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Interactive radiographic image retrieval system

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ABSTRACT

Background and Objective: Content based medical image retrieval (CBMIR) systems enable fast diagnosis through quantitative assessment of the visual information and is an active research topic over the past few decades. Most of the state-of-the-art CBMIR systems suffer from various problems: computationally expensive due to the usage of high dimensional feature vectors and complex classifier/clustering schemes. Inability to properly handle the "semantic gap" and the high intra-class versus inter-class variability problem of the medical image database (like radiographic image database). This yields an exigent demand for developing highly effective and computationally efficient retrieval system.
Methods: We propose a novel interactive two-stage CBMIR system for diverse collection of medical radiographic images. Initially, Pulse Coupled Neural Network based shape features are used to find out the most probable (similar) image classes using a novel "similarity positional score" mechanism. This is followed by retrieval using Non-subsampled Contourlet Transform based texture features considering only the images of the pre-identified classes. Maximal information compression index is used for unsupervised feature selection to achieve better results. To reduce the semantic gap problem, the proposed system uses a novel fuzzy index based relevance feedback mechanism by incorporating subjectivity of human perception in an analytic manner.
Results: Extensive experiments were carried out to evaluate the effectiveness of the proposed CBMIR system on a subset of Image Retrieval in Medical Applications (IRMA)-2009 database consisting of 10,902 labeled radiographic images of 57 different modalities. We obtained overall average precision of around 98% after only 2–3 iterations of relevance feedback mechanism. We assessed the results by comparisons with some of the state-of-the-art CBMIR systems for radiographic images.
Conclusions: Unlike most of the existing CBMIR systems, in the proposed two-stage hierarchical framework, main importance is given on constructing efficient and compact feature vector representation, search-space reduction and handling the "semantic gap" problem effectively, without compromising the retrieval performance. Experimental results and comparisons show that the proposed system performs efficiently in the radiographic medical image retrieval field.

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1. Introduction

Over the last few decades, extensive attempts have been made by various researchers to develop Content Based Medical Image Retrieval (CBMIR) systems for efficient management and access of medical image data. In large hospitals and diagnostic centers, several terabytes of digital medical images are generated and stored every year [1–3]. In today's health-care framework, these images are archived in Picture Archiving and Communication Systems (PACS) [4–6]. For precise diagnosis and treatment planning, often the medical personnel has to browse through similar images in these archives. This necessitates the requirement of developing novel and intelligent techniques for searching images accurately and efficiently from a large medical image database [7–9]. Such systems have immense applications in today's modern health-care domain: not only can these systems be used to reduce the workload of the medical personnel, but these can also be used as cost-effective alternatives in places where medical experts are lacking [2,7,10–12].

The commonly used textual metadata based image retrieval systems have several shortcomings: costly, time-consuming, dependency on the experience of the human annotator, error-prone (error rate up to 16% have been reported) and inefficiency to represent the true content of the medical image semantically [6,13]. Another open challenge for automatic categorization of medical images is the inter-class versus intra-class variability problem [6,7,11]. For instance, considering the X-ray images of Image Retrieval in Medical Applications (IRMA-2009) database [4,14], Fig. 1(a1)-(a2) illustrates the high degree of visual content variability within a particular class. Here, all the radiographs of Fig. 1(a1)-(a2) are plain X-ray images in coronal posterioanterior direction of abdomen body region and of the musculoskeletal biosystem having the same class level. On the other hand, there may be strong visual similarities across different image classes, especially with classes that have the same organ projected at different angles. For example, the image of the Fig. 1(b1) belongs to the "neck" class while the image of Fig. 1(b2) belongs to the "neck side view" class. This is mainly due to different doses of X-ray, varying orientation, alignment and pathology [6]. Moreover, often the images have different contrast variations and non-uniform intensity background, weak signal-to-noise ratio (SNR), projection and other noises [6,15–17].

X-ray radiography is a powerful imaging tool (both in medical and industrial fields), which allows visualization of an object's internal and external structures [12,14,18–20]. Several image retrieval prototypes have been proposed by various researchers for medical radiographs [6,12,14,17,21–24]. For example, Keysers et al. [25] have introduced a Bayesian probabilistic framework for radiograph classification based on an appearance-based approach combining tangent distant measure and image distortion model. Presenting an extensive evaluation of different methods for automatic classification, Lehmann et al. in [26] have proposed a radiographic image categorization scheme using a parallel combination of single classifiers (k-nearest neighbor) based on scaled representations and global texture features. Pinhas et al. [6] have achieved 97.5% accuracy in classifying 1500 radiography images of 17 categories using a Gaussian Mixture Model Kullback–Leibler (GMM-KL) framework based on a high-dimensional feature vector. In Ref. [27], Rahman et al. have presented a novel machine learning based image pre-filtering approach based on a combination of a statistical similarity matching and relevance feedback (RF) scheme. On a database of 9100 medical X-ray images of 40 classes Pourghassem et al. [21] have achieved approximately 94% accuracy (merged 17 classes) using a merging-based hierarchical classifier. Avni et al. [28] have proposed a "bag of visual words" CBMIR approach based on a non-linear kerna-based support vector machine (SVM). Rahman et al. [24] have designed an iterative CBMIR system using bag of features using a query-specific adaptive linear combination of similarity matching approach by relying on the image classification and feedback information from users. Achieving 93% retrieval accuracy, a hierarchical classification structure based on a novel merging and splitting scheme using shape and texture features is proposed by Fesharaki et al. in Ref. [17]. A novel CBMIR system based on a score fusion algorithm for query image classification and a new query expansion method in the relevance feedback level is proposed by Behnam et al. [29]. A novel dictionary learning based clustering method for CBMIR is proposed by Srinivas et al. [30] using mean and variance of pixel intensity values as features based on the K-SVD and orthogonal matching pursuit mechanisms. Recently, few deep neural network based CBMIR systems have been proposed showing promising results [31,32].

Most of the abovementioned CBMIR systems are non-hierarchical and based on single classification/clustering technique using different combinations of feature representation schemes. But it is difficult for a non-hierarchical classification/clustering method to effectively handle the overlapping (inter-vs.-intra class variability) of different classes of medical images [17,21]. Also, due to the use of relatively expensive classifier/clustering scheme, overall cost of computation remains fairly high in these systems. Moreover, in case of hierarchical CBMIR systems, if pre-classification of the query image is wrong, then the retrieval results will be wrong, which results in lowering the accuracy of the system. Furthermore, the dimensions of the image representative feature vectors used in these systems are quite high. This also leads to further computational burden. Even with using such computationally expensive classifier/clustering schemes along with high

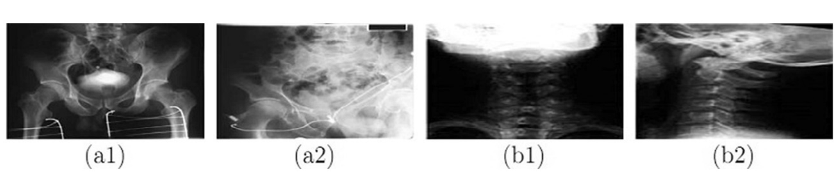

Fig. 1 – Intra-class variability: (a1)-(a2) vs. inter-class variability: (b1)-(b2) (considering IRMA categorization [4]).