest points" detectors and were depicted by local patch descriptors like SIFT. These descriptors were used to classify liver lesions in CT images. In [6], a texture based analysis of lung CT images was proposed through Riesz wavelets. This method used SVM to learn the respective relevance of multiscale components. Guimond et al. [19] introduced user-selected volume of interest (VOI) for the retrieval of pathological brain MRI images. In [21], group sparse representation with dictionary learning for medical image denoising and fusion was used. Wavelet optimization techniques for content based image retrieval in medical database were described in Quellec et al. [22]. Linear discriminate analysis (LDA) based selection and feature extraction algorithm for classification and segmentation of one dimensional radar signals and two-dimensional texture and document images using wavelet packet was proposed by Etemand and Chellappa [23]. Recently, similar algorithms for simultaneous sparse signal representation and discrimination were proposed [24–29]. In [30], Chen et al. proposed in-plane rotation and scale invariant clustering using dictionaries. This approach provides Radon-based rotation and scale invariant clustering as applied to content based image retrieval on Smithsonian isolated leaf, Kimia shape and Brodatz texture datasets. Fei et al. [31] described a CT image denoising based on sparse representation using global dictionary. This approach improved low dose CT abdomen image quality through a dictionary learning based denoising method and accelerated the training time at the same time. Different classes of images (produced by different departments such as dermatology and pathology) were dealt with differently for applications such as CBIR. An excellent review of the state-of-the-art of CBMIR and future directions was presented in [32]. Several multi-resolution analysis techniques via wavelet, ridgelet, and curvelet-based texture descriptors were discussed for CBMIR [33]. The algorithm proposed therein identified various tissues based on the discriminative texture features with the aid of decision tree classification. This method too incorporated some training data for realizing its objectives.

The present paper, nevertheless, has the objective of categorizing medical images that are not restricted to a specific context. In applications of digital radiology such as computer aided diagnosis or case based reasoning, the image category is of importance [3]. It may be emphasized here that our method

- requires no training data for the classification (and retrieval) of medical data, which is in contrast to existing methods

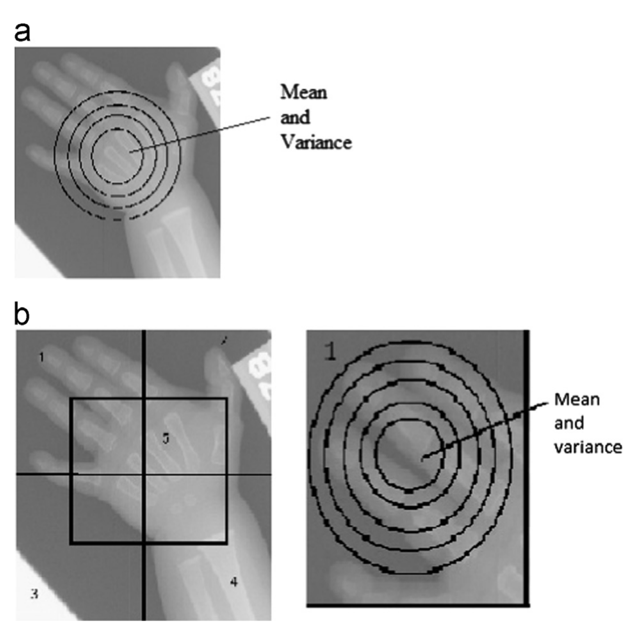

Fig. 1. Proposed feature extraction techniques: (a) image is partitioned into concentric circular regions of equal area. (b) Image is divided into sub-images and each sub-image is partitioned into concentric circular regions of equal area.

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