Multistage Approach for Biomedical Image Processing: A Review

Pragati D. Pawar[1], Sanjay.M.Gulhane[2]

[1]Deptt. of Elect. and Telecomm. Engg, Jawaharlal Darda Inst. Of Engg., Yavatmal, Maharashtra, India

[2]Deptt. of Elect. and Telecomm. Engg, Jawaharlal Darda Inst. Of Engg., Yavatmal, Maharashtra, India

Email: pawar_pragati16@rediffmail.com

Abstract

An intelligent computer-aided diagnosis system can be very helpful for radiologist in detecting and diagnosing microcalcifications' patterns earlier and faster than typical screening programs. Modern computer-aided treatment planning systems enable more effective and reliable treatment, and gains are particularly significant for minimally invasive treatment. These emerging systems readily incorporate multimodal data, which can be difficult to assess otherwise, and provide an objective result based on numerical simulations that improve treatment results (patient outcomes), especially for less experienced physicians. This paper presents a survey on the multistage CAD systems that helps the physicians by either identifying patterns that might have been overlooked or by providing a road map of suspicious areas, making their efforts more efficient. Still there are various of issues to be addressed as discussed below.

***Keywords**: Medical Imaging, Computer aided diagnosis(CAD), Support Vector Machine(SVM).*

1. Introduction

For the past several decades, in medical imaging field researchers have focused on bringing new imaging modalities to clinicians while improving the performance of existing systems. Research is also going on in signal processing field to introduce new softwares, enabling computers to help clinicians to make sense of such an amount of noninvasive medical information. It is well recognized that when the humans enters the older age they are more likely to depend on biomedical systems for their wellbeing. In recent years this has sparked rapid development and wide spread deployment of biomedical systems. These systems have progressed from single purpose systems to massively networked health diagnosis systems with personal health records [1]. Another fact, which leads to the rapid progress, is that these networks distribute an ever increasing amount of biomedical data related to number of diseases. Therefore, our society is nowadays more dependent on a technology which gets more complex. Thus the biomedical image is taking on a more prominent role in the diagnosis and quantitative assessment of disease. Image processing techniques allow a large and complex set of quantitative measures to be derived from images, particularly in a research setting.

Advances in image acquisition technology, computer vision systems, and new clinical/research queries are leading to increasing amounts of quantitative data being derived from medical images. Imaging modalities such as computed tomography (CT) and magnetic resonance are generating large volumes of image data. Lung cancer screening is performed with CT imaging, new multislice CT imaging technology enables higher-resolution imaging of the body—400 images spaced every 1 mm through the chest. However, there are many more images to read, placing a great burden on radiologists in terms of reading time and leading to the potential for missing factors. The increase in the amount of image data to be interpreted causes a common problem throughout medical imaging systems, and therefore, there is great research and commercial interest in computer systems to process the data. The various image processing techniques such as neural network and genetic algorithms form a computer aided diagnosis system is increasingly used in clinical practice to assist physicians in the detection of subtle abnormalities which can be used by a radiologist[2].

The concept of Computer aided multistage approach is relatively broad consisting of multiple stages and it can be applied to both imaging modalities, and bio-signals. This multistage approach can be used for diagnosis and detection of the abnormabilities within the lungs, chest, brain, liver etc. The majority of computer aided schemes developed in the past include the detection of breast lesions on mammograms [3],[4],[11], detection of lung nodules in chest radiographs [16],[10],[31]. Such modules have been tested on private image sets, such as Tree-in-Bud (TIB) Opacities [14]. Detection system for Pulmonary Embolisms [5], [15] (blood clots called deep vein thrombi often develop in the deep leg veins). A pulmonary embolism (PE) occurs when clots break off from the vein walls and travel through the heart to the pulmonary arteries is under research. Alzheimer's disease (AD) of brain is another area to be focused. The detection of microaneurysms in digital color fundus photographs is a critical first step in automated screening for diabetic retinopathy (DR), a common complication of diabetes. Diabetic Retinopathy (DR) is a frequent microvascular complication of diabetes and the most common cause of blindness and vision loss in the working population of the western world [1]. It has been shown that early detection of Diabetic Retinopathy(DR) helps to prevent blindness and visual loss. There are several other problems that needs to be addressed, one of which is presently under the research.

Different approaches, based on image processing techniques, such as conventional pattern recognition methods, and artificial neural networks (ANNs) are documented. To develop a CAD system, a classifier must be trained to automatically recognize patterns of features that indicate a particular abnormality or disease. This classifier training involves collection of a large number of image data sets and then extraction of a large number of features from each data set. In an imaging research setting, there are typically many variables being investigated, for example, variables in lung CT image acquisition are collimation, tube current, reconstruction algorithm, breathing state, etc. For each different imaging protocol, there are also many different quantitative features being extracted to search for the optimal combination of imaging parameters and features to characterize the disease process or clinical question to be answered. This requires a complex data model and queries. Once the meaningful variables are selected for use by a CAD system to perform a particular diagnostic, the queries become less complex since only those variables need be retrieved.

The performance of these systems can be evaluated on the basis of reliability measures. In most cases the reliability assessment is supported by experimental results which yield the required data for statistical analysis. Measures for reliability are sensitivity, specificity and positive predictive value. These reliability measures are of particular importance for classification algorithms. This aspect is well understood in the biomedical research community.

2. Literature Review

The interpretation and analysis of medical images is arguably one of the most difficult and advanced applications of pattern recognition and computer vision. Computer-aided diagnosis using image processing and computer vision techniques can help the doctors in the diagnosis of various diseases and serve as a useful “second opinion.” Infectious lung diseases, such as novel swine-origin, hini influenza, tuberculosis (TB), etc are among the leading causes of disability and death all over the world. Computed tomography (CT) examination of the lungs during acute respiratory tract infections has become an important part of patient care, both at diagnosis and monitoring progression or response to therapy. Although CT examination serves as a primary (imaging) diagnostic tool for assessing lung infections, visual analysis of CT images is restricted by low specificity for causal infectious organisms and a limited capacity to assess severity and predict patient outcomes. Ulas Bagci, Jianhua Yao, Albert Wu [14] proposed a scheme for Automatic Detection and Quantification of Tree-in-Bud (TIB) Opacities from CT Scans. The developed computer aided system in this study is based on fast localization of candidate imaging patterns using local scale information of the images, and M¨obius invariant feature extraction method based on learned local shape and texture properties of TIB patterns [14]. Another problem is blood clots called deep vein thrombi often develop in the deep leg veins. A pulmonary embolism (PE) occurs when clots break off from the vein walls and travel through the heart to the pulmonary arteries. However, the clinical diagnosis of PE is a time-consuming, difficult, and probably unreliable task primarily due to the often vague and nonspecific primary symptoms that make it difficult to identify the critically ill patients who actually suffer from PE. Sang Cheol Park, Brian E. Chapman, and Bin Zheng recently proposed a detection system for Pulmonary Embolisms [5],[15], [25],[26]. This scheme uses tobogganing using ANN, and grouping method achieved quite good detection sensitivity. The applied maximum scoring method achieved the superior performance over other scoring fusion methods; also Genetic algorithm used in this study was able to delete “redundant” features and further improve the performance. It also resulted in limiting the maximum number of cued lesions in an examination. Tuberculosis (TB) is a deadly infectious disease and the presence of cavities in the upper lung zones is a strong indicator that the disease has developed into a highly infectious state. Currently, the detection of TB cavities is mainly conducted by clinicians observing chest radiographs. Diagnosis performed by radiologists are labor intensive and very often there is insufficient health care personnel available, especially in remote communities. Jiantao Pu, Carl Fuhrman, Walter F. Good, Frank C. Sciurba, and David Gur proposed a Differential Geometric Approach to Automated Segmentation of Human Airway Tree [6], [27]. Airway diseases are frequently associated with morphological changes that may affect the physiology of the lungs. Accurate characterization of airways may be useful for quantitatively assessing prognosis and for monitoring therapeutic efficiency. The information gained may also provide insight into the underlying mechanisms of various lung diseases. Few researchers proposed an automated segmentation technique, which takes a hybrid knowledge-based Bayesian classification approach to detect TB cavities automatically [7]. While high-resolution CT (HRCT) scan protocols allow visualization of fine lung structures, only a limited portion of lung parenchyma (LP) is sampled (approximately 10%). Jiantao Pu, Joseph K. Leader, Bin Zheng proposed Geometry Approach to Automated Pulmonary Fissure Segmentation on CT images in [22]. An automatic segmentation scheme for Pulmonary Segments from Volumetric Chest CT Scans was suggested in [23] failed to obtain quantitative evaluation of automatic segmentation of pulmonary segments in scans that contain abnormalities.

P. D. Korfiatis, A. N. Karahaliou presented an automated scheme for volumetric quantification of interstitial pneumonia (IP) patterns, a subset of DPLD utilizing a multidetector CT (MDCT) have provided dataset providing promising results. Studies on lung nodule computer-aided detection (CAD) is proposed for detecting both solid nodules and ground-glass opacity (GGO) nodules (part solid and nonsolid) using lung region segmentation and fuzzy thresholding methods [8]. The system developed for Identification and Characterization of Interstitial Pneumonia Patterns in Lung based on textures also showed promising results in [21]. Some researchers worked on the abnormalities within the chest. Few proposed the scheme for Automatic Detection of Abnormalities in Chest Radiographs Using Local Texture Analysis [16]. Giuseppe Coppini, Stefano Diciotti [10] presented an approach based on multiscale processing and artificial neural networks (ANNs). For nodule detection is faced by using two-stage architecture. When lung nodules overlap with ribs or clavicles in chest radiographs, it can be difficult for radiologists as well as computer-aided diagnostic (CAD) schemes to detect these nodules. Kenji Suzuki, Hiroyuki Abe developed an image-processing technique for suppressing the contrast of ribs and clavicles in chest radiographs by means of a multiresolution massive training artificial neural network (MTANN). An MTANN is a highly nonlinear filter that can be trained by use of input chest radiographs and the corresponding “teaching” images. This technique would be potentially useful for radiologists.

The classifier used for Detection and Grading of Lymphocytic Infiltration in HER2+ Breast Cancer Histopathology which is recently presented in [3] could be employed to characterize LI extent in other tissues and diseases. Alzheimer’s disease (AD) of brain is another area to be focused. This disease is the most common cause of dementia in aged people and affects more than 30 million individuals worldwide. The effects of this disease are of great importance not only in terms of familiar dependence and affliction but also economic. With the growth of the older population in developed nations, the prevalence of AD is expected to triple over the next 50 years. P. Padilla*, M. López, J. M. Górriz presented a novel computer-aided diagnosis (CAD) technique[18] for the early diagnosis of the Alzheimer’s disease (AD) based on nonnegative matrix factorization (NMF) and support vector machines (SVM) with bounds of confidence. This NMF-SVM CAD tool is suggested to be an accurate method for single photon emission computed tomography (SPECT) database and positron emission tomography (PET) images.

Computer aided diagnosis is also recently applied to Nuclear Cataract [19] in which the intensity, color, and texture within the nucleus region can be measured in AGNC system. Another improvement is the intensity measurement of sulcus . In previous works, the intensity of the sulcus is only measured on the visual axis. Diagnosis of breast cancer is also an upcoming research area addressed by Ajay Nagesh Basavanhally, Shridar Ganesan for identification of phenotypic changes in breast cancer (BC) histopathology on account of corresponding molecular changes [3],[20].

3. Limitations and Scope

Literature survey given in section-2, gives brief idea on the techniques which are proposed for diagnosis of various diseases using biomedical image processing. Though the proposed work in the literature addressed various issues they suffer from one or the other limitations. A Multistage Approach is Depicted in [5] for Detection of Pulmonary Embolisms. They reported the maximum detection sensitivity of 79.2% of the tobogganing algorithm for the lower contrast and smaller PE regions depicted on CT image. This needs to develop better grouping methods in order to improve the sensitivity. Also the efficiency can be improved by including more vessels into segmented lung area. Definning a “universally” optimal density mask or a set of optimal density masks that could be adaptively adjusted based on different CT image acquisition protocols could also be a further research. The grouping method for overlapped PE regions on adjacent slices could provide another effective approach for discriminating between TP and FP, PE lesions which has not been included in this study. A better solution can be provided for automatic detection and quantification by Combining different imaging patterns pertaining to lung abnormalities as well as clinical laboratory information into our CAD system. Few methodologies can be tuned with different types of abnormalities to generalize the CAD systems for infectious lung diseases in general. The efficiency of the work proposed on human airway tree could be improved by using triangle mesh simplification and using more modern computers with multiple processors. Also this scheme can be easily generalized to extract other tubular type structures.

There is a scope to develop automatic lung field segmentation technique, which may optimize the adaptive thresholding process and improve the accuracy of initial contour placement, employing other classifiers and features, explore techniques to approximate the geometric attributes of TB cavities. Lung lobe segmentation is also an important step that should be considered in DPLDs systems, since lobar distribution of DPLDs patterns plays an important role in diagnosis.. There is a need to investigate on developing robust methods to classify between incomplete small fissure sections and other nonfissure regions in Automated Pulmonary Fissure Segmentation. Further studies are needed to investigate the impact of viewing automated fissure segmentation results on radiologists’ performance in fissure detection and identify optimal approach to evaluate the performance and reliability of automated fissure detection and segmentation schemes. Correct classification and recognition of the different fissures and their configurations is an important issue that needs to be addressed.

Detection of pulmonary embolism with respect to vessel segments discussed in article [15] requires further testing to investigate potential influence of image quality. In further investigations, it needs to be tested if CAD is also beneficial in a short time frame in a differentiated approach in diagnosing PE and DVT as in a differentiated approach–usually under emergency settings–the initial diagnosis needs to be assessed after pulmonary CTA to be able to perform an indirect CT venography after the initial scan. Automatic Detection of Red Lesions in Digital Color Fundus Photographs addressed in [23],[24] suggested to use more advanced classifiers such as support vector machines or techniques such as boosting. Large red lesions are not always completely segmented by the region growing procedure, by replacing it with a different segmentation method this could be improved.

Scope of research is to address various issues like proposing a methodology to generalize the computer aided diagnosis system for infectious lung diseases with different types of abnormalities, Developing a fast and robust lung boundary reconstruction algorithm to increase computational efficiency, improving the segmentation sensitivity, developing better grouping methods, to present generic methods to combine CAD challenges for different goals, improving the performance of multistage approach using different techniques. Aim of the proposed work is to address such issues.

References

[1] N. Archer, U. Fevrier-Thomas, C. Lokker, K. A. McKibbon, S. E. Straus, "Personal health records: a scoping review", Journal of the American Medical Informatics Association 18 (4) (2011) 515– 522

[2] Oliver Faust, U. Rajendra Acharya, and Toshiyo Tamura, "Formal design methods for reliable computer aided diagnosis: A review", IEEE Review on Biomedical Engineering, 2011.

[3] Ajay Nagesh Basavanhally, Shridar Ganesan, Shannon Agner, James Peter Monaco, Michael D. Feldman, John E. Tomaszewski, Gyan Bhanot and Anant Madabhushi, " Computerized Image-Based Detection and Grading of Lymphocytic Infiltration in HER2+ Breast Cancer Histopathology", IEEE Transactions on Biomedical Engineering, Vol. 57, No. 3, March 2010.

[4] Wenjing Li, Viara Van Raad, Jia Gu, Ulf Hansson, Johan Hakansson, Holger Lange, "Computer-Aided Diagnosis (CAD) for Cervical Cancer Screening and Diagnosis: A New System Design in Medical Image Processing", Springer-Verlag Berlin Heidelberg 2005, pp. 240 – 250, 2005.

[5] Sang Cheol Park, Brian E. Chapman, and Bin Zheng, "A Multistage Approach to Improve Performance of Computer-Aided Detection of Pulmonary Embolisms Depicted on CT Images: Preliminary Investigation", IEEE Trans. on Biomedical Engineering, Vol. 58, No. 6, June 2011.

[6] Jiantao Pu, Carl Fuhrman, Walter F. Good, Frank C. Sciurba, and David Gur, "A Differential Geometric Approach to Automated Segmentation of Human Airway Tree", IEEE Transactions on Medical Imaging, Vol. 30, No. 2, February 2011.

[7] Rui Shen, Irene Cheng, , Anup Basu, "A Hybrid Knowledge-Guided Detection Technique for Screening of Infectious Pulmonary Tuberculosis From Chest Radiographs", IEEE Transactions on Biomedical Engineering, Vol. 57, No. 11, November 2010.

[8] Xujiong Ye, Xinyu Lin, Jamshid Dehmeshki, Greg Slabaugh, Gareth Beddoe, " Shape-Based Computer-Aided Detection of Lung Nodules in Thoracic CT Images IEEE Transactions on Biomedical Engineering, Vol. 56, No. 7, July 2009.

[9] Eva M. van Rikxoort*, Bartjan de Hoop, Saskia van de Vorst, Mathias Prokop, and Bram van Ginneken, " Automatic Segmentation of Pulmonary Segments From Volumetric Chest CT Scans ", IEEE Transactions on Medical Imaging,Vol. 28, No. 4, April 2009.

[10] Kenji Suzuki*, Senior Member, IEEE, Hiroyuki Abe, Heber MacMahon, " Image-Processing Technique for Suppressing Ribs in Chest Radiographs by Means of Massive Training Artificial Neural Network MTANN" ,IEEE Trans. on Medical Imaging, Vol. 25, No. 4, April 2006.,.

[11] Ryohei Nakayama, Yoshikazu Uchiyama, Koji Yamamoto, Ryoji Watanabe, Kiyoshi Namba, " Computer-Aided Diagnosis Scheme Using a Filter Bank for Detection of Microcalcification Clusters in Mammograms", IEEE Trans. on Biomedical Engineering, Vol 53, No. 2, February 2006.

[12] Giuseppe Coppini, Stefano Diciotti, Massimo Falchini, Natale Villari, " Neural Networks for Computer-Aided Diagnosis: Detection of Lung Nodules in Chest Radiograms", IEEE Transaction on Information Technology in Biomedicine, Vol.7, No. 4, December 2003.

[13] Bram van Ginneken, Shigehiko Katsuragawa, Bart M. ter Haar Romeny, Kunio Doi, Max A. Viergever, " Automatic Detection of Abnormalities in Chest Radiographs Using Local Texture Analysis", IEEE Trans. on Medical Imaging, Vol. 21, No. 2, February 2002.

[14] Ulas Bagci, Jianhua Yao, Albert Wu, Jesus Caban, Tara N. Palmore, Anthony F. Suffredini, "Automatic Detection and Quantification of Tree-in-Bud (TIB) Opacities From CT Scans", IEEE Transactions on Biomedical Engineering , Vol. 59, No. 6, June 2012.

[15] Marco Das, Georg Mühlenbruch, Anita Helm, Annemarie Bakai, "Computer-aided detection of pulmonary embolism: Influence on radiologists' detection performance with respect to vessel segments", European Society of Radiology, Published online: 22 February 2008.

[16] Bram van Ginneken, Shigehiko Katsuragawa, Bart M. ter Haar Romeny, "Automatic Detection of Abnormalities in Chest Radiographs Using Local Texture Analysis", IEEE Transactions on Medical Imaging, Vol. 21, No. 2, February 2002.

[18] P. Padilla, M. López, J. M. Górriz, J. Ramírez, D. Salas-González, I. Álvarez, "NMF-SVM Based CAD Tool Applied to Functional Brain Images for the Diagnosis of Alzheimer's Disease", IEEE Transactions on Medical Imaging, Vol. 31, No. 2, February 2012.

[19] Huiqi Li, Joo Hwee Lim, Jiang Liu, Paul Mitchell, " A Computer-Aided Diagnosis System of Nuclear Cataract", IEEE Transactions on Biomedical Engineering, Vol. 57, No. 7, July 2010.

[20] Hsieh-Wei Lee, Bin-Da Liu,King-Chu Hung, "Breast Tumor Classification of Ultrasound Images Using Wavelet-Based Channel Energy and ImageJ", IEEE Journal of Selected Topics in Signal Processing, vol. 3, No. 1, February 2009.

[21] Panayiotis D. Korfiatis, Anna N. Karahaliou, Alexandra D. Kazantzi, " Texture-Based Identification and Characterization of Interstitial Pneumonia Patterns in Lung Multidetector CT", IEEE Transactions on Information Technology in Biomedicine, Vol. 14, No. 3, May 2010.

[22] Jiantao Pu, Joseph K. Leader, Bin Zheng, Friedrich Knollmann, " Computational Geometry Approach to Automated Pulmonary Fissure Segmentation in CT Examinations", IEEE Transactions on Medical Imaging, Vol. 28, No. 5, May 2009.

[23] Meindert Niemeijer, Bram van Ginneken, Joes Staal, " Automatic Detection of Red Lesions in Digital Color Fundus Photographs", IEEE Trans. on Medical Imaging ,Vol. 24, No. 5, May 2005.

[24] Meindert Niemeijer, Bram van Ginneken, Michael J. Cree, "Retinopathy Online Challenge: Automatic Detection of Microaneurysms in Digital Color Fundus Photographs", IEEE Transactions on Medical Imaging, Vol.29, No. 1, January 2010.

[25] ChristopherKoehler, Thomas Wischgoll, "Knowledge Assisted 3D Reconstruction and Visualization of Human Ribcage and Lungs", 2009 IEEE.

[26] Bill Diong, "Modeling Human Respiratory Impedance", IEEE Engineering in Medicine and and Biology Magazine, January/February 2007.

[27] Juerg Tschirren, Eric A. Hoffman, "Intrathoracic Airway Trees: Segmentation and Airway Morphology Analysis From Low-Dose CT Scans" , IEEE Transactions on Medical Imaging , Vol. 24, No. 12, December 2005.

[28] László G. Nyúl, Jayaram K. Udupa, "Incorporating a Measure of Local Scale in Voxel-Based 3-D Image Registration", IEEE Transactions on Medical Imaging ,Vol. 22, No. 2, February 2003.

[29] Ulas Bagci,, Xinjian Chen, "Hierarchical Scale-Based Multiobject Recognition of 3-D Anatomical Structures", IEEE Transactions on Medical Imaging Vol. 31, No. 3, March 2012.

[30] Natasha Lepore, Caroline Brun, Yi-Yu Chou, "Generalized Tensor-Based Morphometry of HIV/AIDS Using Multivariate Statistics on Deformation Tensors", IEEE Transactions on Medical Imaging , Vol. 27, No. 1, January 2008.

[31] Lilla B¨or¨oczky, Luyin Zhao, K. P. Lee, "Feature Subset Selection for Improving the Performance of False Positive Reduction in Lung Nodule CAD", IEEE Transactions on Information Technology in Biomedicine , Vol. 10, No. 3, July 2006.

[32] Wei Jiang, Seong G. Kong, Block-Based Neural Networks for Personalized ECG Signal Classification", IEEE Transactions on Neural Networks, Vol. 18, No. 6, November 2007.

[33] Paolo Soda and Giulio Iannello, "Aggregation of Classifiers for Staining Pattern Recognition in Antinuclear Autoantibodies Analysis", IEEE Transactions on Information Technology in Biomedicine, Vol. 13, No. 3, May 2009.

[34] An. Calisto, M. Galeano, S. Serrano, "A new approach for investigating Intracranial Pressure signal: filtering and morphological features extraction from continuous recording", 2011 IEEE.

[35] Yimo Tao, Zhigang Peng, Arun Krishnan, "Robust Learning-Based Parsing and Annotation of Medical Radiographs", IEEE Transactions on Medical Imaging, Vol. 30, No. 2, February 2011.

[36] Liyang Wei, Yongyi Yang, "Relevance Vector Machine for Automatic Detection of Clustered Microcalcifications", IEEE Transactions on Medical Imaging, Vol. 24, No. 10, October 2005.

[37] Miltiades Gletsos, Stavroula G. Mougiakakou, "A Computer-Aided Diagnostic System to Characterize CT Focal Liver Lesions: Design and Optimization of a Neural Network Classifier", IEEE Trans. on Information Technology in Biomedicine, Vol. 7, No. 3, September 2003.

[38] Tang-Kai Yin, Nan-Tsing Chiu, "A Computer-Aided Diagnosis for Distinguishing Tourette's Syndrome From Chronic Tic Disorder in Children by a Fuzzy System With a Two-Step Minimization Approach", IEEE Transactions on Biomedical Engineering, Vol. 51, No. 7, July 2004.
[39] John Stoitsis, Student Member, IEEE, Spyretta Golemati, "A Modular Software System to Assist Interpretation of Medical Images—Application to Vascular Ultrasound Images", IEEE Transactions on Instrumentation and Measurement, Vol. 55, No. 6, December 2006.
[40] Andrew F. Laine, "In the Spotlight: Biomedical Imaging", IEEE Reviews in Biomedical Engineering, Vol. 4, 2011.