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Medical Image Segmentation with active contour and optimization Techniques: Survey

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ABSTRACT

The principal aim is to improve medical diagnosis through segmented images. Thus, medical image segmentation become one of the key technologies in computer-aided diagnosis. Active contours, or snakes, have been widely used for image segmentation purposes. However, high noise sensitivity and poor performance over weak edges are the most acute issues that hinder the segmentation accuracy of these curves, particularly in medical images. To overcome these issues, a novel external force that integrates gradient vector flow (GVF) field forces and the traditional snake function is proposed in this research. In addition, a novel technique is applied to limit the boundary of the initial contour by set four initial points around the medical issue and then connecting them by polynomial curves. Moreover, the positive effect of Particle Swarm Optimization (PSO) on calculating the final active contour area and its percentage to the entire image area is proved in this work.

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1. Introduction

Nowadays, medical images become an important section of the medical diagnosis process because they easily give essential information about the medical issue. Several medical images like Magnetic resonance imaging (MRI) and computed tomography (CT) offer specific details about the anatomy of the medical objects, even their fine particles. In general, using technology to deal with medical images play an important role during diagnosis and planning of treatment, especially when highlighting the shape and appearance of the medical issue[1][2].

Computer vision is a field that aims to extract, analyze, and comprehend meaningful information from visual data such as photos and videos automatically. In today's environment, it has a wide range of applications. Autonomous vehicles, medical devices, and robotics are just a few examples. Some well-known computer applications include image analysis, robotics, and facial recognition[3].

To extract areas of interest in the image, there are many segmentation methods based on the following dimensions: color, grey values, depth, motion, texture, discontinuity, and similarity.

The main methods of region segmentation are edge detection, region growing, clustering, split and merge, and active contour methods. The techniques available for the segmentation of medical images are specific to the application, imaging modality, and type of body part to be studied; this should be taken into account[4].Image segmentation is one of the most important aspects of image processing and analysis, intending to separate the goal of separating objects[5]. An active contour model is a curve or a surface defined within the image range that can be deformed by the interaction of the internal force of the curve or the surface itself and the external force generated by the image data. the main study concept used in this study will be presented . the program is designed to import the medical image and start work on it. The main initial parameters and boundary conditions, such as the initial size and the iteration number, are specified in this stage. A novel idea for outlining the initial contour is performed for the next step to limit a searching region for the active contour's movement. Thus, the traditional snake function will work inside a specific searching area to be sure it will never move away outside the medical issue. The GVF model will be used to upgrade the resulting active contour to overcome the weakness of the traditional snake function.

2. Active Contour

The active contour's creation and improvement will entirely depend on the medical image's energy by generating internal and external forces. the contour reaches a specific accuracy threshold. Otherwise, the iteration will be repeated, and the GVF model will be applied again. Usually, in the segmentation of medical images field of study, The medical image datasets are entirely imported from the Kaggle website, which is available online under the title CT KIDNEY DATASET: Normal-Cyst-Tumor and Stone That means the entire image's information will be known, such as the size, resolution, and area of active contour. Therefore, the Particle Swarm Optimization (PSO) theory is applied depending on calculating the contour's area and comparing it with the information of the dataset to get the contour's accuracy. Typically, if the area's accuracy is equal to the desired accuracy, the iteration will be stopped, and the final medical image with the active contour will be presented. Otherwise, the program will change the initial parameters and return to running the entire program until the desired accuracy is satisfied.

2.1 Active Contour Model in Medical Image Segmentation

Xuefei Zhang in [2019] he proposed an improved active contour model based on vector field convolution, and combining both the balloon force and gradient directional information. This method improved the energy function of model, has more chances to approximate the complex boundary. The result showed that the improved active contour model has large capture range, are less computationally expensive. Additionally, the improved model can avoid the edge leak by implementing a kind of new stop mechanism of evolution, and the accuracy of the improved model was superior to the traditional active contour model in the medical image segmentation models [6].

Xu Chen1 et.al in [2019] they proposed a new loss function that integrates space and volume information into a dense deep learning model. They evaluated their approach on a dataset of more than 2,000 cardiac MRI scans; the proposed loss function outperforms the other dominant loss function across entropy over two common segmentation networks. The result introduced a new AC loss function that was inspired by ACMs for the segmentation tasks. . The advantage of this new loss function is that it can seamlessly combine the geometrical information (e.g. boundary length) with region similarity thus leads to more precise segmentation. The proposed approach is superior to the most recent approaches [7].

Viacheslav et.al in [2017] a modified segmentation approach based on the active contour method is proposed to extract parts of bones from MRI data sets. Good results are shown in comparison with current methods of segmentation of medical data. They presented a novel segmentation algorithm to extract the parts of bones from Magnetic Resonance Imaging (MRI) data sets. The proposed method is based on LPA-ICI (local polynomial approximation – the intersection of confidence intervals) anisotropic gradient [8].

Chencheng Huang et.al in [2021] they proposed a model can automatically obtain a better initial contour location and reduce the computing cost for segment processing. Second, to improve the accuracy of image segmentation, we considered the similarity of the object contour between adjacent slices, and introduce a punishment term in localized ACM [9].

Huaizhong Zhang and Xianghua Xie in [2012] A Laplacian diffusion scheme is proposed in the MAC model to tackle excessive image noise which can interrupt image gradient vectors and in turn affect the external force field. A derived vector potential field (VPF) is employed to obtain magnetic force and thus a diffusion tensor can be applied to diffuse VPF in terms of both magnitude and directional information, instead of directly diffusing the magnetic field as in the MAC model. The proposed diffusion enhancement can lead to evolving the curve smoothly and thus level set evolution is adapted to approach genuine object of interest [10].

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Mohammad Talebi et.al [2010] they presented a segmental method combined genetic algorithm and active contour with an energy minimization procedure based on genetic algorithms. This method have been proposed to overcome some limits of classical active contours, as contour initialization and local minima (speckle noise), and have been successfully applied on medical ultrasound images. The obtained results also show that this method of ultrasound image segmentation obtains acceptable accuracy [11].

Tingting Liu et.al in [2014] a new hybrid region-based active contour model is presented for segmenting medical images with extreme heterogeneity. The proposed model of the energy function consists of three weighted terms: the global term, the local term, and the regulation term. They proposed a hybrid region-based active contour model for image segmentation. The proposed method could improve the ability of the resume template to handle. Homogenization intensity, meanwhile, it makes segmentation more efficient compared to LRBAC method. Experimental results on both artificial and real images show that the proposed method can deal with better intensity and power heterogeneity of noise compared to CV model and LRBAC method. It should be noted that the functional energy of our model is non-convex and thus has local minima, which makes our model sensitive to ambient configuration. Future work could be done to apply appropriate algorithms to development globally optimal active contours [12].

2.2 Active contour with Convolutional Neural Network

K V Mahesan et.al in [2017] they presented the development process of active contour models and describes the classical parametric active contour models, geometric active contour models, and new hybrid active contour models based on curve evolution and energy minimization techniques. It also discusses challenges and applications of active contour models in medical image segmentation. They discussed a variety of approaches that have been developed over the past decades for the task of segmenting the medical picture [13].

Junyu Chen et.al [2020] they presented a novel learning-based segmentation model that could be trained semi- or un- supervised. Specifically, in the unsupervised setting, they parameterized the Active contour without edges (ACWE) framework via a convolutional neural network (ConvNet), and optimize the parameters of the ConvNet using a self-supervised method. In another setting (semi-supervised), the auxiliary segmentation ground truth is used during training. The results showed, fine-tuning the pre-trained unsupervised model with only 80 GT labels leads to a significant improvement in performance. they presented an unsupervised/semi-supervised ConvNet-based model for image segmentation that can be trained with or without ground truth labels. The resulting DSC values reported demonstrating the effectiveness of the proposed method [14].

Feng-Ping and Jun-e Liu in [2020] they adapted a neural network to medical image features by adding cross-layer connections to a traditional convolutional neural network. An optimized convolutional neural network model is established. The optimized convolutional neural network model can segment medical images using the features of two scales simultaneously; at the same time, to solve the generalizability problem of the deep learning model, an adaptive distribution function is designed according to the position of the hidden layer, and then the activation probability of each layer of neurons is set. They provided a new perspective for research on medical image segmentation. The method proposed an excellent segmentation effect primarily because, first, the deep learning method proposed in this paper solves the problem of network architecture optimization for the deep learning model. Second, the deep learning method proposed in this research addresses the over fitting problem better than previous methods [15].

ASIM NIAZ et.al in [2020] they proposed an active contour method based on a reformed combined local and global fitted function to address breast tumor segmentation. This combined function is strengthened by a proposed average energy driving function to capture obscure boundaries for regions of interest more precisely from inhomogeneous images. The proposed method was tested on the MIAS Mini Mammographic Database, with quantitative analysis to calculate its accuracy, effectiveness, and efficiency. The obtained results from the quantitative comparisons are considered good if the computed values are near to 1. The proposed method offers a powerful tool for early breast cancer detection and consequent mitigation of breast cancer impacts [16].

Chen Hong et.al in [2018] they proposed a model can bring about a more full description of the local intensity distribution. Also, entropy is introduced to improve the performance of robustness to noise of the algorithm. At last, three experiments are carried out to test the performance of the method. The proposed method can complete segmentation and bias correction for brain MR images. Experimental results show our method meets all the four conditions of accurate segmentation of brain tissue: the full description of gray value distribution, robust to serious noise, multiphase segmentation, and bias field estimation [17].

José Micael Delgado Barbosa et.al in [2020] they Proposed Brain imaging acquisition can present different issues, such as noisy images which can result in a problematic diagnosis. Image preparation such as skull stripping and region segmentation is a fundamental step in order to support a better medical diagnosis outcome. Therefore, this study presented a segmentation technique based on the active contour model to perform skull stripping. The Results of active contour method achieved results within the ones presented on the state-of-art values segmentation methods with 96.4% of sensitivity and 96% of specificity using only 4 k-means clusters. Image texture characteristics such as entropy and correlation presented values of 1.8804 and 0.96, respectively. These high evaluation scores demonstrate that the semi-automatic contour-based segmentation algorithm is a powerful tool for segmentation and skull-stripping decreasing loss of image [18].

Chaolu Feng et.al in [2020] they proposed a model is extended to multichannel and multiphase patterns to segment colorful images and images with multiple objects, respectively. Experimental results and comparison with relevant models demonstrate the advantages of the proposed model in terms of bias correction and segmentation accuracy on widely used synthetic and real images and the Brain Web and the IBSR image repositories. The proposed model is effective in segmenting images with inhomogeneous intensities and provides a smooth bias estimation of the inhomogeneity. They improved proposed model which was to extract brain tissues in 3D on public image repositories in our future work [19].

Mo Zhang et.al in [2020] they presented a novel deep active contour network (DACN) for medical image segmentation, which integrates ACM (convexified Chan-Vese model) into the DenseUNet architecture in an end-to-end differential manner. By leveraging the advantage of ACM to locate object edges, the proposed DACN tends to generate more accurate segmentation of contours. Our DACN has better performance on two public datasets compared to UNet, DenseUNet as well as several state-of-the-art models, especially for boundary delineation. Additionally, DACN can also be applied to multi-class semantic segmentation, where the issue of multi-class semantic segmentation should be decomposed into several singleclass segmentations. In the future, it is worth further investigation about the working mechanism of DACN [20].

Amira Ben Rabeh et.al in [2016] they introduced a new automatic method of brain images segmentation based on the Active Contour (AC) model to extract the Hippocampus and the Corpus Callosum (CC). The contribution is to combine the geometric method with the statistical method of the AC. They find that our method Modify Level set to give a good result [21].

[Image segmentation using active contours with modified convolutional virtual electric field external force with an edge-stopping function]

Ke Cheng et.al in [2020] in this paper, they proposed a novel external force for active contours, namely, the MCONVEF model. The proposed MCONVEF model introduced the scale-space parameter h and the edge stopping function gk(|rf|) and employed a piecewise linear approximation to achieve fast calculation. Experimental results on both synthetic and real images have shown that the MCONVEF snake model holds the desirable properties of the GVF and VEF snakes such as the large capture range, initialization insensitivity, and subject contour convergence. Additionally, the proposed model presents better performance in quantitative metrics in terms of noise robustness, weak edge protection and deep concavity convergence. In summary, the MCONVEF model can be considered as a superior alternative to the GVF and VEF models [22].

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2.3 Active Contour with Optimization Techniques

Ali M. Hasan in [2018] in this work they attempted to present a novel automatic segmentation strategy. As a result, the BCBPSO method was used to determine the Using the symmetry advantage of normal brain scanning, researchers were able to find the core of brain tumors in MRI scans. This will be beneficial. to automatically initialize the volumetric active contour without using the edge approach. The proposed strategy beats previous methods in terms of accuracy. A suggestion for Further study is required to optimize the proposed algorithm to achieve speedier implementation in the real world [23].

Rui Li et.al in [2009] they suggested the control point of the algorithm could be expanded. Maximize convergence speed and search area It sets swarm for each control point, then swarm for each swarm collaboratively search for the greatest point As a result, it avoids premature deficiency of information. The classic PSO algorithm when comparing our ideas, the experimental algorithm with the regular algorithm their method outperformed others. Experimentation method outperformed others, according to the results. Lacks the performance of a traditional snake model was spending additional time [24].

Wei Xu, Xiaodong Yue in [2017] to improve contour-based segmentation, they proposed an ensemble technique. Maximizing the weighted average yields the best segmentation ensemble. The probability distributions of various segmentation outcomes Validation of experimental results that the contour-based segmentation ensemble is stable to the biased initialization and gives precise and steady results Images of complex contents yielded outcomes. The robustness of contour-based segmentation against biased initialization is improved using an ensemble technique proposed in this research. The ensemble is carried out by reciprocal information optimization between probabilities multiple segmentation results distributions experiments confirm the efficacy of the proposed ensemble approach [25].

Devraj Mandal et.al in [2014] they suggested a resilient version of the Chan and Vese algorithm in this paper, which should produce good segmentation performance regardless of the initial contour choice. The appropriate energy minimization is formulated in this paper. Problem to be solved with the help of a metaheuristic optimization method, with a successful implementation Particle swarm optimization (PSO) was used to optimize our algorithm. They had created the algorithm for The Chan and Vese model has been successfully used for a two-phase level set implementation. Photos with both scalar and vector values Extensive testing with many sorts of Medical graphics show how the proposed strategy could vastly improve the quality of care. Chan and Vese method obtained segmentation performance with various contour initializations [26].

3.Conclusion

This survey As mentioned above explains different images segmentation were tested and evaluated using deep neural networks and optimization techniques with variety of accuracy values. Active contour models represent the mage segmentation technique with better convergence to concavity boundaries. Theses articles mentioned in different section represent the most applicable projections which benefits to conclude the suitable method or technique need to apply it.

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