Visual Medical Information Analysis

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INTRODUCTION

Images have constituted an essential data source in medicine in the last decades. Medical images derived from diagnostic technologies (e.g., X-ray, ultrasound, computed tomography, magnetic resonance, nuclear imaging) are used to improve the existing diagnostic systems for clinical purposes, but also to facilitate medical research. Hence, medical image processing techniques are constantly investigated and evolved.

Medical image segmentation is the primary stage to the visualization and clinical analysis of human tissues. It refers to the segmentation of known anatomic structures from medical images. Structures of interest include organs or parts thereof, such as cardiac ventricles or kidneys, abnormalities such as tumors and cysts, as well as other structures such as bones, vessels, brain structures and so forth. The overall objective of such methods is referred to as computer-aided diagnosis; in other words, they are used for assisting doctors in evaluating medical imagery or in recognizing abnormal findings in a medical image.

In contrast to generic segmentation methods, techniques used for medical image segmentation are often application-specific; as such, they can make use of prior knowledge for the particular objects of interest and other expected or possible structures in the image. This has led to the development of a wide range of segmentation methods addressing specific problems in medical applications. In the sequel of this article, the analysis of medical visual information generated by three different medical imaging processes will be discussed in detail: Magnetic Resonance Imaging (MRI), Mammography, and Intravascular Ultrasound (IVUS). Clearly, in addition to the aforementioned imaging processes and the techniques for their analysis that are discussed in the sequel, numerous other algorithms for applications of segmentation to specialized medical imagery interpretation exist.

BACKGROUND

Magnetic Resonance Imaging

Magnetic Resonance Imaging (MRI) is an important diagnostic imaging technique attending to the early detection of the abnormal conditions in tissues and organs because it is able to reliably identify anatomical areas of interest. In particular for brain imaging, several techniques which perform segmentation of the brain structures from MRIs are applied to the study of many disorders, such as multiple sclerosis, schizophrenia, epilepsy, Parkinson's disease, Alzheimer's disease, and so forth. MRI is particularly suitable for brain studies because it is virtually noninvasive, and it achieves a high spatial resolution and high contrast of soft tissues. To achieve the 3D reconstruction of the brain morphology, several of the existing approaches perform segmentation on sequential MR images. The overall process usually includes noise filtering of the images and edge detection for the identification of the brain contour. Following, perceptual grouping of the edge points is applied in order to recover the noncontinuous edges. In many cases, the next step is the recognition of the various connective components among the set of edge points, rejection of the components that consist of the smallest number of points, and use of the finally acquired points for reconstructing the 3D silhouette of the brain, as will be discussed in more detail in the sequel.

Mammography

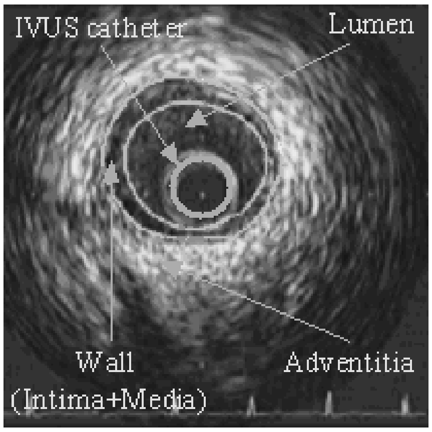
Mammography is considered to be the most effective diagnostic technique for detecting abnormal tissue conditions on women's breast. Being used both for prevention and for diagnostic purposes, it is a very commonly used technique that produces mammographic images by administering a low-dose of x-ray radiation to the tissue under examination. The analysis of the resulting images aims at the detection of any abnormal structures and the quantification of their characteristics, such as size and shape, often after detecting the pectoral muscle and excluding it from the further processing. Methods for the analysis of mammographic images are presented in the sequel.

Intravascular Ultrasound

IVUS is a catheter-based technique that renders two-dimensional images of coronary arteries and therefore provides valuable information concerning luminal and wall area, plaque morphology and wall composition. An example IVUS image, with tags explaining the most important parts of the vessel structure depicted on it, is shown in Figure 1. However, due to their tomographic nature, isolated IVUS images provide limited information regarding the burden of atherosclerosis. This limitation can be overcome through 3D reconstruction techniques in order to stack the sequential 2D images in space, using single-plane or biplane angiography for recovering the vessel curvature (Giannoglou et al., 2006; Sherknies, Meunier, Mongrain, & Tardif, 2005; Wahle, Prause, DeJong, & Sonka, 1999).

The analysis of IVUS images constitutes an essential step toward the accurate morphometric analysis of coronary plaque. To this end, the processing of IVUS images is necessary so that the regions of interest can be detected. The coronary artery wall mainly consists of three layers: intima, media and adventitia, while three regions are supposed to be visualized as distinguished fields in an IVUS image, namely the lumen, the vessel wall (made of the intima and the media layers) and the adventitia plus surroundings. The above regions are separated by two closed contours: the inner border, which corresponds to the lumen-wall interface, and the outer border representing the boundary between media and adventitia. A reliable and quick detection of these two borders in sequential IVUS images constitutes the basic step towards plaque morphometric analysis and 3D reconstruction of the coronary arteries.

Figure 1. Example IVUS image with tags explaining the most important parts of the vessel structure depicted on it



VISUAL MEDICAL INFORMATION ANALYSIS TECHNIQUES

Magnetic Resonance Imaging Analysis

Several techniques have been proposed for the analysis of MR images. In Grau, Mewes, Alcaniz, Kikinis, and Warfield (2004), a modification of a generic segmentation technique, the watershed transform, is proposed for knee cartilage and gray matter/white matter segmentation in MR images. This introduces prior information in the watershed method via the use of a previous probability calculation for the classes present in the image and via the combination of the watershed transform with atlas registration for the automatic generation of markers. As opposed to Grau et al. (2004), other methods are more application specific; in Woolrich, Behrens, Beckmann and Smith (2005), for example, segmentation tools are developed for the study of the function of the brain, that is, for the classification of brain areas as activating, deactivating, or not activating, using functional magnetic resonance imaging (FMRI) data. This method performs segmentation based on intensity histogram information, augmented with adaptive spatial regularization using Markov random fields. The latter contributes to improved segmentation as compared to nonspatial mixture models, while not requiring the heuristic fine-tuning that is necessary for nonadaptive spatial regularization previously proposed.

Because MR images contain a significant amount of noise caused by operator performance, equipment, or even the environment, the segmentation on them can lead to several inaccuracies. In order to overcome the effects of noise, Shen, Sandham, Granat and Sterr (2005) propose a segmentation technique based on an extension to the traditional fuzzy c-means (FCM) clustering algorithm. The segmentation performance is improved using neighborhood attraction, which depends on the relative location and features of neighboring pixels. The degree of attraction is optimized by applying a neural network model. Greenspan, Ruf and