Advancements in Computer Aided Imaging Diagnostics

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INTRODUCTION

Diagnostic imaging is a priceless tool in the field of medicines today. Magnetic resonance imaging(MRI), phase-contrast X-ray imaging (PCI), computed tomography (CT), X-rays, ultrasound scanner, digital mammography, and other imaging modalities provide an effective means for mapping the anatomy of a subject(Phamy, Xu, &Prince, 2001).Knowledge related to the anatomy of normal and diseased tissues has increased a lot because of these technologies. Computer Aided Imaging Diagnostics (CAID) techniques are being used to capture the patterns expressed by disease conditions in the images which can give certain clues to the doctor about the disease. Many such simplified imaging approach can be an inexpensive way to provide an early detection of certain diseases so that a warning message could be given to people who are at places where no sophisticated systems and trained doctors are available to deeply detect and confirm (Shen, Cheng, & Basu, 2010).

Before getting into diagnostics part of medical images, it is worth to have a glance at the features of a typical medical image in the digital format. It is a collection of pixels (point or dot) which contributes to the formation and presentation of that image. Each pixel is associated with some light intensity with a value. In medical images, traditionally, the value associated to each pixel represents the properties of cells within an organ. For example, pixel values represent the radiation absorption in X-ray imaging, acoustic pressure in ultrasound, and RF signal amplitude in MRI. However, new methods and techniques which are using phase contrast and other innovative methods to generate data with better resolution are under research. If a single data is collected (as in radiation absorption in X-ray) from each location or point in the image, then the image is called a scalar image. If more than one data is collected (as in dual-echo MRI), the image is called a vector or multi-channel image. Images can be represented in two-dimensional (2-D), three-dimensional (3-D) or in multi-dimensional space.

The methodology of dealing with medical images for advanced analysis is different from conventional visual verification analysis and validation. In the conventional method, identification of locations of anomalies is done by the radiologists. The radiologist uses apriori knowledge about the location, size, and shape of the structures in the medical image and matches that with clinical evidence as well as case history to make the diagnosis. In CAID, detection of the anomaly and recognition (classification) is done by the computer either in supervised (with help of doctors) or in unsupervised (without human intervention) domain. There are some standard steps to be followed for CAID. Those steps can be described as follows-

- **Pre-processing:** Processing the images to make them ready for the analysis is called pre-processing. It may involve calibration of digital images as the data may have to be resampled to a fixed resolution, cropping of the region of interest (ROI), thresholding, contrast enhancement, noise removal etc. The main purpose of this step is to remove differences between data from different sources to ensure a generalized result.
- **Segmentation:** Image segmentation is defined as partitioning of an image into its constituent regions which are homogeneous with respect to some characteristics such as colour, texture or intensity. Accurate segmentation of medical images is crucial for a correct diagnosis. Incomplete segmentation may miss lesions in the unsegment areas in CAID system.

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Sometimes, automatic methods fail to segment an image correctly due to noise, inhomogeneity, low contrast, and inequality of content with semantic. Hence, selection of right method for pre-processing becomes crucial to achieve desired segmentation result.

- **Feature Extraction:** This involves examination of ROI and selection of unique set of features which can be used to detect the abnormality present in the image. Features may be the mean value across the ROI, the standard deviation, moments of various orders or gradient of the values in various directions, frequency domain parameters like phase angle or other more complex mathematical descriptors of the ROI and its surroundings. It is understandable that an 'n' dimensional feature vector can be represented geometrically by a point in 'n' dimensional feature space. This puts the problem of feature extraction to the well-established domain of pattern classification, a subset of machine learning. Pattern recognition techniques are widely applied in countless applications outside medical image analysis too (Ginneken, Schaefer-Prokop, & Prokop, 2010).
- **Classification:** In the field of CAID, selecting the right set of features is the utmost challenge. Once the right set of features has been identified, classification can be done on the basis of that. We need to classify tissues within an image as normal and diseased or images in a dataset as normal and abnormal. The process is complicated because a part of true lesions may be hiding behind regions mostly occupied by "non-lesions" or vice versa. For example, in case of lung X-ray of the chest affected with tuberculosis, a part of cavity may be hiding behind rib bones. This may make the visible part of the cavity look non circular. If circular feature of the cavity is used for classification, it may go undetected.

A wide variety of pattern classification and recognition techniques exist (Duda, Hart, & Stork, 2001; Bishop, 2007). Techniques are available which automatically select the best features, or combine features to yield more powerful ones. Mathematical models like neural networks (Duin, 1997), support vector machines (Bennet, 2000), and Bayesian techniques (Bishop, 2007), Hidden Markov Models (Ming & Wu, 2013) etc. are useful in this approach but one model may or may not work well for all types of tasks and in all conditions. Hence, CAID researchers should always experiment with several classifiers and feature combinations to get the best classification result (Ginneken, Cornelia, Schaefer, &Mathias, 2010).

Algorithms and approaches used for CAID vary widely depending on the specific application, imaging modality, and other factors. For example, the segmentation of lung tissue has different requirements from the segmentation of the kidney because basic features of these two regions are very different from each other in terms of size, shape, texture and geometry of ROI and its surrounding. External imaging conditions such as noise, lighting conditions, partial volume effects, and motion can also affect performance of segmentation algorithms significantly. Furthermore, each imaging modality has its own peculiarities which has to be dealt with. There is currently no single diagnostic method for an image that yields acceptable results for every medical situation (Phamy, Xu, &Prince, 2001).

BACKGROUND

CAID has become a part of the routine clinical work for detection of breast cancer on mammograms, lung cancer, colon cancer, prostate cancer, large array of orthopaedic issues and muscular issues at many screening sites of advanced hospitals across the world. It is going to be applied widely in the detection of many different types of abnormalities in medical images by use of different imaging modalities (Doi, 2007) and various upcoming interpretation schema.

Automatic detection of a disease has been of interest to many researchers. A number of techniques and approaches have been proposed by researchers but how far they can actually be applied in a field of practice is yet to be verified. Valley-edge detection algorithm (Wang, 2005) is a one-pass line detection algorithm which finds locally dark (or bright) line- like features. This is used for fracture detection and is robust for ridge edge detection and fracture tracing, but for the rough surface

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