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STUDY OF IMAGE SEGMENTATION METHODS WITH MRI IMAGES

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Abstract

Digital image processing is the use of a digital computer to process digital images. Image processing transforms input images into digital form for certain operations to obtain useful information. Segmentation is a well-known process used in image processing that partitions input images into different regions. Image segmentation is a sub-area of computer vision and digital image processing for grouping similar segments of an image under respective class labels. Several methods were performed with neutrosophic sets on dissimilar image-processing domains. However, the denoising and segmentation were not carried out accurately with minimal time complexity. To address these issues, many image segmentation methods are reviewed.

Keywords: Computer Vision, Denoising, Digital image processing, Neutrosophic set, Segmentation,

I. Introduction

Digital Image Processing (DIP) is used to process digital images through a digital computer to obtain enhanced images and to extract essential information. An image includes a million pixels. Segmentation varies the image representation into image features like texture, color, and pixel intensity value. Image segmentation is a sub-type of DIP. Image segmentation is an image processing task where images get segmented or partitioned into multiple regions. The pixels in the same region share similar characteristics. Image segmentation allocates every pixel to the object that divides and groups the exact pixel set. Image segmentation is a collection of segments with a collection of contours taken from images. Image segmentation partitions images into different parts consistent with their features and properties. An image segmentation algorithm was designed to combine the saliency map and neutrosophic set (NS) theory [X]. The guided filter was employed with different channels of natural images to address the weak edges in the image saliency map, local entropy map, and grayscale map. However, it failed to consider modification of algorithm structure and optimization of factor settings. An improved FCM algorithm was designed with anti-noise capability [VI]. A new image segmentation algorithm was employed for noise reduction. An improved FCM was introduced to partition the images with extracted grayscale features depending on areas of interest. However, it failed to reduce computational cost. An iterative contraction algorithm was designed with chi-square similarity and fuzzy logic to remove the speckle noise [II]. Nevertheless, it failed to lessen running time. A distance and similarity measure was designed for a single-valued neutrosophic set model with axiomatic distance and similarity [I]. Pattern recognition and medical diagnosis were carried out to reveal the similarity measure applicability. However, an effective method was not used for converting the script data to real-life databases. A mathematical model was introduced to determine the noise statistics in Magnetic Resonance (MR) images from image fuzziness [VIII]. Image noise variance was determined by the fuzziness of noisy images through a polynomial model. However, the noise affected the randomness of gray levels, gradient, and fuzziness of the image. In addition, the peak signal-to-noise ratio was not improved. Neutrosophic Graph Cut-based Segmentation (NGCS) was carried out over pre-processed cervical images [III]. However, the hybrid graph cut technique was not used. A fully automatic and unsupervised method was designed for brain tumor area extraction [XI]. However, the designed method was robust to noise and proficient in extracting the lesion area regardless of intensity inhomogeneity. An interval neutrosophic set (INS) was used with a set of numbers in a real unit interval [XIII]. However, the segmentation accuracy was not improved by INS. A multi-class image segmentation method was designed with uncertainty management [IV]. But, the segmentation time was not reduced. An image segmentation method was introduced to select threshold value [IX]. However, the NEATSA applicability was not suitable for other types of MR images.GMM fuzzy C-means (GMMFCM) algorithm was designed for pulmonary nodule segmentation [V]. However, time complexity was not reduced. Enhanced Fuzzy Segmentation Framework (EFSF) was designed for segmenting information [XII]. However, minute discontinuities were not repaired with morphological operations. Multi-model medical image processing was developed to enhance the accuracy [VII]. However, it failed to estimate the error rate.

II. Digital Image Segmentation

Digital image processing uses computer algorithms for image processing to improve image quality by removing noise and unwanted pixels. Image analysis is the image processing for finding the objects in the image. Image segmentation is one of the most critical tasks in image analysis. Segmentation has to divide an image into dissimilar parts. Image segmentation is to simplify the image for easy analysis. Image segmentation is used to locate the objects and boundaries in images. Image segmentation is a demanding and difficult task affected by noise, low contrast, illumination, and object boundaries.

II.i. A Fast Image Segmentation Algorithm Based on Saliency Map and Neutrosophic Set Theory

Image segmentation was employed to partition the given image into multiple non-overlapping areas for subsequent image analysis. Neutrosophic set (NS) theory was employed to address the uncertainty issues in image processing with better results. The image segmentation algorithm was introduced with saliency map and NS theory. The saliency map was determined from the local entropy map of the image; guided filtering created a preliminary saliency map and non-linear functional transformation. In the saliency map, useless image details were highlighted and under-segmentation occurred. When the indeterminacy was removed in the NS domain, the useful information was removed and resulted in over-segmentation. An indeterminacy factors were eliminated by NS. Entropy was used as a standard measure to determine the quantification of information and to describe the uncertainty of information sources. In image processing, information entropy was used to determine the richness of image details. The guided filter was employed to filter different channels of natural images by addressing weak edge issues in an image. The guided filter needed guidance pictures with separate input images. The edge was protected with a guided filter. An initial saliency map was generated. The nonlinear function was utilized to generate the final saliency map. The designed algorithm highlighted the foreground information of an image. The saliency map was converted into an NS domain and interpreted through three subsets, namely true (T), indeterminate (I), and false (F). Consistent with NS theory, indeterminacy gets reduced, and segmentation results are attained through the threshold value. The designed algorithm was fast and efficient for the de-noising process.

II.ii. Local segmentation of images using an improved fuzzy C-means clustering algorithm based on self-adaptive dictionary learning

Image segmentation is considered an active research area in image processing. Fuzzy C-means (FCM) clustering analysis was employed in the image segmentation. The noise generated during the imaging process affects successful tissue segmentation with large amounts of delicate tissues like blood vessels and nerves in medical images. The FCM algorithm was not perfect for the segmentation of images with strong noise. An improved FCM algorithm was introduced with anti-noise capability. The dictionary learning process was carried out to reduce noise reduction. A new image segmentation algorithm was introduced with dictionary learning for noise reduction and improved fuzzy C-means clustering. An improved FCM was used to segment the images with grayscale features and extract areas of interest efficiently. The FCM image segmentation algorithm does not require human intervention. A new fuzzy clustering algorithm was introduced with dictionary learning to address the non-convex optimization issue. A new regularization was added to the FCM algorithm for constructing the non-convex model. The logDet non-convex function was selected because convergence was stable in function minimization. An FCM algorithm implementation was carried out with the minimum Euclidean distance between the target pixels and the clustering center. The KFCM algorithm was introduced based on a kernel function with high sensitivity to noise. The images segmented by dictionary learning a Fuzzy C-mean clustering (DLFCM) algorithm attained higher partition coefficient, lesser partition entropy, improved visual perception, improved clustering accuracy, and clustering purity.

II.iii. Optical coherence tomographic image denoising based on Chi-square similarity and fuzzy logic

Optical coherence tomography (OCT) is a high-resolution optical imaging technology in different fields like medical diagnostics, biological systems, and materials science. OCT images were destroyed through speckle noise due to low-coherence interference of light to remove the speckle noise. An iterative contraction algorithm was introduced depending on chi-square similarity and fuzzy logic. An OCT image was partitioned into overlapping image blocks. Chi-square distance similar block matching was carried out to form a low-rank group matrix. The singular values were contracted through diverse weights with fuzzy logic. The denoising effect was enhanced. The designed algorithm achieved objective indicators and visual inspection. Block matching was employed as a similarity criterion depending on Chi-square distance. Block matching uses non-local self-similar redundancy information to gather similar blocks to construct a low-rank group matrix. Chi-square distance-based similarity measures were employed in a low-rank framework for OCT image denoising. Stopping criteria for employed to perform SNR as well as SSIM. SNR and SSIM were efficient quantitative indicators for determining the denoising effect.

III. Comparison Analysis of MRI Image Segmentation Methods

Experimental evaluation of existing MRI image segmentation techniques is implemented using Matlab software. The experiment of existing MRI image segmentation techniques is conducted using the Brain MRI Segmentation Dataset from Kaggle. The URL of the dataset is given as https://www.kaggle.com/datasets/mateuszbuda/lgg-mri-segmentation?msclkid=818e9627adcc11ec89b21a30a31ba4bc.
Brain MRI Segmentation Dataset comprises brain MRI images together with a manual FLAIR abnormality segmentation mask. Result Analysis is carried out using existing methods with parameters that are, segmentation accuracy, segmentation time, and error rate.

III.i. Analysis of Segmentation Time

Segmentation time 'ST' is described as the product of several MRI images and time consumed to perform segmentation of one MRI image. It is determined in terms of milliseconds (ms). It is computed as,

$$ST = N * time\ consumed\ to\ perform\ efficient\ segmentation\ of\ one\ data \qquad (1)$$

From (1), segmentation time is determined.

Table 1 : Tabulation for Segmentation Time

Number of MRI Images (Number)	Segmentation Time (ms)		
	Image Segmentation Algorithm	Improved Fuzzy C-means Clustering	Iterative Contraction Algorithm
50	15	25	34
100	18	27	36
150	20	30	39
200	17	28	37
250	15	25	35
300	12	22	33
350	14	26	36
400	16	28	39
450	19	30	41
500	22	33	43

Table 1 explains the performance analysis of segmentation time versus number of MRI images. From the above table, it is clear that the segmentation time of the Image Segmentation Algorithm is less than the Improved Fuzzy C-means Clustering and Iterative Contraction Algorithm.

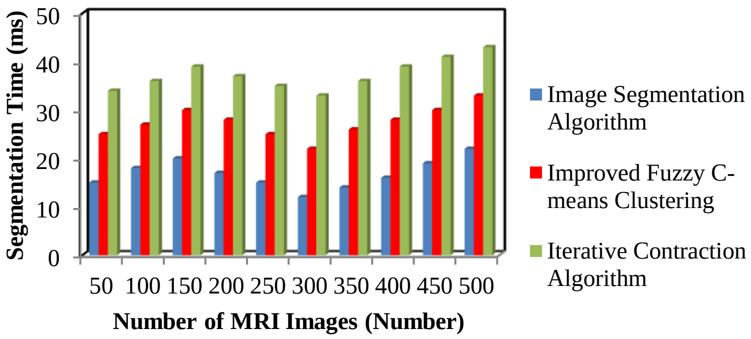

Fig. 1. Measurement of Segmentation Time

Figure 1 describes the segmentation time comparison for three existing image segmentation methods. The blue color bar represents the segmentation time of the Image Segmentation Algorithm, whereas the red color bar and green color bar represent the segmentation time of the Improved Fuzzy C-means Clustering and Iterative Contraction Algorithm. It is observed that the segmentation time using the Image Segmentation Algorithm is less when compared to the Improved Fuzzy C-means Clustering and Iterative Contraction Algorithm. This is due to the application of guided filters to different channels of natural images by solving the weak edge issues in images. The guided filter needed the guidance picture with a separate input image. In this way, segmentation time gets reduced. Research on the Image Segmentation

Algorithm consumed 39% less segmentation time than Improved Fuzzy C-means Clustering and 55% higher segmentation time than the Iterative Contraction Algorithm.

III.ii. Analysis of Segmentation Accuracy

Segmentation Accuracy '(SA)' is described as the ratio of the number of MRI images that are correctly segmented concerning pixel value to the total number of MRI images. It is calculated in terms of percentage (%). It is given as,

$$SA = \frac{Number\ of\ MRI\ images\ that\ are\ correctly\ segmented}{Total\ number\ of\ MRI\ images} * 100 \qquad (2)$$

From (2), segmentation accuracy is determined.

Table 2: Tabulation for Segmentation Accuracy

Number of MRI Images (Number)	Segmentation Accuracy (%)		
	Image Segmentation Algorithm	Improved Fuzzy C-means Clustering	Iterative Contraction Algorithm
50	72	85	77
100	75	87	79
150	73	84	76
200	70	82	73
250	74	85	75
300	77	87	78
350	79	89	81
400	82	91	84
450	78	90	82
500	82	93	85

Table 2 explains the performance analysis of segmentation accuracy versus number of MRI images. From the above table, it is observed that the segmentation accuracy of Improved Fuzzy C-means Clustering is higher than the Image Segmentation Algorithm and Iterative Contraction Algorithm. Figure 2 explains the segmentation accuracy comparison of three existing image segmentation methods. The blue color bar denotes the segmentation accuracy of the Image Segmentation Algorithm, whereas the red color bar and green color bar represent the segmentation accuracy of the Improved Fuzzy C-means Clustering and Iterative Contraction Algorithm. It is observed that the segmentation accuracy using Improved Fuzzy C-means Clustering is less when compared to the Image Segmentation Algorithm and Iterative Contraction Algorithm. This is due to the application of a fuzzy clustering algorithm with dictionary learning for solving the non-convex optimization issue. A new regularization added an FCM algorithm for designing the non-convex model.

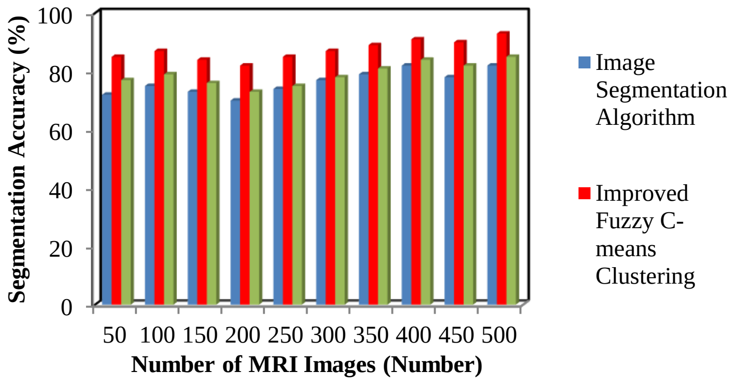

Fig. 2. Measurement of Segmentation Accuracy

In this way, segmentation accuracy gets improved. Research in Improved Fuzzy C-means Clustering has attained 15% higher segmentation accuracy than the Image Segmentation Algorithm and 11% higher segmentation accuracy than Iterative Contraction Algorithm.

III.iii. Analysis of Error Rate

Error Rate (ER) is described as the ratio of the number of MRI images that are incorrectly segmented to the total number of MRI images. It is determined in terms of percentage (%). It is calculated as,

$$ER = \frac{Number\ of\ MRI\ images\ that\ are\ incorrectly\ segmented}{Total\ number\ of\ MRI\ images} * 100 \tag{3}$$

From (3), the error rate is determined. When the error rate is lesser, the method is said to be more efficient.

Table 3: Tabulation for Error Rate

Number of MRI Images (Number)	Error Rate (%)		
	Image Segmentation Algorithm	Improved Fuzzy C-means Clustering	Iterative Contraction Algorithm
50	35	48	21
100	37	50	23
150	34	47	19
200	32	45	17
250	30	42	14
300	28	39	12
350	31	43	15
400	34	46	18
450	36	49	21
500	38	52	23

Table 3 describes the performance analysis of the error rate versus number of MRI images. From the above table, it is clear that the error rate of the Iterative Contraction Algorithm is less than the Image Segmentation Algorithm and Improved Fuzzy C-means Clustering.

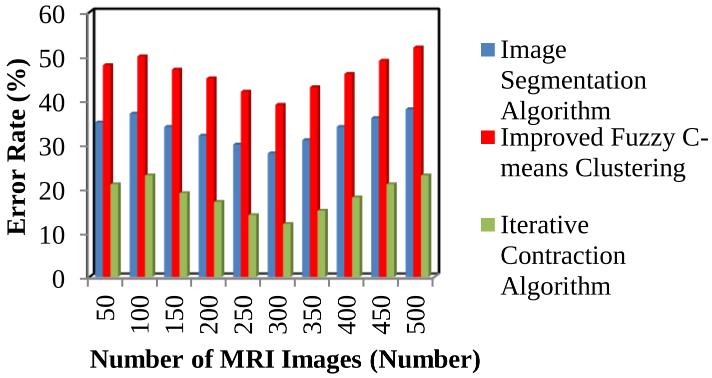

Fig. 3. Measurement Analysis of Error Rate

Figure 3 illustrates the error rate comparison for three existing image segmentation methods. The blue color bar denotes the error rate of the Image Segmentation Algorithm, whereas the red color bar and green color bar represent the error rate of the Improved Fuzzy C-means Clustering and Iterative Contraction Algorithm. This is because of applying a Chi-square distance-based similarity measure to determine the similarity between the reference block and the candidate block. The fuzzy theory partitioned the reference block into structural blocks and texture blocks. The denoised image removed the noise adequately and preserved the image texture information. In this way, the error rate is minimized. Research in the Iterative Contraction Algorithm has attained a 46% less error rate than the Image Segmentation Algorithm and a 61% lesser error rate than Improved Fuzzy C-means Clustering.

IV. Discussion on Limitations MRI Image Segmentation Methods

An image segmentation algorithm joined the saliency map and neutrosophic set (NS) theory to partition the natural image into an exact binary image. The guided filter removes the natural image channels to address weak edge issues in the image. Indeterminacy was minimized and segmentation results were attained through threshold value. The performance of the SMNS model was enhanced. An improved FCM algorithm was introduced with dictionary learning for noise reduction. An improved FCM was introduced to segment the images by removing the non-target areas with grayscale features of images. The designed algorithm removed the non-target areas and extracted the areas of interest. The designed algorithm has improved segmentation accuracy, either noise or noise-free with minimal running time. The computational cost was not minimized by an improved FCM algorithm. Speckle noise was eradicated by an iterative contraction algorithm. An OCT image was partitioned into overlapping image blocks and a Chi-square. A distance similar block matching was utilized to form a low rank group matrix. The designed algorithm attained better objective indicators and visual inspection. The designed method preserved the fine layer structure of the OCT image while removing the speckle noise. The running time needs to be reduced to the required level.

V. Future Work

In the future, ML utilized to perform proficient image segmentation for reducing time as well as maximizing precision.

VI. Conclusion

In image segmentation, the salient region is the most attractive area. Comparison of different image segmentation methods with MRI images is studied. At first, image segmentation was combined by employing a saliency map and NS. An improved FCM algorithm was discussed for enhancing clustering accuracy. Also, the Iterative Contraction Algorithm was developed to eradicate noise. The computational cost was not minimized by an improved FCM algorithm. In addition, adjustment of algorithm structure and optimization of parameter settings was not explored to increase the objective performance of the SMNS model. Running time was not decreased with the Iterative Contraction Algorithm. Simulation conducted to performance of segmentation algorithms with drawbacks. ML methods are performed by reducing time as well as maximizing accuracy.

VII. Data Availability and Material Statement:

The Brain MRI Segmentation Dataset and URL of the dataset are considered. Brain MRI Segmentation Dataset is taken from Kaggle. The URL of the dataset is considered from https://www.kaggle.com/datasets/mateuszbuda/lgg-mri-segmentation?msclkid=818e9627adcc11ec89b21a30a31ba4bc.

Conflict of interest:

The author declares that there was no conflict of interest regarding this paper.

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