Journal of King Saud University – Computer and Information Sciences (2016) 28, 110–124

King Saud University

Journal of King Saud University – Computer and Information Sciences

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A unified learning framework for content based medical image retrieval using a statistical model

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Received 22 October 2013; revised 3 June 2014; accepted 23 October 2014
Available online 31 October 2015

KEYWORDS

Full Range Autoregressive Model;
Bayesian approach;
Color autocorrelogram;
Edge orientation autocorrelogram;
Micro-textures;
Relevance feedback

Abstract This paper presents a unified learning framework for heterogeneous medical image retrieval based on a Full Range Autoregressive Model (FRAR) with the Bayesian approach (BA). Using the unified framework, the color autocorrelogram, edge orientation autocorrelogram (EOAC) and micro-texture information of medical images are extracted. The EOAC is constructed in HSV color space, to circumvent the loss of edges due to spectral and chromatic variations. The proposed system employed adaptive binary tree based support vector machine (ABTSVM) for efficient and fast classification of medical images in feature vector space. The Manhattan distance measure of order one is used in the proposed system to perform a similarity measure in the classified and indexed feature vector space. The precision and recall (PR) method is used as a measure of performance in the proposed system. Short-term based relevance feedback (RF) mechanism is also adopted to reduce the semantic gap. The Experimental results reveal that the retrieval performance of the proposed system for heterogeneous medical image database is better than the existing systems at low computational and storage cost.

1. Introduction

Medical images play a vital role in disease analysis, education, research, etc. Evolution of computer vision and digital imaging modalities has generated a vast amount of digital images in the medical domain. Consequently, the task of retrieving heterogeneous medical images from a large-scale image database becomes more difficult than ever before for a computer vision system due to the noise, variation in size, shape, color, illumination, etc. Hence, it is necessary to build up an appropriate system for medical image retrieval with efficient storage and effective retrieval to assist the physicians.

The conventional text-based image retrieval systems use textual keywords that are manually annotated on images. With the vast and diversity of images, textual keywords hold the disadvantages of laborious, tedious and time-consuming. Moreover, the manual annotation of the images strongly depends on what the users focus on and it may vary between persons, and also vary in time for the same person. Thus, textual keywords are inefficient in providing sufficient and distinctive discriminatory power of the images (Stricker and Orengo, 1995; Rui et al., 1999). The picture archival and communication

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Peer review under responsibility of King Saud University.

ELSEVIER Production and hosting by Elsevier

http://dx.doi.org/10.1016/j.jksuci.2014.10.006
1319-1578

system (PACS) (Müller et al., 2004) compliant with digital imaging and communications in medicine (DICOM) format is used by most hospitals to handle huge collections of medical images. The PACS uses textual information stored in the DICOM header such as patient identity, date, type of examinations, modality, body parts examined, etc. for the image retrieval operations. The literature reveals (Müller et al., 2004) that the DICOM headers include a high rate of errors and storing the DICOM format images in any of the compressed formats such as JPEG, TIFF, etc. leads to loss of DICOM header information. In order to improve the performance of PACS, content based image retrieval (CBIR) techniques have been proposed by several researchers in the PACS environment (Müller et al., 2004). Consequently, a number of researches have been focused on content based medical image retrieval (CBMIR) to facilitate the physicians such as CBMIR system for HRCT images of the lung (Shyu et al., 1999), PET images of the human brain (Cai et al., 2000), X-ray images of the human cervical and lumbar spines (Long and Thoma, 2001), histological images of GI tract (Tang et al., 2003), CT images of chest (Yu and Chiang, 2004), a PathMiner system for pathological images (Chen et al., 2005), X-ray images of spine (Hsu et al., 2009), X-ray images of chest (Avni et al., 2010), mammogram images of breast (Wei et al., 2011), etc. However, the aforesaid literature is distinct to modalities, biological system, body orientation etc.

In the last two decades, only a little effort has been taken to develop a framework for heterogeneous medical image retrieval. For instance, Orphanoudakis et al. (1994) reported I^2C system based on object oriented architecture and it uses global level image features for image indexing, storage and retrieval. KMeD (Knowledge based multimedia medical distributed database) system presented by Chu et al. (1998) exploits four semantic layers for information modeling and it uses shape, texture and alphanumeric information with spatial and temporal constructs for image retrieval. El-Kwae et al. (2000) introduced a system called COBRA, which is an open architecture based on widely used healthcare and technology standards and it improves the capability of PACS by exploiting global level color, shape and texture features extracted from the automatic segmented image regions. The MedGIFT/GIFT (GNU Image Finding Tool) (Müller et al., 2005) is also an open source framework for medical image retrieval. It uses textual features and visual features such as Gabor blocks, histogram of Gabor filter responses, color blocks and global color histogram for image retrieval. The IRMA (Image Retrieval for Medical Applications) system presented by Lehmann et al. (2005) and Güld et al. (2007) employs six semantic layers to formalize the local level features and their spatial relationship. Rahman et al. (2007) presented a probabilistic multi-class support vector machine (SVM) learning based image pre-filtering scheme with the combination of statistical similarity measure and relevance feedback (RF) mechanism. Later, a retrieval framework based on feature and similarity level fusion is proposed by Rahman et al. (2008). Subsequently, Rahman et al. (2009) developed a framework in which the images are represented in local visual and semantic concept based feature spaces toward semantic based image retrieval by utilizing the self-organizing map (SOM) and multi-class SVM. Furthermore, an advance in feature representation and similarity matching techniques of the aforesaid work (Rahman et al., 2009) is reported in Rahman et al. (2011).

Recently, a multimodal hierarchical modality classification approach for image filtering system is reported by Rahman et al. (2013) for retrieving heterogeneous medical images and it uses color layout descriptor (CLD), edge histogram descriptor (EHD), color moments, gray level co-occurrence matrix (GLCM), edge frequency, primitive length, Gabour moments, Tamura moments, Scale Invariant Feature Transform (SIFT), Local binary pattern (LBP), LBP-I, color and edge directivity descriptor (CEDD), fuzzy color and texture histogram (FCTH), autocorrelation coefficient as visual features and "Bag of words" as textual feature to represent the image. The "Bag of words" contains image-related text such as title, modality, region of interest, problem, anatomy of the image, etc.

Subsequently, Sudhakar and Bagan (2014) described a heterogeneous medical image retrieval framework, which performs phase congruency process in L*a*b* color space to extract edge co-operative maps and is processed using the SIFT to drive keypoints. The extracted keypoints are quantized to build a codebook using Spherical Self-Organizing Map (SOM) built with a geodesic data structure.

Although many research works have been contributed to CBMIR, the retrieval accuracy of the existing CBMIR systems for heterogeneous medical image database is still limited and unsatisfactory due to the lack of techniques used to extract the efficient and effective features of the medical images.

Though the system presented by Rahman et al. (2013) has shown significantly better results when compared to the systems previously reported in the literature, the high dimensionality of the feature vector results in high computational and storage cost. Correspondingly, even if the system reported by Sudhakar and Bagan (2014) uses low feature vector dimension than the system of Rahman et al. (2013), it results in less retrieval accuracy and the feature vector dimension is also not significantly less.

The main objective of the proposed system is to develop a more accurate, and cost effective systems for supporting physicians. Thus, the proposed system employed the color autocorrelogram (Huang et al., 1997; Chun et al., 2008; Penatti et al., 2012) to represent color and its spatial information, edge orientation autocorrelogram (EOAC) to represent shape and its spatial information and micro-textures (Seetharaman and Palanivel, 2013) to represent global and local level texture information of the gray-scale and color medical images respectively. The proposed features are extracted automatically by using a framework based on FRAR model with the BA (Seetharaman and Krishnamoorthi, 2007; Seetharaman and Palanivel, 2013), which avoids the cumbersome process owing to the complementariness of techniques used for extracting various kinds of visual features.

Mahmoudi et al. (2003) constructed EOAC using the edges detected by the Sobel edge detector, which is sensitive to noise and fails to detect very minute and fine edges. Moreover, the Sobel edge detector extracts the edges of color images from its gray-scale version, which leads to loss of some edges due to chromatic changes and also detecting the edges from H or S or V component image loses some edges due to the spectral variations (Liu et al., 2011), which might play a significant role in efficient medical image retrieval.

Medical images are more complex in structure and diverse in the collection. Specifically, the microscopic images are far more complicated and diverse than other types of medical images and contains many different and minute cytological