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Improved Segmentation of Cardiac MRI Using Efficient Pre-Processing Techniques

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ABSTRACT

Cardiac magnetic resonance imaging is a popular non-invasive technique used for assessing the cardiac performance. Automating the segmentation helps in increased diagnosis accuracy in considerably less time and effort. In this paper, a novel approach has been proposed to improve the automated segmentation process by increasing the accuracy of segmentation and laying focus on efficient pre-processing of the cardiac magnetic resonance (MR) image. The pre-processing module in the proposed method includes noise estimation and efficient denoising of images using discrete total variation-based non-local means method. Segmentation accuracy is evaluated using measures such as average perpendicular distance and dice similarity coefficient. The performance of all the segmentation techniques is improved. Further segmentation comparison has also been performed using other state-of-the art noise removal techniques for pre-processing, and it was observed that the proposed pre-processing technique outperformed other noise removal techniques in improving the segmentation accuracy.

KEYWORDS

Discrete Total Variation, Left-Ventricle, Noise Removal, Non-Local Means, Segmentation

INTRODUCTION

These days, one of the popular non-invasive technique used for assessing the cardiac performance is Magnetic Resonance (MR) Imaging. The cardiac health is governed by various parameters which include end systolic volume, end diastolic volume, ejection fraction and myocardium mass. The heart consists of two chambers, the right and left ventricle. The right ventricle pumps blood to the lungs, whereas the left ventricle (LV), which is the largest chamber, pumps blood to rest of the body. The Left ventricle plays an important role in the entire function of the heart. LV segmentation helps in governing cardiac health. Reading these MR images is a very time consuming work for the radiologist and technicians. Hence if automation is performed in determining the cardiac parameters and functions, it will aid the diagnosis process. The LV segmentation is not an easy task and mainly includes the detection of LV contour. Performing this task manually is very time consuming as the quality of MR images vary at the top, bottom and middle. Automating the LV segmentation helps in

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increased diagnosis accuracy in considerably less time and effort. In this paper we work to improve this automated segmentation process. This paper aims to boost the segmentation accuracy by a novel method which includes efficient pre-processing.

Image pre-processing is an important and necessary step in performing any kind of analysis of the medical images. Pre-processing is of great importance when the captured images are used for further medical application or diagnosis. Pre-processing improves the image by supressing the distortions or enhancing some useful features, which in turn, helps in further processing of the image. For efficient pre- processing, it is desirable to have prior knowledge about three factors: firstly, the device from which the image has been acquired, secondly the type of noise which effects the image and lastly the degradation which occurs due to the addition of noise in the signal. The degradation can be corrected by having knowledge about the above factors. Noise can be estimated if it is unknown.

BACKGROUND

Segmentation Techniques

LV Segmentation is a tedious and hard task and numerous techniques have been developed for the same. Vincent et al. (1991) suggested a watershed algorithm which combines region merging and thresholding. The image gradient map is found and threshold is set on the image gradient's magnitude. Some methods have also been suggested which directly estimate the volume of the right and left chamber of the heart, without performing the process of segmentation (Ashfin et al. 2014; Wang et al. 2014; Zhen et al. 2015). Single atlas based as well as multi atlas-based segmentation approaches have been applied on cardiac MR images (Heckemann et al. 2006; Artaechevarria et al. 2009; Sabuncu et al. 2010; Warfield et al. 2014; Asman & Landman 2011).

Lee et al. (2009) proposes LV segmentation method by using Iterative Thresholding method and deep convolutional encoder-decoder model. Tran (2017) makes use of a fully convolutional neural network for segmentation. Medical images have also been segmented by using the U-Net architecture (Ronneberger et al. 2015). The accuracy of segmentation has been improved by removing the uncertainty of deep neural network (Norouzi, 2019). LV segmentation is used to analyse the blood flow in the heart and the segmentation is improved by making use of intramodality image registration (Gupta et al. 2018). Luo et al. (2018) uses hierarchical extreme learning machine model for performing segmentation of the LV. ZhenZhou (2016, 2017) has suggested remarkable work in the field of LV segmentation.

State-of-the-art segmentation techniques include the use of fully convolution network which perform semantic segmentation (Long et al. 2015) and various modifications have also been performed to it (Garcia et al. 2017). Various researchers have used machine learning algorithms in combination with deformable models (Ngo et al. 2013). Dynamic programming approach has also been used for fast segmentation of cardiac MRI (Santiago et al. 2017). Chen et al. (2020) presents a review of cardiac image segmentation methods which make use of deep learning. Deep learning has its own challenges as well. Mahony et al.(2019) has provided the limitations that are faced by deep learning methods in comparison to the traditional computer vision techniques. Deep learning methods require high computational cost and a strong graphics processing unit for training the model. In this paper A novel approach has been proposed in this paper which increases the segmentation accuracy without making use of deep learning methods.

Pre-Processing

Pre processing has a vital role in the task of image analysis. A pre processed image aids segmentation to a great extent. Three dimensional visualization of the images greatly helps in image analysis, when the images are clean and noise free. The final segmentation result varies if the given input image

is noisy or has inhomogeneities. Pre-processing consists of three basic steps, which include noise estimation from MR image, MR intensity inhomogeneity correction and lastly the process of denoising.

Noise Estimation From MR Image

There are various methods for MRI noise level estimation (Lee et al. 2009; Coupe et al. 2010; Aja-Fernandez et al. 2009; Pyatykh et al 2013). In most of the noise estimation methods it is assumed that noise is stationary over the entire image. But in many cases, this assumption might fail, such as the case when the MR images are acquired by a method of parallel imaging like SENSE. Manjon et al. (2010) and Coupe et al. (2010) developed an approach for estimation of stationary noise. Pan et al. (2012) designed a noise estimation technique for Gaussian distributed noise which was based on local kurtosis measures. Maggioni et al. (2013) proposed another noise estimation method using local DCTs which removed Rician noise from the images. A non local maximum likelihood method for MR images has been proposed by Lili & Greenshields (2009) which removes rician noise. Fernández et al.(2009) suggested a method for noise estimation by making use of linear minimum mean square error. The median absolute deviation based noise estimation method was developed for Gaussian noise by Donoho et al. (1995).

MR Intensity Inhomogeneity Correction

Magnetic field is not homogeneous everywhere. The magnetic susceptibility of different tissues is different. The magnetic field has many distortions at the air-tissue interface. Field inhomogeneity effects the task of registration, segmentation and quantification. The human brain has lots of susceptibility variation, which makes the magnetic field inhomogeneous and thereby, resulting in distortion of the image captured by the MR scanner. This greatly effects the process of image analysis and segmentation. The intensity value of the tissues slowly keep varying with time, resulting in intensity inhomogeneity. The various sources for the intensity inhomogeneity of MR images are as follows:

1. Sometimes a perfectly uniform field is difficult to be created due to some technical issues, which results in the formation of inhomogeneity of the static field and also some spatial distortions. Inhomogeneity of the static field can be rectified by use of phantoms whose reference points and reference intensities are known.
2. Some defects in the gradient coils lead to abnormal currents which further result in inhomogeneities of the static field.
3. Radio frequency (RF) coil or any ferromagnetic material present in the scanned object also cause intensity inhomogeneity.
4. RF signal gets absorbed by the body.
5. Same tissues of the subject may also have inhomogeneous intensity.
6. There can be variation in the intensity of the images (of same object) captured at different point of time.

Haselgrove and Prammer (1986) proposed using smoothing for reducing inhomogeneity. The low frequency inhomogeneity effects were reduced by dividing every MR slice by its spatially smoothed copy. Lim and Pfefferbaum (1989) also suggested smoothing process for correcting the brain MRI scan's inhomogeneities. Homomorphic filtering smoothes the image by separating the high frequency inhomogeneity field from the low frequency field. Intensity inhomogeneity was firstly modelled as a parametric inhomogeneity field by Vannier et al. (1988). A better model was proposed later, in which a fourth-order polynomial was fitted to the line-by-line histogram. Both additive as well as multiplicative inhomogeneity effects (Tncher et al. 1993) have been assumed by researchers. But in case of MRI, multiplicative inhomogeneity effect has been modelled better.

Denoising

The MR images should be noise free before the analysis task or any other operation can be performed on the images. A number of ways can be used to remove noise, including linear and non linear filtering. In the linear filtering approach, every pixel in the image is treated with same convolution, whereas in non linear filtering, each pixel is treated with varying intensity depending upon its neighbourhood. A vast number of non linear filtering techniques exist which help in smoothening the image.

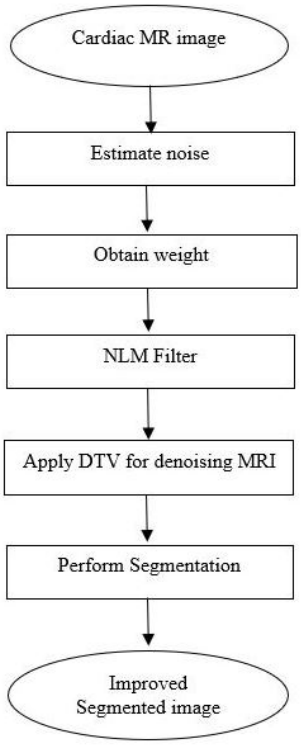
Non Local Means (NLM) filter (Buades et al. 2005) performs effective noise removal by using the self similarity present in the image and then averaging them. A lot of work has been carried out on NLM filter by Coupe et al.(2008) and Manjón et al. (2008). Denoising methods based on sparseness assume that the lower dimensionality space can be used to represent data. Some of the techniques using this are based on Discrete Cosine Transform (DCT) or Fast Fourier Transform (FFT) transforms (Guleryuz 2003; Yarolavsky et al. 2000). Various techniques exist which learn the bases from the noisy images (Elad et al. 2006; Mairal et al .2008; Protter& Elad 2009) or from noise free images and a dictionary is created in which the image patches are sparsely represented as a fusion of dictionary entries (Aharon et al. 2006). The dictionary based methods give a better separation of noise from the signal. Many recent methods (Bao et al. 2008; Fernandez et al. 2009) have used sparse theory on MR images. Principal Component Analysis (PCA) based method (Muresan et al. 2003; Bydder & Du 2008; Deledalle 2011) have been widely used for noise reduction of diffusion weighted images (Bao et al. 2013, Lam et al. 2017; Manjon et al. 2013). Joshi et al (2016) provides a review of different variations that have been proposed in the NLM techniques, particularly to be used on MR images. Joshi et al. (2016) further proposed a technique for noise removal using NLM method with wiener and median filter. Condat et al (2017) proposed a Discrete total variation (DTV) method for noise removal. Joshi et. al (2018) discussed the effect of regularization parameter lambda on discrete total variation based denoising of MR images. A robust approach was further proposed by Joshi et al (2020) for application of morphological operations on MR images using the DTV and NLM methods.

METHODOLOGY

The task of image segmentation as well as other image operations can be highly improved when the images acquired from the MRI scanner are preprocessed effectively. Preprocessing the MR images is an important task for correct and accurate diagnosis. If medical analysis and other medical operations are carried out without performing the pre processing of images, then the results might be misleading and unsatisfactory. To overcome this issue, a new approach has been proposed which includes the pre-processing of cardiac MR images before it is used for the segmentation task. The pre-processing step includes three steps: firstly the noise estimation from the MR image, secondly the correction of intensity inhomogeneity and lastly image denoising. The noise estimation method estimates the type and quantity of noise that has been introduced in the MR acquisition process. Once the noise has been estimated, the intensity inhomogeneity needs to be corrected so that the image can be saved from the distortions due to inhomogeneous intensities. After this, the image needs to be denoised before it can be used for the purpose of image analysis and other medical operations. In the proposed method the MR images have been denoised using the DTV based NLM method proposed by Joshi et. al. (2020). DTV based NLM technique remove noise from MR images without blurring the image and also retains fine details in the image. Once the LV MR image has been pre-processed successfully, it is ready for the segmentation task.

Figure 1 depicts the block diagram of the proposed method. The proposed method effectively pre-processes the image before segmenting it. As a result, the accuracy of segmentation is increased. Firstly the noise in the test image is estimated. Once the noise estimation process is complete, weights are calculated and NLM filter is applied. The NLM filter uses similarity window of size 2 and search window of size 11. Followed by the NLM filter, DTV method is applied which uses

Figure 1. Block diagram of the proposed segmentation technique



1000 iterations. The DTV method further removes any remaining noise in the image. After this pre processing of the image is completed, the cardiac image is then segmented using various state-of-the-art segmentation techniques. The performance of various segmentation techniques namely Active Contours Without edges, Localizing Region-Based Active Contour, Fuzzy threshold, Otsu Method and Expectation Maximization has been assessed quantitatively as well as qualitatively on measures such as average perpendicular distance (APD) and dice similarity coefficient (DSC). Further a comparitive study has also been carried out by performing segmentation using DTV based NLM technique of denoising and other noise removal techniques such as Anisotropic Diffussion (Aniso), NLM and Total Variation method.

EXPERIMENT AND RESULTS

Dataset for Experiment

The experiment was carried out on MATLAB 2016a using optimal parameters. The Cardiac MR images with its benchmark manual contours were obtained from Medical Image Computing and Computer Assisted Intervention (MICCAI) 2009 [60].

Tools and Configuration Used

Operating System: Windows 10
Processor: Intel® core™ i5-8250 CPU @1.60 GHz
RAM: 8.00 GB
Tool: MATLAB 2016a

MATLAB is a programming language developed by Mathworks and offers an easy and comfortable environment for visualization, analysis, computing and programming. There is a wide range of MATLAB applications which include financial modelling and analysis, communications, signal and image processing, computational biology, control design and test and measurement. Various add-on toolboxes are present which help in the above application.

Validation Strategy

The performance of the proposed method has been assessed quantitatively on parameters like APD (in mm) and DSC:

- **Average Perpendicular distance (APD):** It is calculated by finding the distance between the automatically segmented contour and the corresponding manually segmented contour and then averaging over all contour points. Higher value of APD shows that the automatically segmented contour and manually segmented contour (by expert) do not match closely. APD is measured in millimeter.
- **Dice similarity Coefficient (DSC):** It is used to compute the spatial overlap between automatic segmented region X and the manually segmented region Y and is defined as:

$$DSC\left(X,Y\right) = 2\left(\left(X \cap Y\right)\right) / \left(\left(X + Y\right)\right)$$

DSC ranges from 0 to 1 where 1 signifies greatest similarity between the two regions.

Performance Testing of Proposed Pre-Processing Technique on Different Segmentation Techniques

The experiment performed in this paper has been tested on the following segmentation techniques:

- **Active Contours Without edges:** This method segments the images having different background and foreground. Segmentation was carried out with 1000 iterations.
- **Localizing Region-Based Active Contour:** Localization was performed using a square window having side length of 9 and the method used 1000 iterations.
- **Fuzzy threshold:** The threshold for segmentation was computed by using fuzzy entropy method.
- **Ostu Method:** Ostu's N-thresholding method was used for segmenting the image into 2 classes.
- **Expectation Maximization:** Segmentation of the images was carried out using expectation maximization method by working with 2 classes.

In this paper, improved segmentation is referred as the segmentation process performed using the proposed pre-processing approach with the respective segmentation technique, thereby fetching improved APD and DSC values. The original APD which is obtained without using any denoising technique in segmentation process is referred as APD(O) and Improved APD refers to the APD obtained when the proposed pre-processing approach is used prior to segmentation. The original value of DSC which is obtained without using any pre-processing approach in segmentation process is referred as DSC(O) and Improved DSC refers to the DSC obtained when the pre-processing approach is used prior to segmentation.

Performance Comparison Using Different Denoising Techniques for Pre-Processing

Experiment has also been performed by replacing the DTV based NLM technique of denoising technique with other noise removal methods like Anisotropic diffusion (Aniso), NLM and Total variation (TV) method and then conducting the segmentation process. Five different segmentation

techniques namely Active Contours Without edges, Localizing Region-Based Active Contour, Fuzzy threshold, Otsu Method and Expectation Maximization have been used in the experiment.

FINDINGS

In this paper, two experiments have been performed. Firstly the test image is pre-processed using the DTV based NLM technique of denoising and then segmentation is performed by the above mentioned five segmentation techniques. The segmentation accuracy is evaluated on parameters such as APD and DSC similarity. It was observed that the segmentation accuracy was increased by a decrease in APD and increase in DSC. Performance of all the five segmentation techniques was improved when the test image was efficiently pre-processed using the proposed pre-processing method. Results can be seen from Table 1. Secondly, the test image is pre-processed using other denoising methods like Anisotropic diffusion, NLM and total variation method and then segmentation accuracy is calculated. It was seen that the impact of the proposed pre-processing method which used DTV based NLM technique for noise removal was satisfactory when compared to other denoising methods used.. Each segmentation technique was tested with different denoising methods and it was observed that when the DTV based NLM method of denoising was used, all the above mentioned segmentation techniques gave better results in terms of decreased APD and increase DSC values (Table 4 and Table 5). The improved segmentation results with the proposed pre-processing method can be observed in Table 2 and Table 3.

CONCLUSION AND FUTURE WORK

This paper suggests a novel technique which improves the segmentation process. Segmentation is improved by effectively pre-processing the input images before applying the respective segmentation

Table 1. Comparison of original segmentation and improved segmentation on APD and DSC values using the proposed pre-processing technique

S. No.	Segmentation Technique	Original APD	Improved APD	Original DSC	Improved DSC
1.	Active Contours Without edges	0.7539	0.7104	0.9421	0.9449
2.	Localizing Region-Based Active Contour	0.7835	0.7316	0.9454	0.9491
3.	Fuzzy threshold	0.9053	0.8229	0.9321	0.9381
4.	Otsu	0.9053	0.8525	0.9321	0.9353
5.	Expectation Maximization	0.7334	0.697	0.9487	0.9561

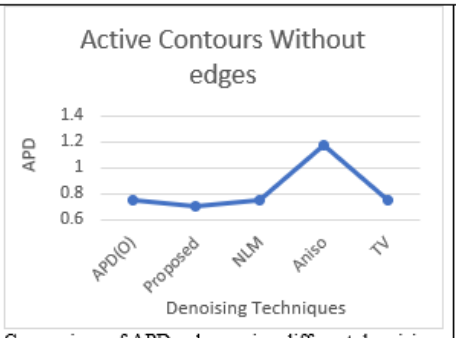
Table 2. Comparison of APD values using different denoising methods for various segmentation technique

S. No.	Segmentation Technique	APD(O)	Proposed	NLM	Aniso	TV
1.	Active Contours Without edges	0.7539	0.7104	0.7505	1.1761	0.7571
2.	Localizing Region-Based Active Contour	0.7835	0.7316	0.7529	1.5712	0.7165
3.	Fuzzy threshold	1.2681	1.2775	1.2985	2.0123	3.4696
4.	Otsu	0.9053	0.8229	0.8414	1.1769	0.8387
5.	Expectation Maximization	0.7334	0.597	0.6748	1.3798	0.5513

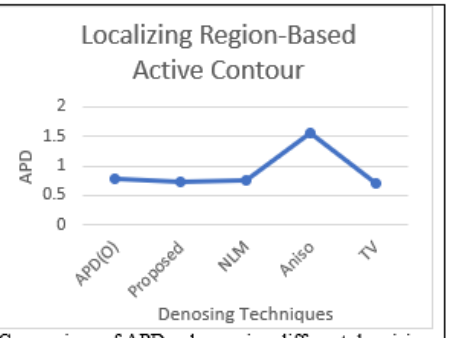
Table 3. Comparison of DSC values using different denoising methods for various segmentation techniques

S.No.	Segmentation Technique	DSC(O)	Proposed	NLM	Aniso	TV
1.	Active Contours Without edges	0.9421	0.9449	0.9424	0.9316	0.9423
2.	Localizing Region-Based Active Contour	0.9454	0.9491	0.9454	0.9091	0.9499
3.	Fuzzy threshold	0.9128	0.9117	0.9105	0.8849	0.8332
4.	Otsu	0.9321	0.9381	0.9365	0.9314	0.9373
5.	Expectation Maximization	0.9487	0.9561	0.9582	0.9316	0.9653

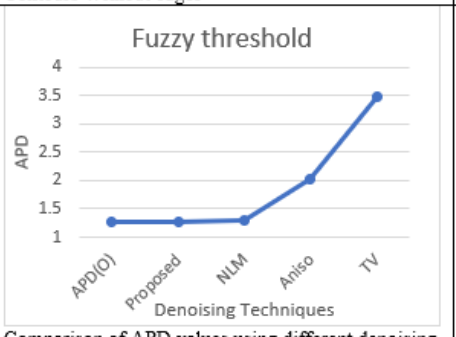
Table 4. Comparative plot of APD values using different denoising techniques for various segmentation methods



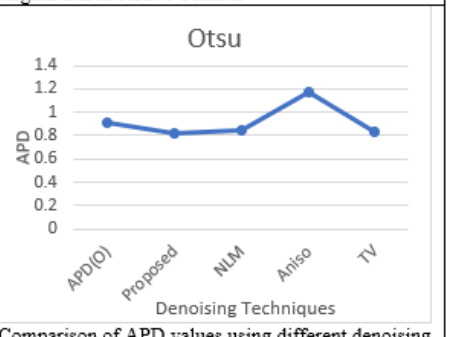
Comparison of APD values using different denoising techniques for Segmentation method :Active Contours Without edges



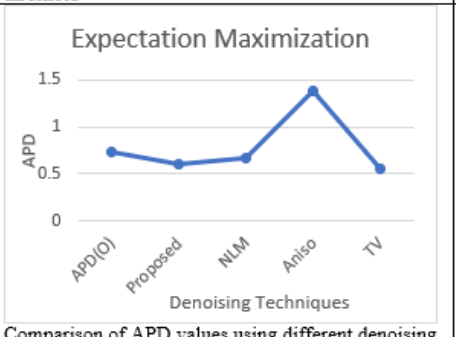
Comparison of APD values using different denoising techniques for Segmentation method :Localizing Region-Based Active Contour



Comparison of APD values using different denoising techniques for Segmentation method: Fuzzy threshold

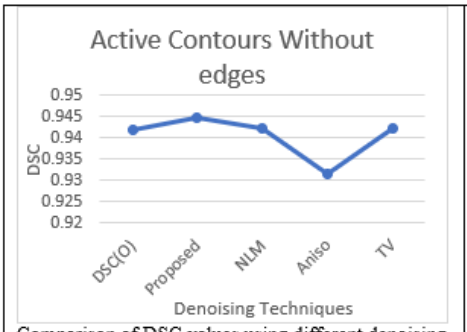


Comparison of APD values using different denoising techniques for Segmentation method : Ostu Method

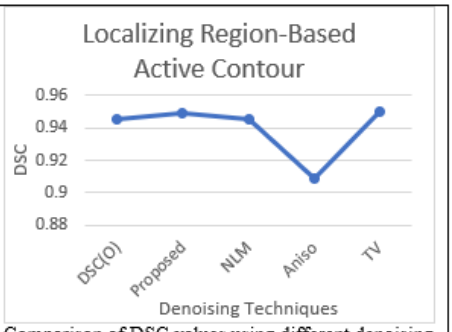


Comparison of APD values using different denoising techniques for Segmentation method : Expectation Maximization

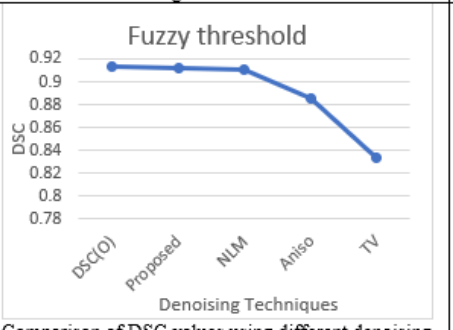
Table 5. Comparative plot of DSC values using different denoising techniques for various segmentation methods



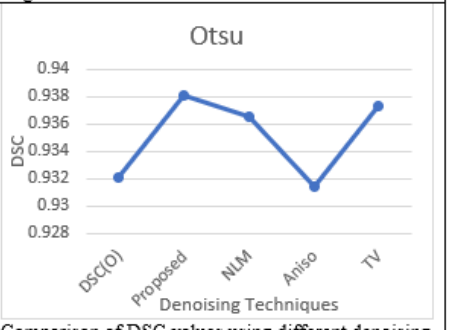
Comparison of DSC values using different denoising techniques for Segmentation method :Active Contours Without edges



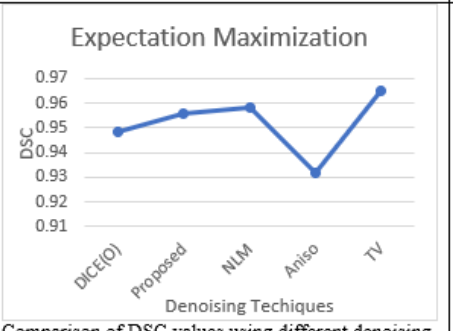
Comparison of DSC values using different denoising techniques for Segmentation method :Localizing Region-Based Active Contour



Comparison of DSC values using different denoising techniques for Segmentation method: Fuzzy threshold



Comparison of DSC values using different denoising techniques for Segmentation method : Ostu Method



Comparison of DSC values using different denoising techniques for Segmentation method : Expectation Maximization

algorithms. Effective pre-processing plays a major role in the segmentation process. It can be clearly seen from the findings of the experiment that the performance of various segmentation techniques is improved when the images are pre-processed before segmentation. The improved performance can be observed from a decrease in APD and an increase in DSC values. Further, it has also been concluded that pre-processing is better when DTV based NLM technique of denoising is used in the pre-processing phase. When any different denoising technique is used in pre-processing, then the segmentation accuracy degrades. Therefore, the proposed method of pre-processing, which uses DTV based NLM technique for denoising, can be used to increase the segmentation accuracy. The pre-processed noiseless images are better used in various medical applications which involve diagnosis

from the scanned images. Apart from LV segmentation, the pre-processed images prove helpful in various medical operations like angiography, osteoporosis and bone strength detection, molecular imaging and surgical operations where the surgery is either performed by a robot or a doctor. A noise free image greatly helps in performing these above mentioned procedures The LV segmented images have low contrast and hence contrast enhancement techniques can be deployed further. Apart from the segmentation techniques, the use of deep learning in the pre-processing stage can also be explored.

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