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Editorial

Large-Scale medical image analytics: Recent methodologies, applications and Future directions

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ABSTRACT

Despite the ever-increasing amount and complexity of annotated medical image data, the development of large-scale medical image analysis algorithms has not kept pace with the need for methods that bridge the semantic gap between images and diagnoses. The goal of this position paper is to discuss and explore innovative and large-scale data science techniques in medical image analytics, which will benefit clinical decision-making and facilitate efficient medical data management. Particularly, we advocate that the scale of image retrieval systems should be significantly increased at which interactive systems can be effective for knowledge discovery in potentially large databases of medical images. For clinical relevance, such systems should return results in real-time, incorporate expert feedback, and be able to cope with the size, quality, and variety of the medical images and their associated metadata for a particular domain. The design, development, and testing of the such framework can significantly impact interactive mining in medical image databases that are growing rapidly in size and complexity and enable novel methods of analysis at much larger scales in an efficient, integrated fashion.

1. Introduction

An important goal in medical image analytics is transforming raw images into a quantifiable symbolic form for indexing, reasoning and analysis. This task, of interest to medical imaging research, medical practice and the healthcare industry, is challenging because medical image content quantification is complex and not a solved problem. More importantly, few methods are able to analyze large-scale medical image databases (e.g., hundreds of thousands of images or more) in real-time, let alone to incorporate user-provided criteria or domain knowledge interactively. These are important requirements for medical doctors to analyze and use these databases. These drawbacks limit the effectiveness of current approaches in medical imaging research and industry applications to analyze the ever-growing number of medical images stored digitally.

Given the fact that the development of large-scale medical image analysis algorithms has lagged greatly behind the increasing quality (and complexity) of medical images and the imaging modalities themselves, there is an urgent need to develop innovative and integrated frameworks enabling robust and timely medical imaging and analysis, disease detection and characterization, and search in relevant databases. Recent advances in web-scale image analytics and multimodal databases have paved the way for large-scale, data-driven methods for robust detection and modeling, fine-grained disease classification, and semantic segmentation. In medical image analytics, the ever-increasing amount of medical images provides a foundation for novel semantic analysis methods. Transforming these raw medical images into a quantifiable, symbolic form will facilitate indexing and retrieval and potentially lead to new avenues of knowledge discovery and decision support (Fang et al., 2016). Therefore, it is now feasible to advance large-scale medical data analytics and information retrieval such that interactive systems can be effective for knowledge discovery in large databases of medical images.

This research direction needs a strong multidisciplinary component that involves a nexus of ideas from machine learning, image analysis, modeling, information retrieval and visual analytics. Conceptually, a potential solution can be considered consisting of three inter-related modules: (1) a robust parsing, modeling and segmentation module that provides automatic delineation and measurement of both healthy and abnormal cases, enabling effective extraction and analysis of information within specific regions, (2) a scalable learning-based image query module that retrieves instances among large databases in real-time, with morphological profiles most relevant and consistent to a query image for decision

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support, and (3) an intelligent visualization and interaction module that integrates a user's input using learning methods, for improved accuracy and performance of the system. In this paper, motivated by our own research methods and results, we elaborate on each of these modules, and also discuss potential future directions.

2. Robust segmentation and modeling

An essential first step in medical image analytics is to locate and segment regions-of-interest (e.g., organs, cells) in images before extracting important features. Image segmentation in images is a key step in almost all medical image analysis methods. Despite the intense research in this area, automated and robust medical image segmentation is still an unsolved problem, due to many factors, such as imaging texture non-uniformity inside and outside organs, complex organ shape, limitations of imaging methods, scanner variability, imaging artifacts and image noise. To address these issues we have pioneered the use of deformable models as methods for simultaneous segmentation and modeling of medical imaging methods (Metaxas, 1997). Deformable models are curves or surfaces that move under the influence of internal smoothness and external image forces. There are two major classes of deformable models: parametric (explicit) models and geometric (implicit) models. Physics-based parametric models represent deformable curves and surfaces in their parametric form and deform the model by minimizing an energy function (Kass et al., 1988). Geometric deformable models represent curves and surfaces implicitly as level sets of a higher dimensional scalar function (Chan and Vese, 2001; Osher and Fedkiw, 2006). Despite the different formulations and implementations of these models, many of them rely on primarily edge information from image gradient to derive external image forces to drive a shape-based model. Thus, they are sensitive to image noise and artifacts.

To address these limitations, we developed a new class of deformable models, named "Metamorphs" (Huang and Metaxas, 2008). This method naturally integrates both shape and texture information and unifies the boundary and interior region information into a variational framework. The novelty of this approach is that the model is a deformable disk, where the probability density function of the interior texture also changes while both the interior texture and the boundary information modify the shape/volume of the deformable model. This type of method is suitable for medical image segmentation, where both boundary and texture information are important, while the texture is non stationary. When available, shape priors (Cootes et al., 1995; Heimann and Meinzer, 2009) have proved to be an effective strategy to ensure the robustness of deformable models, since they ensure that the segmented result follows the shape patterns learned from a training database. Inspired by compressed sensing, we proposed sparse representation-based shape priors for robust segmentation (Zhang et al., 2012), based on the observation that a small subset of the existing data is necessary to represent the statistical variation of shapes. Therefore, this extension leads to less sensitivity to weak or misleading image appearance cues. Instead of assuming any particular parametric model of shape statistics, our method incorporates shape priors on-the-fly through Sparse Shape Composition to handle outliers, preserve shape details, or model complex shape variations in a unified framework. We employ two types sparsity: (1) given a large shape repository for an organ, a specific shape instance of the same organ can be approximated by the composition of a sparse set of instances in the shape repository; and (2) gross errors from local appearance cues might exist, but these errors are sparse in spatial space. By incorporating these two sparsity priors into deformable models, the model becomes robust to gross errors, and it can preserve shape details even if they are not statistically significant in the training repository. This shape composition method benefits both the model initialization and refinement. Together with our methods of deformable segmentation, we are able to delineate the contours accurately.

In order to model topologically complex organs we also introduced the incorporation of topological information into deformable models. For example, we have used them to obtain accurate segmentation of the papillary muscles and the trabeculae of the heart's left ventricle from high resolution CT images (Gao et al., 2013). This is critical in understanding the anatomical function and geometric properties of the heart and the formation of clots in case of pathologies, such as the cardiac hypertrophy. This novel coupling of deformable models with persistent homology ensures the accurate segmentation, modeling and analysis of the cardiac trabeculation (Fig. 1).

3. Efficient retrieval in large-Scale medical databases

Once segmentation results are acquired, we can extract image features and use them based on machine learning techniques for computer aided diagnosis (CAD) and decision support[1]. Traditional classification-based methods may not be efficient or effective enough to discover information in large-scale databases. In recent years, researchers have become increasingly interested in content-based image retrieval (CBIR) for medical image analysis. Compared to traditional classification methods, which directly compute the likelihood of the diagnostic result, large-scale CBIR approaches open a new avenue for mining knowledge from large data and supporting clinical diagnosis. Therefore, a new research area has emerged that requires the development of large scale analytic methods that are capable of efficiently analyzing large data sets. Specifically, it is necessary to design a scalable learning-based query system that allows users (e.g. doctors, medical school students) to search large-scale medical image databases at different levels in real-time. Users can query based on either the low-level region information, the mid-level tissue/object information, or the high-level annotation information, using different features. An example of such an approach for histopathological image analysis is shown in Fig. 2.

Regarding the workflow in Fig. 2, given cell detection and segmentation results (Xing and Yang, 2016), image data can be represented by various "signatures" or features, such as image histograms, local texture/shape features and bag-of-words, when comparing the similarity among different clinical cases. However, such features lie in a high-dimensional space, and there is a very large number of features in large databases. To address these challenges, we have proposed scalable query methods designed for high-dimensional features (Zhang et al., 2015a; 2015b). Specifically, we developed kernelized and supervised hashing methods for efficient retrieval in high dimensional feature spaces, and validated this preliminary work on the cell-level analysis of thousands of breast tissue images, for the image-guided diagnosis of intraductal breast lesions. Hashing has been widely used to compress high-dimensional features into binary codes with tens of bits (Wang et al., 2016). Therefore, such short binary features allow mapping easily into a hash table for real-time search. To improve the accuracy of traditional hashing methods, we incorporated a kernelized scheme to handle imaging data that are linearly inseparable, a common phenomenon of medical images. We also leveraged supervised information to design discriminative hash functions that are suitable for medical data retrieval. This supervised information incorporates domain knowledge into feature similarities and has the

[1] Deep neural networks have been widely investigated in this field for feature learning and/or CAD (Greenspan et al., 2016). In this paper, we do not provide a comprehensive review due to different focuses.