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Visual Medical Information Analysis

Maria Papadogiorgaki
Informatics and Telematics Institute, Centre for Research and Technology Hellas, Greece

Vasileios Mezaris
Informatics and Telematics Institute, Centre for Research and Technology Hellas, Greece

Yiannis Chatzizisis
Aristotle University of Thessaloniki, Greece

George D. Giannoglou
Aristotle University of Thessaloniki, Greece

Ioannis Kompatsiaris
Informatics and Telematics Institute, Centre for Research and Technology Hellas, Greece

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

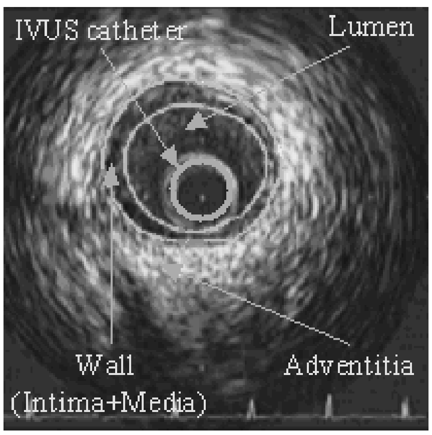
Mammography is considered to be the most effective diagnostic technique for detecting abnormal tissue conditions on women's breast. Being used both for prevention and for diagnostic purposes, it is a very commonly used technique that produces mammographic images by administering a low-dose of x-ray radiation 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

Goldberger (2006) have also developed an algorithm for the automated brain tissue segmentation on noisy, low-contrast (MR) images. Under their approach, the brain image is represented by a model that is composed of a large number of Gaussians. For the algorithm's initialization an atlas or parameter learning are not required. Finally, segmentation of the brain image is achieved by affiliating each voxel to the component of the model that maximizes an a posteriori probability. In Valdes-Cristerna, Medina-Banuelos and Yanez-Suarez (2004) a hybrid model for the segmentation of brain MRI has been investigated. The model includes a radial basis network and an active contour model. The radial basis network algorithm generates an initial contour, which is following used by the active contour model to achieve the final segmentation of the brain.

Mammography Image Analysis

Several applications have been proposed, which process the mammographic images in order to assist the clinicians in their diagnostic procedure. In Székely, Toth and Pataki (2006) the mammographic images are analyzed using segmentation in order to identify regions of interest. The applied segmentation technique includes texture features, decision trees, and a Markov random field model. The extracted features which refer to the object's shape and texture parameters are linearly combined to lead to the final decision. Because the pectoral muscle should be excluded from processing on a mammogram intended for the breast tissue, its identification is important. Kwok, Chandrasekhar, Attikiouzel and Rickard (2004) have developed an adaptive segmentation technique for the extraction of the pectoral muscle on digitized mammograms. The method uses knowledge about the position and shape of the pectoral muscle. Other approaches, such as Cascio, Fauci, Magro, Raso, Bellotti, De Carlo et al. (2006) use supervised neural networks for detecting pathological masses in mammograms. A segmentation process provides features of geometrical information, or shape parameters which constitute the input to the neural network that computes the probability of the lesion existence.

IVUS Image and Image Sequence Analysis

Traditionally, the segmentation of IVUS images is performed manually, which is a time consuming procedure with results affected by the high inter- and intra-user's variability. To overcome these limitations, several approaches for semi-automated segmentation have been proposed in the literature. In Herrington, Johnson, Santago and Snyder (1992) after the manual indication of the general location of the boundary of interest by the user, an edge detection filter is applied to find potential edge points within the pointed neighborhood. The extracted image data are used for the estimation of the closed smooth final contour. Sonka, Zhang, Siebes, Bissing, DeJong, Collins et al. (1995) implemented a knowledge-based graph searching method incorporating a priori knowledge on coronary artery anatomy and a selected region of interest prior to the automatic border detection. Quite a few variations of active contour model have been investigated, including the approach of Parissi et al. (2006), where a user interaction is required, by drawing an initial contour as close as possible to its final position. Thus, the active contour is initialized and tends to approximate the final desired border.

The active contour or deformable models principles have been used to allow the extraction of the luminal and medial-adventitial borders in three dimensions after setting an initial contour in Kovalski, Beyar, Shofti and Azhari (2000). However, the contour detection fails for low contrast interface regions such as the luminal border where the blood-wall interface in most images corresponds to weak pixel intensity variation. In order to improve the included active surface segmentation algorithm for plaque characterization, Klingensmith, Nair, Kuban and Vince (2004) use the frequency information after acquiring the radiofrequency (RF) IVUS data through an electrocardiogram scheme. Radio frequency data are also used in Perrey et al. (2004), after in vivo acquisition for the segmentation of the luminal boundary in IVUS images. According to this approach, tissue describing parameters are directly estimated from RF data. Subsequently, a neuro-fuzzy inference system trained to several parameters is used to distinguish blood from tissue regions.

For clinical practice the most attractive approaches are the fully automatic ones. A limited number of them has been developed so far, such as the segmentation based on edge contrast (Zhu, Liang, & Friedman, 2002); the latter is shown to be an efficient feature for IVUS image analysis, in combination with the gray level distribution. Specific automated approaches which utilize the deformable models principles in combination with other various techniques and features reported in the related literature have been investigated. Brusseau, de Korte, Mastik, Schaar and van der Steen (2004) exploited an automatic method for detecting the endoluminal border based on an active contour that evolves until it optimally separates regions with different statistical properties without using a preselected region of interest or initialization of the contour close to its final position. Another automated approach based on deformable models has been reported by Plissiti, Fotiadis, Michalis and Bozios (2004), who employed a Hopfield neural network for the modification and minimization of an energy function as well as a priori vessel geometry knowledge. An automated approach for segmentation of IVUS images based on a variation of an active contour model is presented in Giannoglou et al. (2007). This technique is in vivo evaluated in images originated from human coronary arteries. The initialization of the contours in each IVUS frame is automatically performed using an algorithm, which is based on the intensity features of the image. The initially extracted boundaries constitute the input to the active contour model, which then deforms the contours appropriately, identifying their correct location on the IVUS frame.

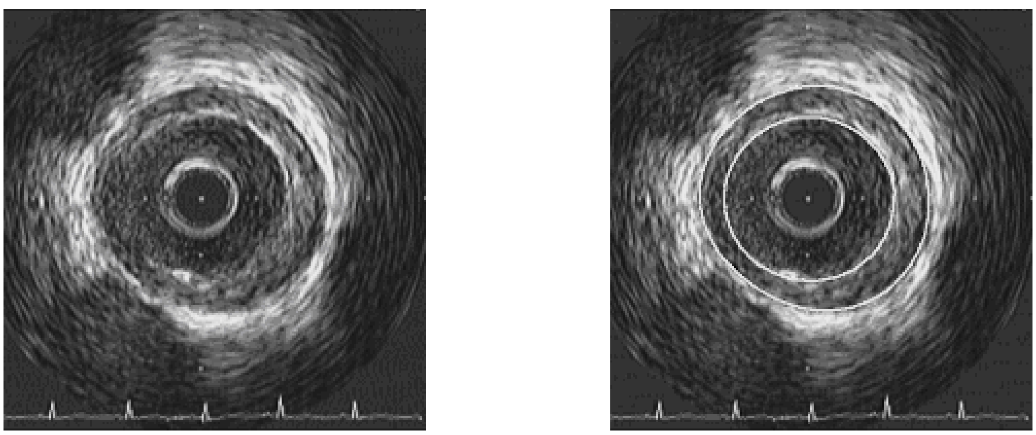
A fuzzy clustering algorithm for adaptive segmentation in IVUS images is investigated by Filho, Yoshizawa, Tanaka, Saijo and Iwamoto (2005). Cardinal et al. (2006) present a 3D IVUS segmentation applying Rayleigh probability density functions (PDFs) for modeling the pixel gray value distribution of the vessel wall structures. Other approaches are based on the calculation of the image's energy. In Luo, Wang and Wang (2003) the lumen area of the coronary artery is estimated using the internal energy, which describes the smoothness of the arterial wall and the external energy which represents the grayscale variation of images that constitute an IVUS video. The minimal energy which defines the contour is obtained using circular dynamic programming. Other methods include statistical analysis, such as Gil, Hernandez, Rodriguez, Mauri and Radeva's (2006), where the presented approach uses statistical classification techniques for the IVUS border detection.

In Papadogiorgaki, Mezaris, Chatzizisis, Kompatsiaris and Giannoglou (2006), a fully automated method for the segmentation of IVUS images and specifically for the detection of luminal and medial-adventitial boundaries is presented. This technique is based on the use of the results of texture analysis, performed by means of a multilevel Discrete Wavelet Frames decomposition. Following image preprocessing, to remove catheter-induced artifacts, a two-step process is employed for the detection of the boundaries of interest. Objective of the first step, termed contour initialization, is the detection of pixels that are likely to belong to the lumen and media-adventitia boundaries, taking into consideration the previously extracted texture features. As a result of this step, initial contours are generated; however, these are not smooth and are characterized by discontinuities, as opposed to the true lumen and media-adventitia boundaries. Thus, at the second step, a filtering or approximation procedure is applied to the initial contour functions, so as to result in the generation of smooth contours that are in good agreement with the true lumen and media-adventitia boundaries. This approach does not require manual initialization of the contours and demonstrates the importance of texture features in IVUS image analysis. A sample IVUS image and the corresponding analysis result of this approach are illustrated in Figure 2.

FUTURE TRENDS

With the number of medical imaging techniques used in everyday practice constantly rising and the quality of the results of such imaging techniques constantly increasing, to the benefit of the patients, it is clear that the need for accurate and automated to the widest possible extent analysis of medical images is a key element in supporting the diagnosis and treatment process for a wide range of medical conditions. To this end, future research will continue to concentrate on the development of analysis methods that are automated, robust and reliable. In addition to that, particular emphasis is expected to be put on the coupling of the results of automated analysis with techniques for the formal representation of them.

Figure 2. Sample IVUS image (left) and the corresponding analysis result of a texture-based approach to the detection of luminal and medial-adventitial boundaries (right)



Examples of early systems for the formal representation of knowledge extracted from medical images, though not in an automated manner, include those discussed in Dasmahapatra et al. (2006), Hu, Dasmahapatra, Lewis and Shadbolt (2003). These are concerned with the annotation of medical images used for the diagnosis and management of breast cancer, such as those generated by mammography and MRI, by expressing all the extracted features and regions of interest using domain knowledge and assigning them to specific concepts of a knowledge structure. In an analogous approach, in Gedzelman, Simonet, Bernhard, Diallo and Palmer (2005) a knowledge structure of cardiovascular diseases is constructed in order to be used for the representation of the findings of the relevant imaging techniques, so as to support concept-based information retrieval.

Combining automated analysis results with techniques such as those briefly discussed above for the formal representation of them will empower new possibilities in the areas of retrieval in extensive medical databases and reasoning over the results of analysis, consequently providing the physicians not only with the analysis results themselves but also with hints on their meaning, minimizing the risk of misinterpretation.

CONCLUSION

In this article, visual medical information analysis was discussed, starting with an introduction on the current use of medical imaging and the needs for its analysis. The current article then focused on three important medical imaging techniques, namely Magnetic Resonance Imaging (MRI), Mammography, and Intravascular Ultrasound (IVUS), for which a detailed presentation of the goals of analysis and the methods presented in the literature for reaching these goals was given. The future trends identified in the relevant section provide insights on how the algorithms outlined in this article can be further evolved, so as to more efficiently address the problem of medical image analysis and consequently pave the way for the development of innovative doctor decision support applications that will make the most out of the available image data.

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KEY TERMS

Active Contour Model: Energy-minimizing parametric curve that is the basis of several medical image analysis techniques.

Computer-Aided Diagnosis: The process of using computer-generated analysis results for assisting doctors in evaluating medical data.

Coronary Angiography: X-ray diagnostic process for obtaining an image of the coronary arteries.

Intravascular Ultrasound (IVUS): Diagnostic catheter-based technique that renders two-dimensional images of coronary arteries.

Magnetic Resonance Imaging (MRI): Imaging technique that uses a magnetic field to provide two-dimensional images of internal body structures.

Mammography: Diagnostic X-ray technique which produces breast images and is used to detect breast tissue abnormalities.

Medical Image Segmentation: The localization of known anatomic structures in medical images.