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A Comparative Study of Image Segmentation Techniques for Medical Imaging Problems

Mr A. Venugopal M.Sc, M.Phil[1], CM Sulaikha[2]
Assistant Professor, Department of Computer Science, Sree Narayana Guru College, Coimbatore, Tamil Nadu, India [1]
M.Phil Scholar, Department of Computer Science, Sree Narayana Guru College, Coimbatore, Tamil Nadu, India [2]

Abstract: Analyzing the medical image in image processing is the most important research area. Capturing the image and analyzing them to detect different medical imaging problems is the major research process. Robust organ segmentation is a prerequisite for computer-aided diagnosis (CAD), quantitative imaging analysis, pathology detection and surgical assistance etc. Some of the organs in the human body have high anatomical variability, so segmentation of such organs is very convoluted process. The earlier work on organ segmentation are analyzed and reviewed in this paper. In this paper, a numerous image segmentation algorithms are studied and finally the problems of the earlier works are outlined. This survey brings the appropriate solutions for the future work.
Keywords: Image Processing, Medical Image Mining, Organ segmentation, computer-aided diagnosis, Pancreas segmentation.

I. Introduction

Digital image processing is one of the fastest growing technologies around the world. It has impacted almost all the areas and has emerged as a subject of interdisciplinary study. Digital Image Processing is useful in two prime application areas first being the improvement of pictorial information for human interpretation and the other is processing of image data for storage, transmission, and representation for autonomous machine perception [1]. It is the use of computer algorithms, which helps to perform image processing on digital images. Medical image processing is one of the most popular trends and it has wide range of applications to evaluate medical pathology medical image analysis and surgical assistance etc. There are various areas in medical imaging process where image segmentation has come up with very good solutions. Image segmentation refers to the process of partitioning a digital image into multiple regions (set of pixels) [2]. The aim of image segmentation is to simplify or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in an image. In this paper the various popular segmentation algorithms for image segmentation are discussed. The paper reviews the various methods for better enhancement of the future work. The algorithms and methods developed for handling numerous medical images like MRI, CT images, and dermatology images in real time applications.

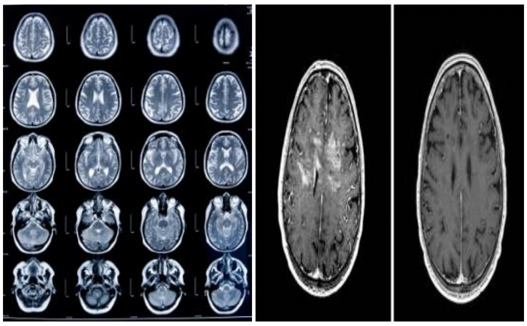

Fig 1.0Sample medical images

Fig 1.0 shows the sample medical images, which is used as an input. These images can be segmented and processed to diagnose different types of diseases and medical abnormalities. In image segmentation process, the image is divided into its constituent parts, which is going to discuss in this section. Image segmentation approaches can be broadly grouped into the five different categories such as Region Based Methods, Edge Based Methods, Thresholding or Histogram based techniques, Morphology based and Hybrid Techniques. Image segmentation algorithms are generally based on the two basic concepts that are similarity and discontinuity with respect to the intensity values.

II. Literature Survey

A. Organ Segmentation:

In the paper [3], authors find the Automatic organ segmentation process. Authors analyzed the organ detection is the important part of medical diagnosis. In the human body, the abdomen organs are having high anatomical variability, the abdomen organs such as pancreas, liver and kidneys. The author presents a probabilistic approach using multi-level deep convolution to perform image classification tasks. These methods have the advantage that used classification features are trained directly from the imaging data. The authors developed a fully automated bottom-up method for pancreas segmentation in abdomen computed tomography (CT) images. The method is based on hierarchical coarse-to-fine classification of local image regions (super pixels). These preserved super pixels assist as a highly sensitive initial input of the pancreas. They evaluate the method on CT images of 82 patients (60 for training, 2 for validation, and 20 for testing). Using ConvNets they achieve average Dice scores of 68%+-10% (range, 43-80%) in testing. The results in the paper show the pancreas segmentation is more accurate when a deep learning approach is used.

In the paper [4], Organ segmentation is a prerequisite for a computer-aided diagnosis (CAD) system to detect pathologies and perform quantitative analysis. In this paper, a complete automated bottom-up method is presented for pancreas segmentation. This used the abdominal computed tomography (CT) scans as input. The method is based on hierarchical two-tiered information propagation by classifying image patches. The segmentation is performed by the Simple Linear Iterative Clustering approach. A supervised random forest (RF) classifier is trained on the patch level and a two level cascade of RFs is applied at the super pixel level, coupled with multi channel feature extraction, respectively. On six-fold cross-validation using 80 patient CT volumes, they achieved 68.8% Dice coefficient and 57.2% Jaccard Index, comparable to or slightly better than published state-of-the-art methods.

In the paper [5], authors used three phase contrast-enhanced CT data. These CT data’s are initially registered together for a particular patient and then registered to a reference patient by the second phase. The second phase is the landmark-based deformable registration. Patient-specific probabilistic atlas guided segmentation is conducted, followed by an intensity-based classification and post-processing. provided the best overall pancreas organ-level boundary recall by partitioning each 2D CT axial slice into over-segmentation label maps of all patients. Their final binary labeling masks can be straightforwardly stacked and projected back into the 3D CT scan space, to form the pancreas segmentation mask. Random forest classifier and cascade of RF classifiers were trained at the image patch- and super pixel-level respectively, via extracting multi-channel features. Based on a six-fold cross validation of the 80 CT datasets, the results are comparable and slightly better than the state-of-the art work.

In the paper [6], Remarkable results have been obtained using image models based on image patches, for example sparse generative models for image inpainting, noise reduction and super-resolution, sparse texture segmentation or texton models. In this paper they propose a powerful and yet simple approach for segmentation using dictionaries of image patches with associated label data. The approach is based on ideas from sparse generative image models and texton based texture modeling. The intensity and label dictionaries are learned from training images. These are associated with the label information of the pixels based on a modified vector quantization approach. For new images the intensity dictionary is used to encode the image data and the label dictionary is used to build a segmentation of the image. They demonstrate the algorithm on composite and real texture images and show how successful training is possible even for noisy image and low-quality label training data. In the experimental evaluation they achieve state-of-the-art performance for segmentation.

In the paper [7], authors proposed and evaluated several variations of deep ConvNets in the context of hierarchical, coarse-to-fine classification on image patches and regions, i.e. super pixels. They first present a dense labeling of local image patches via P-ConvNet and nearest neighbor fusion. Then they describe a regional ConvNet (R1−ConvNet) that samples a set of bounding boxes around each image super pixel at different scales of contexts in a “zoom-out” fashion. The ConvNets learn to assign class probabilities for each super pixel region of being pancreas. Last, they study a stacked R2−ConvNet leveraging the joint space of CT intensities and the P−ConvNet dense probability maps. Both 3D Gaussian smoothing and 2D conditional random fields are exploited as structured predictions for post-processing. They evaluate on CT images of 82 patients in 4-fold crossvalidation.

In paper [8] authors presented an automated bottom up approach for pancreas segmentation in abdominal computed tomography (CT) scans. The method generates a hierarchical cascade of information propagation by classifying image patches at different resolutions and cascading (segments) super pixels. The system contains four steps: 1) decomposition of CT slice images into a set of disjoint boundary-preserving super pixels; 2) computation of pancreas class probability maps via dense patch labeling; 3) super pixel classification by pooling both intensity and probability features to form empirical statistics in cascaded random forest frameworks; and 4) simple connectivity based post-processing. Dense image patch labeling is conducted using two methods: efficient random forest classification on image histogram, location and texture features and more expensive (but more accurate) deep convolutional neural network classification, on larger image windows.

B. Image de-noising:

In paper [9], authors discussed the tampered image related issues. In the acquisition stage of medical images, there are chances that the medical image might be tampered because of issues occurring during the acquisition stage. Hence, the original image may not be useful for examination. Image segmentation can be defined as the partition or segmentation of a digital image into same type of regions with an important goal of simplifying the image considered, into something that can be comprehended and easy for visual analysis. Image segmentation is a highly significant process in the whole field of medical image analysis. The image under test obtained by the acquisition device is vulnerable to damage by the environment. Hence, a basic issue in the image processing is the enhancement of their quality by the removal of the noise. Image preprocessing techniques are useful for the improvement of the quality of an image before getting it processed in an application.

A large variety of techniques devoted for carrying out this task is available. All of them depend on the type of the noise in images. Image preprocessing techniques are useful for the improvement of the quality of an image before getting it processed in an application. In the paper [10] authors utilizes a small neighborhood of a pixel in an input image to obtain new brightness value in the output image. These preprocessing methods are also referred to as filtration and resolution enhancement. The medical image quality parameters are noise and resolution chiefly. The important aim of this section is the improvement of the image quality by de-noising and resolution enhancement. Many of the imaging techniques are deteriorated by noise Denoising is applied as a preprocessing step in many image processing and analysis operations such as registration or segmentation for reducing the random noise which arises from the acquisition process. This technique, even though is able to reduce some image noise and also eliminates high-frequency signal components, produces blurred edges in the images. A big number of edge-preserving techniques have been proposed for overcoming the observed blurring effects. Still, this filter takes a long time for the removal of noise, during which a few significant details would also be reduced in the de-noising process. Other transforms that have been employed for denoising images are Principal Component Analysis (PCA) and the Discrete Cosine Transforms (DCT).

In paper [11], authors proposed a new technique for Gaussian noise reduction. The image noise is eliminated by making use of over complete linear transforms and thresholding mechanisms. Actually, author employed a classical sliding-window DCT thresholding, but overlapping estimations adaptive combination was applied for the reduction of the Gibbs effects.

All these approaches come up from the fact that an image can be represented as the linear combination of a set of image bases with very less non-null coefficients. This characteristic, referred to as sparseness, is the heart of the JPEG and JPEG2000 compression standards. For instance, anisotropic diffusion filters are capable of removing noise by making use of gradient information without damaging important image structures. Even though many algorithms have been innovated to serve the purpose of image de-noising, the issue of noise image suppression has remained a challenge unresolved, since noise removal brings in artifacts and leads to blurring of the images. Few popular de-noising filters for MRI are Non-local Means, Anisotropic Diffusion, Bilateral and Total Variation filter. This may also result in misguiding visual impression of importance, as the smoothness of the resulting curve may often be taken as an indication that few visible features would be important, even if they are just normal noise. Hence, the Non Local Means (NLM) filter, a novel technique proposed in the paper [12], has emerged as a very easy and effective means of limiting noise with minimal deterioration to the actual structures of the image. This method is in accordance with the original redundancy of patterns within the images. Enhanced recently, the NLM filter has been employed for the denoising of MR images and has been proved with better results in comparison with other available methods.

In paper [13], authors presented the integration of a discrete cosine transform (DCT) into NLM filter to have an improvement over its limitation and suggested a new filter. In the new filter, during the denoising, transformation of image patches are first done from time domain to frequency domain, making use of DCT and lower-dimensional frequency coefficients subspace of DCT is got by Zigzag scan. As a result, similarity weights are calculated in this subspace with being hard to noise instead of the full space. Hence, the accuracy of similarity weights is enhanced and same kind of more pixels can be found in the search window. Lastly, taking the characteristics of Rician noise into consideration in MR image, the unbiased correction operation is carried out for the elimination of the biased deviation. The filter proposed has been compared with many methods introduced recently, which show that the proposed filter outperforms the rest of the methods with regard to both vision and complexity.

In paper [14], authors evaluated the Anisotropic Smoothing Regularizer (AnSR) which uses edge-detection and denoising inside the Demons framework for the regularization of the deformation field at each iteration of the registration in a more aggressive manner in homogeneously oriented displaced regions. Simultaneously it regularizes in a less aggressive manner in areas comprising of non-homogeneous local deformation and tissue interfaces. On the contrary, the traditional Gaussian Smoothing Regularizer (GaSR) performs a uniform averaging over the entire deformation field, with no care in considering transitions across tissue boundaries and local displacements in the deformation field. In this work AnSR is applied within the Demons algorithm and performs pair wise registration on 2D synthetic brain MRI, with and without noise, after the induction of a deformation that simulates shrinking of the target region anticipated from Laser induced Interstitial Thermal Therapy (LITT). The Demons with AnSR are employed for registration of clinical T1-weighted MRI for one epilepsy and one (GBM) patient pre and post LITT.

In paper [15] authors gave the introduction for a method for heavily accelerating the computation of patch distances and hence in NLM, considering only the difference between important features related to the pixels to be weighed. In comparison to other related works, the technique has a number of key benefits that are tested over the usual MRI data sets: first, the calculation maintains the statistical characterization of patches in the original NLM, and thereby its optimality properties. But, this approach is chiefly oriented to MRI, which is implicitly non-textured.

In paper [16], authors assessed a method with the purpose of noise removal in MRI. An implementation of an improved version of anisotropic diffusion filter is realized. In this schema, the modified diffusion equation of the filter is useful for considering the edge’s direction. This permits the filter only to blur uniform areas, while preserving the edges.

In paper [17], authors showed the preprocessing, based on bilateral filtering, that can localize activated brain near to regions of abnormal tissue such as tumors with more accuracy. In comparison with Gaussian spatial smoothing, this has better performance believing that activation signal does not create any blur across sharp intensity “edges” produced by tissue interfaces. This alternative technique of spatial smoothing may be helpful, especially for comparatively stronger activation signal as needed at higher field strength. Bilateral filtering is shown to increase the statistical importance of activated areas, while preserving boundaries between tissue classes and between activated versus non-activated regions inside the same tissue class.

Authors in [18] studied and produced the assessment of a bilateral filter for the smoothing of diffusion MRI fibre orientations preserving anatomical boundaries and supporting multiple fibres per voxel. In this technique, distances and local estimators of weighted collections of multi-fibre models are defined and are shown that these provide the ground for effective bilateral filtering algorithm for orientation data. This method has significant applications in diffusion MR tractography, brain connectivity mapping, and cardiac modeling. The authors presented a useful technique for the improvement of noisy magnetic resonance image utilizing bilateral filter in the undecimated wavelet domain. The extent of the restored magnetic resonance image is helpful for diagnosis and automated computer analysis. Undecimated Wavelet Transform (UDWT) is applied for effectively representing the noisy co-efficient.

III. Conclusion

In this paper, a set of image segmentation and image denoising related techniques and approaches were studied. This summary and analysis is used for the purpose of effective medical image analysis. It is found that there is no perfect method for image segmentation for abdomen organs. Due to the high level anatomical variability, the abdomen organs are tedious to detect, because the result of image segmentation is depends on many factors especially in medical images it is not clear always. Therefore, it is not adequate for the medical image segmentation particularly abdomen organ segmentation. The literature survey brings the overview of the earlier works along with its complications. Hence, it is good to use hybrid solution consists of multiple methods for abdomen scanned image segmentation problem for organ detection. From the analyses of the problem in medical image analysis is identified.

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