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A Survey on Advanced Methods in Computer vision And Pattern Recognition for Soft Tissue Image Processing

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Abstract: *Automated Medical image Analysis is a most challenging interdisciplinary research field. From past decades enormous research work is ongoing in the field of Computer vision and Pattern Recognition [PR] for the development robust algorithms for computerized diagnosis. The advanced computational intelligence based algorithms has a significant potential for faster and accurate clinical diagnosis, surgical planning and have paved the way for a new digital era of Quantitative analysis. Computerized clinical diagnosis methods also has substantial implications for improved clinical care, provide diagnostic second opinions, prognosis especially for Medical Professionals practicing in rural areas. With an increasing research on better algorithms for quantitative analysis, it is important to summarize the existing methods, on conceptual basis. So this paper presents a brief survey on the recent advanced computational methods for Soft tissue Image segmentation based on Texture analysis, Machine learning, and other automated /semi automated energy based methods.*

Keywords: *Deeplearning, Convolutional Neural Network, Active contour,Texture Analysis*

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I. Introduction

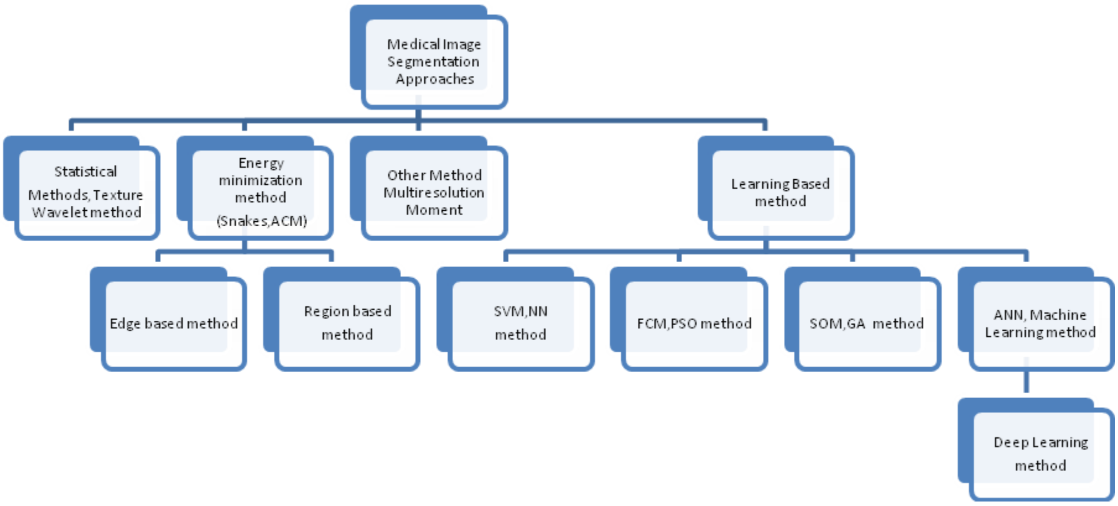
In most clinical diagnosis manual delineation of target volumes (Tissues/organs) at risk is customary. This is often subjective, time consuming and prone to intra and inter observer variations. Advanced radiation therapy (RT) based treatment planning requires a fast and accurate segmentation of medical images, especially in image guidance and treatment adaptation. Therefore the automated segmentation methods seek to reduce delineation workload and unify the organ boundary definition. [G. Sharp et al., 2014].Accurate segmentation of medical images is a key step in contouring during radiotherapy planning. Computed topography (CT) and Magnetic resonance (MR) imaging are the most widely used radiographic techniques in diagnosis, clinical studies and treatment planning. [Neeraj Sharma and Lalit M. Aggarwal.,2010].

Soft Tissues are in general complex geometrical structures, with variable granular structures as Texture. Texture is an image feature that provides important characteristics for surface and object identification from image. Texture analysis is a major component of image processing and is fundamental to many applications such as medical imaging, remote sensing, quality inspection etc[Sivapriya et al.,2011]. In medical image processing, Texture is especially important, because it is difficult to classify human organ tissues using shape or gray level information. Imaging the anatomical organs is most challenging as structure of organs are non homogeneous and inconsistent, on the other hand gray level intensities overlap considerably for soft tissues [Dettori et al.,2007]. One of the best approaches to overcome these challenges is automating medical imaging diagnosis to simplify the objective of the analysis and to exploit some kind of hypothetical information about the imaged structures.

Over last few years greater prominence is been given to develop automated ,interactive systems capable of assisting physicians in medical imaging task.[Okuboyejo et al.,2013].The combination of human experts and machine intelligence can provide improved efficiency with minimal user intervention [Lee et al., 2008].The interactive segmentation methods facilitates radiologists for accurate segmentation of anatomical structures, measurement and diagnosis of various diseases, tissue volumes for proper surgery planning etc [FZhou et al.,2013].Unsupervised(no prior knowledge of anatomy) and interactive type of segmentation methods have become more popular for medical imaging recent years. In this Survey, we briefly will focus on some of the latest automated and interactive segmentation methods popular for medical image analysis. The remainder of this paper is organized as follows. Section II contains the survey of related works on interactive segmentation methodologies, learning-based approaches, and energy minimization-based approaches and finally this paper is concluded in Section III.

II. Literature Survey

A Stratified classification of modern automated image segmentation methods is depicted in the below diagram Fig1, followed by brief literature survey



A) Statistical Segmentation Methods

In Medical Imaging, Texture analysis is a statistical method to intuitively quantify the anatomical structures by knowledge of their typical appearance (shape and grey levels) and spatial distribution. Many textural parameters are commonly proposed, viz; coarseness, contrast, density, roughness, directionality, frequency, regularity, uniformity, orientation, and so on [Tamura et al., 1978]. Texture analysis on the other hand uses methods such as co-occurrence matrices calculus; evaluation of texture features (such as energy, entropy, contrast and correlation during image processing), successful classification or segmentation requires an efficient description of image Texture. In this paper we surveyed some of the Texture Analysis methods available for Soft tissue Image analysis.

Sharma et al.,[2008] introduced a new auto-segmentation and tissue characterization system. The authors utilized texture-primitive features for soft tissue characterization and selected bidirectional associative memory (BAM)-type artificial neural network for segmentation and classification of CT images. This research work was tested on Markov texture, and has achieved 100% accuracy. However, this method was limited to only 17 features, which cause the curse of dimensionality. An improvement for this dimensionality and feature vector is discussed in next section.

A. Padma and R.Sukanesh, [2011] developed an improved BAM type Artificial Neural Network for Texture feature based Analysis of Segmenting Soft Tissues from Brain CT Images .The authors have designed a computer aided system for the automatic segmentation of brain CT images. Image analysis methods were applied to the images of 30 normal and 25 benign, 25 malignant images. Textural features extracted from the gray level co-occurrence matrix of the brain CT images and bidirectional associative memory is employed for the design of the system. The best classification accuracy was achieved by four textural features and BAM type ANN classifier. This research work provides new textural information and segmenting normal and benign, malignant tumor images, especially in small tumor regions of CT images efficiently and accurately with lesser computational time. Soft tissues segmentation from brain computed tomography image data is an important yet difficult task performed manually by medical experts today, automating this process is challenging due to the high diversity in appearance of tumor tissue among different patients and in many cases, similarity between tumor and normal tissue.

A.Padma. and R.Sukanesh,[2013] have proposed an automated SVM based Classification method of Soft Tissues in Brain CT Images. The Support Vector machine (SVM) classifier classifies and segments the brain soft tissues from computed tomography images using the wavelet based dominant gray level run length feature extraction method. A dominant gray level run length texture feature set is derived from the high frequency sub bands of the image to be decomposed using 2 level discrete wavelet transform. The selected optimal run length texture features are then fed to the SVM to classify and segment the brain soft tissues .The authors have also addressed the problem of dimensionality of feature vector stated with Multi level dominant eigenvector estimation algorithm and the Bhattacharyya distance measure. From these corrective measures a high degree of correlation between neighborhood features is achieved.

A.Padma. and R.Sukanesh, [2011] have also introduced dominant gray level run length statistical texture feature, and optimized them by Genetic Algorithm (GA).Finally, the optimal texture features are fed to the SVM classifier to classify and segment the tumor region in brainCT .The 10-fold cross validation results showed that the highest accuracy they achieved was above 98%, tested on 240 CT brain images, half for training and half for testing. However, the performance can be improved by reducing excessive features

A.Padma. and R.Sukanesh,[2014] have also investigated a novel wavelet texture feature based statistical method for segmentation of soft tissue tumors. In this approach Wavelet Statistical Texture features (WST) and Wavelet Co-occurrence Texture features (WCT) were extracted using 2-level DWT from CT brain images. A Genetic Algorithm (GA) is employed to reduce the dimension of the feature vector. Probabilistic Neural Network (PNN) and Feed Forward Neural Network classifiers (FFNN) are chosen to segment the tumor region. This method has achieved the accuracy of 97% and 95% for PNN and FFNN on 100 CT brain images, respectively. However, the performance can be improved by using other classifiers such as Radial basis function neural network with Particle Swarm Optimization (PSO).The hybrid PSO based automated segmentation schemes are discussed in next section.

b) Hybrid approaches

Soft computing techniques can be hybridized. One such technique is PSO-based FCM algorithm. PSO-FCM [Particle swarm optimization together with fuzzy clustering method] is a unique automated segmentation technique based on Artificial intelligence [PSO] and fuzzy logic [FCM] methods. Particle swarm optimization (PSO) is one of the current approaches that can be adopted in a wide variety of applications. It is an evolutionary stochastic computing method based on colony aptitude which is an important parallel searching algorithm.

Chun et al.,[2008] proposed a method that uses fuzzy c-mean (FCM) clustering together with PSO. The main objective of FCM clustering is to search cluster centers that maximizes a similarity function and/or minimizes the dissimilarity function. Here the PSO is used for the allotment of each pixel of an image to a particular cluster naturally. This hybridized FCM clustering and PSO algorithm generate better segmented images. The basic FCM algorithm is affected by the number and initial location of the centre of the predetermined clustering. Riddhi.S.Kapse et al.,[2016] have presented an advanced Hybrid PSO based FCM clustering method in their research work for Brain tumor detection.

V. Sheejakumari and B. Sankara Gomathi,[2015] have developed a new clever algorithm method using practical swarm optimization and neural network for Classification of Healthy and Pathological tissues from MRI Images. The new classification method uses improved particle swarm optimization (IPSO) technique to classify the healthy and pathological tissues from the given MRI images. This proposed scheme includes the same four stages, namely, tissue segmentation, feature extraction, heuristic feature selection, and tissue classification.

Mehdi vatankhah et al.,[2014]proposed fully automated classification magnetic resonance images of the human brain that can be able detect the healthy or sick person. The Automatic classification of images uses the models and formal criteria involving key stages of feature extraction, feature reduction and learning algorithms. The authors have used best-known and most effective feature extraction algorithms, reducing the features, such as wavelet transform principal component analyses are used. Also a hybrid approach to improve the efficiency of the support vector classifier using Cuckoo evolutionary algorithm has been employed. The results of the combined classification accuracy, sensitivity and specificity are above 98% that stronger and more effective compared with other recent work.

Ali A Sakr et al.,[2014] have devised a new method for automated identification and classification of various stages of focal liver lesions based on the Multi-Support Vector Machine (Multi-SVM). This system can be used to discriminate focal liver infections such as Cyst, Hemangioma, and Hepatocellular carcinoma along with normal liver. With a multi-class scenario the discrimination between cysts, cavernous hemangioma, hepatocellular carcinoma, and normal tissue as a supervised learning problem, and apply Multi-SVM to classify the diseases using Haralick local texture descriptors and histogram based features calculated from Regions Of interest (ROIs), as input. Selection of ROI significantly impact the classification performances, thus an automatic ROI selection using Fuzzy c-means initialized by level set technique. For multi-class classification, they adopt the One-Against-All (OAA) method. The proposed Multi-SVM based system is compared with the K-Nearest Neighbor (KNN) based approaches. Experimental results have demonstrated that the Multi-SVM based system greatly outperforms KNN-based approaches and other methods in the literature. The good performance of the proposed method shows a reliable indicator that can improve the information in the staging of focal liver lesion diseases.

Bilwaj Gaonkar et al.,[2011] formulated a wavelet based approach for Abnormality detection and Automated segmentation cortical Necrosis from brain FLAIR-MR Images. Cortical necrosis is regions of dead brain tissue in the cortex caused by cerebrovascular disease (CVD). The accurate segmentation of these regions is difficult as their intensity patterns are similar to the adjoining cerebrospinal fluid (CSF). The authors devised a new model of normal variation using MR scans of healthy controls. The model is based on the Jacobians of warps obtained by registering scans of normal subjects to a common coordinate system. For each patient scan a Jacobian is obtained by warping it to the same coordinate system. Large deviations between the model and subject-specific Jacobians are flagged as 'abnormalities'. Abnormalities are segmented as cortical necrosis if they are in the cortex and have the intensity profile of CSF.

c) Energy Minimization [Active contour methods]

In energy based segmentation methods, segmentation is the result of minimizing an energy function. The energy function can be defined in the continuous domain or the discrete domain. Snakes [C.Xu and J.L Prince,1998; Philips, Carl, et al.,2007] and Level set segmentation methods [Tsai A et al.,2003; Li, Chunming, et al., 2011; Drakopoulos et al.,2012]are examples of continuous domain methods and graph based segmentation methods[Freedman et al.,2005; Xu et al.,2007] are examples of discrete domain methods. Active contour or Snakes is an evolving interface whose motion is guided by internal and external forces. The external force is defined based on regional properties of the image. Snakes evolve as an initial curve and the curve grows until it reaches the boundaries. The level set method, which is also an evolving interface, can handle topology changes such as self-intersection better than Snakes

Jin Mikulka et al., [2012] proposed a 2D active contour model for Soft-tissues Image Processing for the classification of healthy/unhealthy tissues in MR or other imaging. In this research work the authors have focused on solving partial differential equations for image segmentation .This is a modern method for image processing, often called the active contour method which is of great advantage in the segmentation of real images degraded by noise with fuzzy edges and transitions between objects. The authors have also compared the results with existing methods in medical image segmentation.

Arie Nakhmani et al., [2014] have proposed a new semi-automatic tumor segmentation scheme for detection of Necrosis using Adaptive Soboloev Snakes. This new method uses tumor probability density estimation and adaptive segmentation in the probability space. Anisotropic 3D diffusion technique is used to estimate the probability density. Finally, the estimated density is segmented by the Sobolev active contour (snake) algorithm to select smoothed regions of the maximum tumor probability. The segmentation approach is robust to noise it is appropriate for low contrast imagery.

Jan Mikulka et al., [2013] proposed improved method for segmentation using an active contour model-based segmentation followed by SVM-based classification for Perfusion weighted MRI Images. The segmentation process starts with a new generation of active contour models i.e., vector field convolution (VFC) on modified brain images. VFC results are brain images with the least non-brain regions which are passed on to the SVM classification. The SVM features are selected according to the structure of brain tissues, gray matter (GM), white matter (WM), and cerebrospinal fluid (CSF). SVM classifiers are trained for each brain tissue based on the set of extracted features. The goal of the design of segmentation method was to have a tool for differentiation individual parts of the pathological tissue viz of the tumor, surrounding edema and the necrotic tissue. Segmentation of pathological tissue parts is needful for the further processing.

Interactive segmentation techniques are very important for fast and reliable extraction of regions of interest [roi]. The GrabCut technique [Rother et al., 2004] is based on the discrete graph-cut approach, where image pixels represent graph vertices. The partitioning of the image into object and background regions is obtained by solving the mincut problem in graphs. The user controls the segmentation by labeling regions, which are correspondingly assigned to either the source or the sink of the graph. The selected regions provide color statistics that characterize the object and the background and are utilized for segmentation.

Uma Maheswari R and Visnu Priya Dalai, [2013] proposed graph cut based Segmentation for Liver tumor analysis, This paper discussed "Grab-Cut" technique, and "Graph Cut" techniques. Grab Cut is a way to perform 2D segmentation in an image which is s very user friendly. "Grab Cut" is a segmentation technique that uses graph cuts to perform segmentation. Like most segmentation techniques "GrabCut" uses information encapsulated in the image. Most segmentation techniques make use of either edge information or region information in the image. "GrabCut" makes use of both edge and region information. This information is used to create an energy function which, when minimized, produces the best segmentation. Other segmentation techniques use either contour or edge segmentation to perform segmentation. The Graph Cut techniques use both contour and edge detection.

Tudor barbu.,[2013]proposed An automatic moment-based texture feature extraction, segmentation approach for texture feature extraction, this texture recognition process, produces a set of moment-based feature vectors. For each image pixel, a texture feature vector is computed as a sequence of area moments, an automatic pixel classification method is used. The feature vectors are clustered using an unsupervised classification algorithm, the optimal number of clusters being determined using a measure based on validation indexes. From the resulted pixel classes one determines easily the desired texture regions of the image.

P. Dvořák et al.,[2015] proposed a fully automated method for pathological area extraction from multi-parametric 2D M images of brain. The proposed method is based on multi-resolution symmetry analysis and automatic thresholding. The proposed algorithm first detects the presence of pathology and then starts its extraction. T2 images are used for the presence detection and the multi contrast MRI is used for the extraction, concretely T2 and FLAIR images. The extraction is based on thresholding, where Otsu's algorithm is used for the automatic determination of the threshold. This method is purely based on symmetry it works for both axial and coronal planes. In both these planes of healthy brain, the approximate left-right symmetry exists and it is used as the prior knowledge for searching the approximate pathology location.

d) Neural network and Machine learning based methods

Neural networks based methods attract more attentions for their abilities of self learning, fault tolerance, and optimum search. They organize themselves in a data driven manner. SOM (Self organizing Maps) is an unsupervised neural network that use competitive learning algorithm. SOM [Kohonen, 1990] projects a high dimensional space to a one or two dimensional discrete lattice of neuron units. An important feature of this neural network is its ability to process noisy data. The map preserves topological relationships between inputs in a way that neighboring inputs in the input space are mapped to neighboring neurons in the map space.[Logeswari. T and M. Karnan, 2010]have proposed an improved and a hybrid method for detection of Brain tumor using Hierarchical Self organizing maps[HSOM] and Fuzzy C means clustering[FCM].The authors describe a new segmentation method for delineation of tumor pathological tissue and healthy tissues from tumors. This method consists two phases. In the first phase, the MRI brain image is acquired from patient database. In that film artifact and noise are removed. In the second phase (MR) image segmentation is to accurately identify the principal tissue structures in these image volumes. A new unsupervised MR image segmentation method based on fuzzy C-Means clustering algorithm for the Segmentation is presented

Mehta et al.,[2011] devised a genetic algorithm a method to automatically generate fuzzy rules for tissue classification in MRI. The proposed scheme was based on hybrid approach of two popular genetic algorithm based machine learning (GBML) techniques, Michigan and Pittsburg approach. In this research work the authors have utilized a training dataset generated from manual segmented images with the aid of an expert in MRI. Features from image histogram and spatial neighborhood of pixels have been employed in fuzzy rules. This research work has been tested for classifying brain T2 weighted 2D axial images obtained by different pulse sequences into three main tissue types, namely, white matter (WM), gray matter (GM), an cerebrospinal fluid (CSF). The experts have compared and matched the performance of this research work with the results of manual segmentation approaches.

e) Deep learning methods

Deep learning has been the biggest turning point in the history of computer vision and Machine Learning .Deep learning techniques are the trend of current day research and have been remarked as the gold standard for interactive and automated image segmentation, classification. Deep learning-based segmentation approaches are gaining more interest due to their robust self-learning and generalization ability over large amounts of data. As the deep learning architectures are becoming more mature, they gradually outperform previous state-of-the-art classical machine learning algorithms. The Convolutional Neural Networks (CNN) have gained significant attention for solving computer vision tasks such as object recognition, classification and segmentation [Li, Na, et al.,2016; Srinivas, Suraj, et al.,2016]often out-competing state-of-the art for fully automated methods. CNN methods have proven to be highly robust and rapidly become a methodology of choice for analyzing medical images due to its robust and fast computation methods are that yield promising results.

Mohammad Havaei et al., [2016] presented a fully automatic brain tumor segmentation method based on deep neural networks. The proposed networks were tailored segment both low and high grade gliomas pictured in MR images. These glioblastomas [glail cells] are tumors with different size, shape and contrast and can appear in any region of brain. The authors motivated by these reasons have explored an extremely efficient machine learning solution that exploits a flexible, high capacity DNN. The authors have also given the description of different model choices that were found to be necessary for obtaining competitive performance. In this research work the authors have explored in particular different architectures based on Convolutional Neural Networks (CNN), i.e. DNNs specifically adapted to image. A novel CNN architecture is presented that exploits both local features as well as more global contextual features simultaneously. This architecture is different from most traditional computer vision based machine learning method .This method of CNN use a final layer that is a convolutional implementation of a fully connected layer which allows a 40 fold speed up. Also describe a 2-phase training procedure that allows us to tackle difficulties related to the imbalance of tumor labels. The authors also explored cascaded CNN architecture, in which the output of a basic CNN is treated as an additional source of information for a subsequent CNN. It is reported in 2013 BRATS [Brain Tumor segmentation] test that this architecture is 30 times faster than conventional state of art CNN. However an etiological diagnosis at early stage is necessary for accurate, efficient and focused tumor analysis. An improved multiscale CNN based approach for focused tumor diagnosis is discussed next.

Liya Zhao and Kebin Jia,[2016] proposed a novel multiscale CNN automatic brain tumor segmentation method. The traditional standard CNNs only focus on local textual features. As a result, some important global features are lost inevitably. The multiscale CNNs extract both local and global features. As both local and global features play an important role in image recognition tasks the authors proposed a specific CNNs architecture combining all these features for brain tumor segmentation. In this architecture, multiscale concept is introduced to design traditional single-scale CNNs.The pixel classification is predicted by integrating information learned from all CNNs. The authors have designed a three-stream framework named as Multiscale CNNs which could automatically detect the optimum top-three scales of the image sizes and combine information from different scales of the regions around that pixel. Datasets provided by Multimodal Brain Tumor Image Segmentation Benchmark (BRATS) organized by MICCAI 2013 are utilized for both training and testing. The designed Multiscale CNNs framework also combines multimodal features from T1, T1-enhanced, T2, and FLAIR MRI images. Besides, multimodality MRI images are trained at the same time for utilizing complementary information. Experiments show promising tumor segmentation results through multiscale CNN. In comparison with traditional CNNs this Multiscale CNN framework shows advances in brain tumor segmentation accuracy and robustness, also facilitates faster, accurate and early diagnosis.

III. Conclusion

In this paper we have briefly described some of the different Computer vision and Pattern recognition based automated/semi automated techniques for detection and segmentation of soft tissue pathological disorders. Compared to traditional method of image segmentation these computerized algorithms paves way for automated diagnosis and provides more accurate objective basis on quantitative and qualitative analysis. These automated texture feature based image analysis methods, minimizes variability and biases, provide faster, computationally efficient clinical results. The advanced hybrid machine learning techniques with interactive segmentation algorithms provide early diagnosis of pathological soft tissue disorders can significantly reduce mortality rate.

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