MINI-REVIEW

Advances in Optimal Detection of Cancer by Image Processing; Experience with Lung and Breast Cancers

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Abstract

Clinicians should looking for techniques that helps to early diagnosis of cancer, because early cancer detection is critical to increase survival and cost effectiveness of treatment, and as a result decrease mortality rate. Medical images are the most important tools to provide assistance. However, medical images have some limitations for optimal detection of some neoplasias, originating either from the imaging techniques themselves, or from human visual or intellectual capacity. Image processing techniques are allowing earlier detection of abnormalities and treatment monitoring. Because the time is a very important factor in cancer treatment, especially in cancers such as the lung and breast, imaging techniques are used to accelerate diagnosis more than with other cancers. In this paper, we outline experience in use of image processing techniques for lung and breast cancer diagnosis. Looking at the experience gained will help specialists to choose the appropriate technique for optimization of diagnosis through medical imaging.

Keywords: Cancer - early detection of cancer - image processing - lung neoplasm - breast neoplasm

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Introduction

Cancer has the highest mortality rate, among other non-communicable diseases in the world (Fallahzadeh et al., 2014). According to Globocan latest report, there are 14.1 million new cancer cases, 8.2 million cancer deaths and 32.6 million people who living with cancer in 2012 worldwide. Almost 57% (8 million) of new cancer cases, 65% (5.3 million) of the cancer deaths and 48% (15.6 million) of the 5-year prevalent cancer cases occurred in the less developed regions (Globocan, 2012a). Therefore, because of high incidence, mortality and burden costs of cancer disease, there is an urgent need for early detection strategies (Mohammadzadeh and Safdari, 2014; Vemuri et al., 2014; Azadmanjir et al., 2015; Shridhar et al., 2015).

In this regard medical images have lots of information about the anatomical structures that are valuable for accurate and early diagnoses, selecting the suitable treatment approach and analyzing treatment outcome (Gao et al., 2003; Dobrescu et al., 2010; Remenyi et al., 2011). Hence, accurate processing and interpreting of medical images, such as a variety of other data in the health care industry, lead to explore the relationship between these data and improvement of clinical performance (Abramoff et al., 2004; Alhadidi et al., 2007; Kannadhasan et al., 2013; G, 2014; Patil et al., 2014). Overall, as defined "Image processing refers to manipulation of the gray level information contained within the pixels of a digital image" (Strickland, 2002). Anyway, because of the human intellectual and visual limitations in accurate image processing, computer-based image processing with image detailed analyzing, and recognizing any abnormal tissue changes can help with early detection of cancer (Giger, 2004; Jain and Vijay, 2013; Hasanabadi et al., 2014). In recent decades, medical image processing has advanced increasingly (He et al., 2012) .

In general, computer-assisted image analysis are used to determining the prognosis and diagnosis diseases, particularly cancers, since the early 1970s (Loukas et al., 2003). Similarly, computerized image processing helps to early and correct detection of malignant tissue and decreases unnecessary biopsies (Polakowski et al., 1997; Ganesan et al., 2013; Sundari et al., 2014). Studies indicated that computer- aided image processing increase cancer detection rates about 20% (Chen et al., 2012; Kannadhasan et al., 2013). This amount is substantial for decreasing mortality rate. This technique can be used for less experienced physician and learners to cancer diagnosis and correct treatment (Sampat et al., 2005; Rajyalakshmi et al., 2014; Santosh and Sadashivappa, 2014).

The cancer diagnosis with the aid of image processing include following phases: image acquisition, preprocessing (segmentation, enhancement and noise elimination), processing, post processing and diagnosis (Demir and Yener, 2005; He et al., 2012; Patil and Jain, 2014). The preliminary task in processing is eliminating of image

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noise that performed in preprocessing step (Demir and Yener, 2005). In addition, image segmentation is an essential process that used to identify the region of interest (ROI), and critical for content analysis and image understanding (Upadhyay and Wasson; Zhang et al., 2008; Kekre et al., 2010; Ramteke and Jain, 2013). Also, image enhancement improves the images qualities and used to correct image's resolution, reduce the noise of content or highlight its details (Leela and Kumari, 2014). This paper describes some of the image processing techniques that applied to improve and accelerate diagnosis of lung and breast cancers.

Lung Cancer Diagnosis Through Image Processing

Lung neoplasm which has 12.7% incidence rate and 18.2% mortality rate per year (Mukti and Ahmed, 2013) is the most common cancer in the world (Globocan, 2012b; Kemal[1] et al., 2014). Studies showed that 80% of patient with lung cancer died during first five years of diagnosis, and early detection of lung cancer increase survival rate about 10-50 fold (Guo, 2010; Zahir and Mirtalebi, 2012; Kaur et al., 2014). Due to insidious onset, the diagnosis of lung cancer in primary stage is very difficult (Chen et al., 2011); thus image processing through early detection can help increasing the survival rate of lung cancer (Shriwas and Dikondawar, 2015).

Digital image processing can be used for tissue discriminating, lung lesions and nodules detection, types of tumors classifying and tumor growth measurement (Lee et al., 2009) . Image processing for detection of lung cancer has some stages includes image capture, image enhancement, image segmentation and feature extraction. Noise, corruption and interferences of images can be eliminating through the image enhancement techniques.

The next stage, image segmentation has important role in recognition the details of objects in important areas. (Abdulbaki, 2012; Al-Tarawneh, 2012; Tripathy, 2013; Usman et al., 2013).

Experiences in lung cancer diagnosis through image processing

Bae et al. (2005) developed an automated pulmonary nodule detection program for 20 samples of thin-section multi- detector row CT images of the thorax. The number, size, and location of nodules that detected by the computer program compared with the radiologists' interpretation of images. The results show that nine small nodules were missed in the initial radiologist's reading. Whereas, the overall sensitivity with this technique was 95.1% for all nodules 3 mm and larger, for nodules 3 mm to less than 5 mm, the sensitivity was 91.2% and For 5 mm to less than 10 mm nodules was 97.2% as well. Therefore, precision of detection through the computer program was higher than radiologist detection for small nodules (Bae et al., 2005).

Whiles the mentioned study focused on the detection of cancerous or non-cancerous nodules in another study by Aoyama et al proposed a computer based technique to differentiate types of nodules (benign or malignant) in chest radiographs samples. To discrimination of radiographs they use the Linear Discriminate Analysis (LDA) and Artificial Neural Network (ANN). In comparing with manual discrimination, LDA had an area under the curve (AUC) value of 88.6%, whilst manual identification resulted in an AUC value of 85.4%. Results show that the effectiveness of distinguishing by a radiologist between benign and malignant solitary pulmonary nodules will increase with the aid of this system (Aoyama et al., 2002).

In relation to the process of computer aided image processing methods different experiences obtained. Al-Fahoum et al proposed a technique for lung image processing with the following stages: segmentation, labeling the regions of interest and extracting diagnostic features of the regions. Study results show that accuracy of radiologist's detection rate for small lung nodules improved 98.13% by using the computerized image processing technique. It improved physician diagnosis in early stage of lung cancer and increased effectiveness (Al-Fahoum et al., 2014). Sankar in order to detection of lung cancer by image processing in 2000 samples of lung CT images used stages includes, preprocessing, histogram generation, segmentation, and template matching. The results proved that accuracy of lung cancer detection increased with this image processing approach (Sankar and Prabakaran, 2014). About segmentation and thresholding, approaches are different. Usman et al suggested a segmentation technique to remove images noises in lung region. They demonstrated that in the segmentation stage, Marker-Controlled Water-shed Segmentation technique with accuracy (5.165%) and quality (81.835%) is better than thresholding technique. This technique improved earlier detection of disease and treatment stages; although needs long time for computation in large data sets (Usman et al., 2013). In addition, Sharma et al that developed automatic lung cancer detection system by image processing technique, and used bit plane slicing technique in extraction phase. The result of their study shows almost 80% accuracy improvements in the physician diagnosis during reading CT images (Sharma and Jindal, 2011).

On classification of normal or abnormal findings or even malignant or benign lesions in image processing, different algorithms or methods can be used. For example, Ada et al used 909 CT images in DIACOM format with 8 bit resolution for their study, proposed a method consists of images collected, pre-processing of images, feature extraction, principle component analysis, and neural network classifier. For classification of the images the first, they extracted 16 features, then the classification of images (normal or abnormal) performed according to those features. For classification of features, they select neural network algorithm because it gives highest rate of correctly classified instances in compare with ZeroR classifier, Naive Bayes classifier and Support Vector Machine classifier (SVM). The findings demonstrated that, the neural network algorithm with 96.04% (true positive rate) had the best performance (Ada[1], 2013). In contrast, Arzhaeva et al presented a system to distinguish normal and abnormal tissues by two-class supervised classification method. The analysis was done by means of the multi scale Gaussian filter ban, linear discriminant analysis (LDA), and an SVM classifier (i.e. support vector machine) for 44 abnormal and 8 normal cases. The best performance was 0.78% with an area under the ROC curve, which achieved by the linear discriminant and SVM classifiers. The best performance to differentiate between abnormal and normal tissues was 0.90% (Arzhaeva et al., 2007).

In addition, Kato et al suggested a bag of features approach for classification of lung disease with diverse tissues. They use intensity descriptor and scale-invariant feature transformation (SIFT) for feature extraction. Finally, in the 1109 ROIs, classification accuracy to 5 different image class was about 92.8% using this method (Kato et al., 2009). Moreover, Lingayat et al proposed a computer-based algorithm for feature extraction of lung nodules in X-ray images that helps physicians and radiologist's early diagnosis and deffirentiate between benign and malignant tissues. The developed system with this algorithm, acts as a second opinion to the physicians and radiologists. The results show malignant and benign lung tumor's distinguishes has been improved (Lingayat and Tarambale, 2013).

For higher levels of differentiation, Al-Kadi et al applied CE-CT (Contrast Enhanced Computer Tomography) images to tumor stage prediction. Purpose of this study was improving accuracy of differentiate between aggressive (advanced stage) and non-aggressive (early stage) tumors. Images were in DICOM format and differentiated by Box Counting (DBC) algorithm. The accuracy of this system to differentiate between aggressive and non-aggressive tumor was up to 83%. For this reason, system can be recognized for providing the aggressiveness rate for lung tumors (Al-Kadi and Watson, 2008).

Breast Cancer Diagnosis Through Image Processing

The second most common cancer overall in the world, the most incidence and the first cause of death for women ages 40-55 is breast cancer (Smith et al., 2004; Karabatak and Ince, 2009; Globocan, 2012b; Gucuk and Uyeturk, 2013). According to GLOBOCAN estimates, 52.9% of 1.67 million new breast cancers were diagnosed in developing countries in 2012 (Globocan, 2012b). breast cancer is the cause of death in 16% of cancer-related mortalities (Najmabadi et al., 2014).

An important factor to reduce mortality rate and increase long term survival in breast cancer is early detection and effective treatment (Guo, 2010; Choudhari et al., 2012; Tripathy, 2013; Kazerouni et al., 2014; Mohaghegh et al., 2015; Vithana et al., 2015). Also treatment of breast cancer is very expensive, therefore, early detection leads to reduce personal, health and socio-economical complication (Zadeh et al., 2012; Kulakci et al., 2015). But because of the similarity between normal and cancerous breast tissues, early detection of breast cancer is difficult. To have an accurate diagnosis, physicians have to detect subtle signs of breast lesions (Abdel-Qader et al., 2006). In this regard, digital image processing can be used to distinguish between breast normal tissues and cancerous lesions. For this purpose, in image processing, segmentation phase plays important roles in differentiate between malignant and benign breast cancer (Zadeh et al., 2009)

Experiences in breast cancer diagnosis through image processing

About the general effect of the technology for diagnosis of breast cancer, note to research of Freer and et al who developed computer aided detection (CAD) to analysis 2,500 mammograms. They surveyed the effect of CAD on the recall rate, positive predictive value for biopsy, cancer detection rate, and stage of malignancies at detection in compare with radiologist performance. By using of this method increase in breast cancer detection and recall rate was 19.5% and 1.2%. also detection rate of malignancy in early stage increase 5% (improvement from 73% to78%). In positive predictive value for biopsy, there was no significant difference between the radiologist and CAD system (Freer and Ulissey, 2001). However, various methods can be selected and used for it based on the experience gained. For instances Nagaraj and his colleagues proposed Effective Statistical Texture Detection algorithm (ESTD) that had four core stages and can be used to MRI, magnetic resonance angiography, and ultrasonography imaging techniques with different visual attributes. The four steps is include de-noising, statistical treshholding, identify suspicious objects with statistical measure and determine selection criteria to selecting suspicious objects. The algorithm applied for 100 mammographies in a database. Evidences have been showed that the proposed algorithm achieved 70% true result with simulation (Nagaraj et al., 2014). But for mammographic digital images, Mencattini proposed wavelet transform for enhancement and de-noising. This algorithm applied for many mammography images. It is reported that the boundaries of the mass were more differentiable and region of interest could distinguish better. In total, the algorithm had effective performance (Mencattini et al., 2008).

Guzman-Cabrera et al proposed a technique to identify the region of interest in masses and micro-calcifications from tissue by feature extraction through texture analysis in eight-bit gray scale mammography images (benign or malignant); and detects the amount of area that should be identified and extracted (reference gray level). The performance of the algorithm depends on the size of reference area that should be removed after segmentation. As a result, for micro-calcifications when large area was removed correlation coefficient increased, and for masses when small area was removed correlation coefficient increased. This distinguishes between micro-calcifications and masses help physician to have better image analysis and more effective diagnosis (Guzman-Cabrera et al., 2013).

For thermographs also, researchers applied an automated algorithm. The methode involves edge detection, breast boundaries detection, feature extraction, asymmetry description and cumulative histogram. These algorithm used for diagnosis of cancer regions. Results show this method was effective in diagnosing the asymmetric abnormalities (Kapoor et al., 2010). In contrast, Abaspur Kazerouni used the principal component analysis (PCA) and the two-dimensional principal component analysis (2D PCA) and the two-directional two-dimensional principal component analysis ((2D) 2PCA) to best analysis of the thermographic images. Also, the support vector machine (SVM) with RBF kernel (radial basis function kernel) used for image retrieval. This approach applied for 400 thermographic images. As the result, the highest precision value was 99.33% for (2D)2PCA and 90.86 % for 2DPCA and 82.98 for PCA (Kazerouni et al., 2014).

However, other researchers in their time, proposed a novel image detection method for boundary detection of tumors in breast cancer digital mammographies by Neural Network Classifier. This technique use NN classifier with N-ary morphological operator to eliminate the boundary errors. Moreover, for large number of images they used from Gabor filter for elimination of noise and classifying the tissues abnormalities to benign or malignant. This method applied for natural and synthetic 512 × 512 pixel 8-bit grayscale images successfully. It has been reported that diagnosis was improved by this technique (Reddy et al., 2010). In the study of Shanthi and et al, proposed an integration of intuitionistic Fuzzy C-Means clustering and Self Adaptive Resource Allocation Network classifier to classification of breast cancer status according to the mammogram images. This technique applied for 322 normal, benign and malignant images. Proposed system's precision, recall and F-means compared with four classifiers (RBFN, MLP, Navie bayes and C4.5) and at the result the proposed system had the highest precision, recall and F means for classification of image as normal, benign or malignant. With this system early detection of breast cancers improved (Shanthi and Bhaskaran, 2012). In other research, applied image processing threshold, edge-based and watershed segmentation for mammogram breast cancer images; and test three algorithms with MatLab software. By comparing time consuming and simplicity in these three methods, It was concluded that threshold method was faster than other methods but two other methods had better output images (Alhadidi et al., 2007). In the same study by Shareef applied morphological operation and segmentation watershed transformation to process the images that captured from ultrasound and X-ray mammography devices among women aged between 40-60 years. Similar diagnosis found in the different types of images by using this algorithm. The accuracy of diagnosis was acceptable about 84.84% (Shareef, 2014).

In conclusion, because, images are essential components in many fields of medicine, especially for the diagnosis process of tumors, technology based approaches such as digital image processing help physicians to have better interpretation, faster detection and increases accuracy and objectivity of diagnosis. In cancer diagnosis and treatment field the goal of digital image processing is to locate and extract meaningful items from images and classify the type and stage of cancer. Looking at the experiences gained will help specialists to choose the appropriate technique for optimization of diagnosis through medical imaging. But it is necessary to emphasize that, although the literature review indicates that digital image processing techniques have an important role in easing and early detection of lung and breast cancers, but this technology cannot replace human judgment and just have an assistant role in judgment for diagnosis and treatment of cancers. These approaches decrease expert's disagreements and lead to better and common understanding of stage of disease.

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