Computer Methods and Programs in Biomedicine 158 (2018) 53–69

Contents lists available at ScienceDirect

Computer Methods and Programs in Biomedicine

journal homepage: www.elsevier.com/locate/cmpb

A novel biomedical image indexing and retrieval system via deep preference learning☆

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ARTICLE INFO

Article history:
Received 1 May 2017
Revised 23 November 2017
Accepted 2 February 2018

Keywords:
Biomedical image retrieval
Deep learning
Convolutional neural network
Preference learning

ABSTRACT

Background and Objectives: The traditional biomedical image retrieval methods as well as content-based image retrieval (CBIR) methods originally designed for non-biomedical images either only consider using pixel and low-level features to describe an image or use deep features to describe images but still leave a lot of room for improving both accuracy and efficiency. In this work, we propose a new approach, which exploits deep learning technology to extract the high-level and compact features from biomedical images. The deep feature extraction process leverages multiple hidden layers to capture substantial feature structures of high-resolution images and represent them at different levels of abstraction, leading to an improved performance for indexing and retrieval of biomedical images.
Methods: We exploit the current popular and multi-layered deep neural networks, namely, stacked denoising autoencoders (SDAE) and convolutional neural networks (CNN) to represent the discriminative features of biomedical images by transferring the feature representations and parameters of pre-trained deep neural networks from another domain. Moreover, in order to index all the images for finding the similarly referenced images, we also introduce preference learning technology to train and learn a kind of a preference model for the query image, which can output the similarity ranking list of images from a biomedical image database. To the best of our knowledge, this paper introduces preference learning technology for the first time into biomedical image retrieval.
Results: We evaluate the performance of two powerful algorithms based on our proposed system and compare them with those of popular biomedical image indexing approaches and existing regular image retrieval methods with detailed experiments over several well-known public biomedical image databases. Based on different criteria for the evaluation of retrieval performance, experimental results demonstrate that our proposed algorithms outperform the state-of-the-art techniques in indexing biomedical images.
Conclusions: We propose a novel and automated indexing system based on deep preference learning to characterize biomedical images for developing computer aided diagnosis (CAD) systems in healthcare. Our proposed system shows an outstanding indexing ability and high efficiency for biomedical image retrieval applications and it can be used to collect and annotate the high-resolution images in a biomedical database for further biomedical image research and applications.

1. Introduction

1.1. Motivation

As one of the most valuable visual resources and references, biomedical images play an important role for physicians and biomedical researchers in the field of biomedical analysis and disease diagnosis and treatment [1,2]. In addition, owing to broad applications of biomedical image technology [3], a wide variety of images are generated by numerous biomedical imaging devices and stored in a multitude of formats, including X-ray, ultrasound (US), magnetic resonance imaging (MRI) and computer tomography

☆ This work was supported by the project of Science and Technology Development Plan of Jilin Province, China (Grant 20150204007GX) and Specialized Research Fund for the Doctoral Program of Higher Education of China (Grant 20120061110045), and National Natural Science Foundation of China (Grants 61702214, 51409117, 51679105).

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https://doi.org/10.1016/j.cmpb.2018.02.003

(CT) [4]. It is, however, extremely hard and unfeasible for experts to manually distinguish and annotate all the images produced and collected from hospitals and medical institutions. In order to better serve the doctors and accelerate the process of biomedical image processing, we should make the utmost use of biomedical image data and further promote computer-aided diagnosis (CAD) technology in intelligent healthcare.

Therefore, on the one hand, we need to make sure that biomedical images can be searched and retrieved efficiently to facilitate their effective use by researchers and practitioners alike. On the other hand, allied computer-aided diagnosis technology, such as our proposed intelligent biomedical image indexing and retrieval system, is also necessary to assist physicians and biomedical practitioners in the diagnosis and care of patients. In particular, assuming that there are large collections of biomedical images of different diseases from various body parts in different formats and sizes, one of the most important challenges is to develop biomedical image indexing and retrieval methods and techniques that are both accurate and efficient [5]. When given a patient image captured by modern medical equipment, that is, a query, an effective biomedical image retrieval system should index and return the reports of the relevant patient images which have been structured and stored before with detailed diagnostic messages and clinical reports for this kind of a disease condition. Such a biomedical image retrieval system could assist doctors and physicians effectively by improving the speed and accuracy of the identification of an exact disease condition and will prove to be an indispensable technological innovation in healthcare.

1.2. Related work

To meet the requirements for biomedical image analysis, content-based image retrieval (CBIR) technology has been widely investigated in the literature. The existing CBIR technology used in biomedical image indexing and retrieval leverages conventional visual cues to represent all the biomedical images in an image database. The traditional visual content descriptors used in the systems include color histograms, edges, texture, shape and a wide variety of their variants. As we can see from the previous works [6–17], feature extraction in CBIR, has become a key factor in the success of biomedical image indexing and retrieval systems, which aims at removing redundant information through reducing the dimensions of the image data [18,19]. The visual feature descriptors can be broadly categorized into global features and local features of images. As is known, global features of images can be easily disturbed by illumination, size and rotation interferences. Local features can effectively combat such problems, but most of the existing CBIR methods for biomedical image retrieval have mainly used global features [6–10,16,17].

For instance, Muller et al. [6] proposed a medical image retrieval method based on CBIR in a medical case database, by comparing different features with color quantization and texture analysis. Quellec et al. [7] exploited wavelet transforms to construct an image signature from pixel values in a given image. Scott and Shyu [8] directly used the combinations of texture and spectral analysis, shape descriptors and morphological features to generate an image feature vector, and then focused on building an entropy balanced statistical k-d tree to speed up the retrieval of biomedical images. Rahman et al. [9] proposed a retrieval framework by exploiting the link between classification and retrieval of biomedical images. The supervised learning process used in their work aims to filter out irrelevant images based on image categories. However, feature extraction still relies on a combined color and texture feature vector. Quddus and Basir [10] proposed a novel technique for retrieving 2D MR images in 3D brain volumes, using multiscale wavelet decompositions (WTM) to detect and produce multiscale edge information of 2D images and corresponding feature vectors. Wei et al. [16] used shape and margin features to represent the characteristics of mammographic lesions in order to exploit the valuable resources in aiding medical diagnoses and research. De Oliveira et al. [17] presented a new medical image retrieval system using two-dimensional principal component analysis based on texture features.

In recent years, the newest and most popular methods for biomedical image retrieval have focused on local features. One of the local features, the Local Binary Pattern (LBP) descriptor introduced by Ojala et al. [11], has been widely used for biomedical image indexing and retrieval. LBP efficiently depicts the fundamental property of a local image structure and has the rotation invariant characteristic based on grayscale. Due to the highly efficient performance of LBP as a feature representation of biomedical images, several different and improved variants of LBP have been proposed in biomedical image retrieval [12–15].

For instance, Murala and Wu [12] proposed a local mesh pattern (LMP) for biomedical image indexing and retrieval. In LMP, the relationship among the surrounding neighbors for a given referenced pixel is encoded. Dubey et al. [13] considered not only the relationship between the center pixel and the local neighboring information but also the relationship among the local neighboring pixels in their local wavelet pattern (LWP). To calculate the value of LWP, they used local wavelet decomposition and transformed center pixel values. The peak valley edge pattern (PVEP) for biomedical image retrieval applications introduced by Murala and Wu [14] can represent the local region of an image, where the directional edge information is extracted based on the first-order derivative with four directions in an image. Dubey et al. presented a local bit-plane decoded pattern (LBDP) with the local bit-plane transformed values as a modified feature descriptor for indexing biomedical images [15].

Due to the large computation workload and high dimensionality of local features, most of the biomedical image indexing methods usually result in a low retrieval efficiency and incur a high online calculation cost, which makes it hard to satisfy the practical needs. Very recently, deep learning technology has been introduced for biomedical image classification in a relevant study [20], but research in this direction still very scarce. Meanwhile, a remarkable progress has been made in various computer vision areas, primarily due to the appearance of large-scale annotated image datasets and high computing capability of GPUs. However, in biomedical or medical imaging domains, there are still no other benchmark datasets that are as comprehensively annotated like ImageNet [21,22]. Furthermore, there have been only several studies [23–25] leveraging deep learning for biomedical image indexing and retrieval. Kundu et al. [23] proposed to use coupled neural networks and shape features as a novel feature vector to represent medical radiographic images. Pei [24] first trained a convolutional neural network on a large collection of medical images, however, the used emphysema database has only 168 images. So, he subsequently trained a network with 25,000 CT images generated by following the same parameters from the emphysema database. However, this method has a weak applicability to different sizes of images for training or testing and it needs a long time to return the retrieval result in its online training process. Karabulut and Ibrikci [25] used the Caffe deep learning framework [20] to build and train their deep neural network from scratch to discriminate emphysema subtypes from Raw HRCT images. However, this method uses 138 images out of 168 database images to train its model and another set of 30 images as the testing dataset, and hence the small training dataset may result in an overfitting problem. Besides, the online training process cannot meet the real-time requirements in biomedical image retrieval applications. Recently, a system for biomedical image indexing and retrieval has been pro-