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DESPECKLING AND SEGMENTATION OF ULTRASOUND IMAGES OF CAROTID ARTERY FOR PLAQUE DIAGNOSIS IN HEALTH CARE

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ABSTRACT

A new method for segmentation of the carotid artery for classifying it as diseased or normal towards plaque diagnosis is proposed in this paper. Kernel Fuzzy C- Means clustering is used for segmenting the longitudinal section of the carotid artery using which the wall layers of the artery are identified for classifying it as diseased or normal. As a pre-processing step a–nonlinear mean filter is used for speckle filtering among a set of various traditional filters after measuring its performance. Removing speckle noise may remove useful information in the images like small lesions or artefacts, plaque or calcification in the arteries. Hence a filter that detects the speckle in each and every pixel and suppresses the speckled pixel is proposed in this paper. The algorithm was applied on ultrasound images of the carotid artery for extracting the boundary of the arterial wall and detecting the wall layers for clinical purposes. The results show excellent performance of the method.

Keywords: *Carotid Artery, Clustering, Speckle, Plaque, Segmentation.*

1. INTRODUCTION

Ultrasound imaging is considered to be noninvasive among the currently available medical imaging modalities and is practically harmless to the human body, portable, accurate, and cost effective. These features have made the ultrasound imaging the most prevalent diagnostic tool. Medical ultrasound images are often corrupted by noise during acquisition and transmission. However, the main disadvantage of medical ultrasonography is the poor quality of images, which are affected by multiplicative speckle noise. It tends to degrade the resolution and contrast of ultrasound images, thus may lead to eliminate some useful and important diagnostic information. Conventional speckle suppression methods are based on arithmetic mean filter, geometric mean filter and median filtering [1]. These filters can reduce speckle but it does not preserve useful details such as edges of the image properly. Although low-pass filtering is a common technique to reduce speckle noise, this technique is not applicable for ultrasound images since low-pass filters often blur the edges and cause loss of details in low contrast border regions making the image unsuitable for segmentation [2]. An alternative method of filtering speckle using non-linear mean filter is proposed in this paper.

2. PROPOSED FILTERING METHOD

As speckle in ultrasound images is ongoing research issue in medical imaging and it is a multiplicative noise that is formed due to reflection of ultrasound signals at irregular phase angles during ultrasound imaging. Various filters have been proposed for speckle reduction where as removing the speckle noise may remove useful information in the image like small lesions or artefacts, plaque or calcifications and smoothes out edges [3], [4]. To overcome this problem an algorithm is proposed in this paper that uses neighbourhood pixel information to detect the speckled pixel and replaces it. Any speckled pixel will have a maximum deviation from its neighbours [5]. Hence a pixel whose deviation is greater than

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the mean in the neighbourhood is considered to be the speckled pixel and is replaced by the mean.

Algorithm of the proposed method:

- start
- Define window size
- Measure the deviation p(i) of the pixel from its neighbours in the window
- Compare with the threshold(T)-mean of the neighbours
- if p(i)>T- bad pixel else - good pixel
- Replace only bad pixels with mean of neighbours
- End

3. SEGMENTATION

Image segmentation plays a crucial role in many medical imaging applications. With the increasing size and number of medical images, the use of computers in facilitating their processing and analyses has become necessary. In particular, as a task of delineating anatomical structures and other regions of interest, image segmentation algorithms play a vital role in numerous biomedical imaging applications such as the quantification of tissue volumes, diagnosis, study of anatomical structure, and computer-integrated surgery. Classically, image segmentation is defined as the partitioning of an image into non-overlapping, constituent regions which are homogeneous with respect to some characteristics such as intensity or texture.

Image segmentation has an important role in the field of image understanding, image analysis, pattern identification. The foremost essential goal of the segmentation process is to partition an image into regions that are homogeneous with respect to one or more self characteristics and features. Clustering has long been a popular approach to untested pattern recognition. The fuzzy c-means [6] algorithm, as a typical clustering algorithm has been utilized in a wide range of engineering and scientific disciplines such as Medical imaging, bioinformatics, pattern recognition, and data mining.

For fuzzy segmentation of ultrasound image data, the algorithm is realized by modifying the objective function in the conventional fuzzy C-means (FCM) algorithm using a kernel-induced distance metric and a spatial penalty on the membership functions. Firstly, the original Euclidean distance in the FCM is replaced by a kernel-induced distance, and thus the corresponding algorithm is derived and called as the kernelized fuzzy C-means (KFCM) algorithm[7],[8], which is shown to be more robust than FCM. Then a spatial penalty is added to the objective function in KFCM to compensate for the intensity in homogeneities of ultrasound image and to allow the labelling of a pixel to be influenced by its neighbours in the image. The penalty term acts as a regularizer and has a coefficient ranging from zero to one.

4. FUZZY C-MEANS CLUSTERING

Given a data

$$X=\{\ X = \{x_i \dots\dots\dots . x_n\} \subset R^p \ \dots\dots \qquad (1)$$

the original FCM algorithm partitions X into c fuzzy subsets by minimizing the following objective function

$$J_m(U,V) \equiv \sum_{i-1}^{c} \sum_{k-1}^{n} u_{ik}^{m} \left\| x_i - v_i \right\|^2 \quad ....(2)$$

where c is the number of clusters and selected as a specified value in the paper, n the number of data points, u_k the member of x_k in class i, satisfying $\sum_{i-1}^{c} u_{ik}$, m the quantity controlling clustering fuzziness and v is set of control cluster centres or a prototypes $v_i \in R^p$.

The function J_m is minimized by the famous alternate iterative algorithm. Since the original FCM uses the squared-norm to measure inner product with an appropriate 'kernel' function, one similarity between prototypes and data points, it can only be effective in clustering 'spherical' clusters and many algorithms are resulting from the FCM in order to cluster more general dataset. Most of those algorithms are realized by replacing the squared-norm in (1) the object function of FCM with other similarity trial (metric) [6-7].

Kernel-based fuzzy c-means algorithm adopts a new kernel-induced metric in the data space to restore the original Euclidean norm metric in FCM. By replacing the inner product with an appropriate 'kernel' function, one can absolutely perform a nonlinear mapping to a high dimensional feature space without increasing the number of parameters.

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5. KERNEL FUZZY C-MEANS CLUSTERING

Define a nonlinear map $\varphi\colon \rightarrow \varphi(x) \in F$,where $x \in X \cdot X$ denotes the data space and F is the transformed feature space with higher even infinite dimensions.

KFCM minimized the following objective function:

$$J_m(U,V) \equiv \sum_{i-1}^{c}\sum_{k-1}^{n} u_{ik}^{m} \left\|\phi(x_i)-\phi(v_i)\right\|^2 \;...... \quad (3)$$

Where

$$\|\varphi(x_i)-\varphi(v_i)\|^2 = \{K(x_k,x_k)+K(v_i,v_i)-2K(x_k,v_i)\} \;.(4)$$

where $K(x,y) = \varphi(x)^T\varphi(y)$ is an inner product of the kernel function. If we adopt the Gaussian function as a kernel function,

$$K(x,y) = \exp\left(-\frac{\|x-y\|^2}{2\sigma^2}\right) \quad ... . \quad (5)$$

and then $K(x,x) = 1$ according to (4), (2) can be rewritten as

$$J_m(U,V) \equiv 2\sum_{i-1}^{c}\sum_{k-1}^{n} u_{ik}^{m}\left(1-k(x_k,v_i)\right) ... (6)$$

Minimizing (6) under the constraint of $u_{ik}, m > 1$ we have

$$u_{ik} = \frac{\left(1/1-K(x_{k,},v_i)\right)^{\frac{1}{(m-1)}}}{\sum_{k=1}^{c}\left(1/(1-K(x_k,v_i))\right)^{\frac{1}{(m-1)}}} \quad .... \quad (7)$$

$$v_i = \frac{\sum_{k=1}^{n} u_{ik}K(x_{k,},v_i)}{\sum_{k=1}^{n} u_{ik}^{m}K(x_{k,},v_i)} \quad ... ... \quad (8)$$

Here we now utilize the Gaussian kernel function for straight forwardness. If we use additional kernel functions, there will be corresponding modifications in (7) and (8). In fact, (4) can be anayzed as kernel-induced new metric in the data space, which is defined as the following

$$\left\|\phi(x)-\phi(y)\right\| = \sqrt{2(1-k(x,y))} \quad ....(9)$$

And it can be proven that *k(x,y)* is defined in (9) is a metric in the original space takes as the Gaussian kernel function. According to (8), the data point x_k is capable with an additional weight, $K(x_k,v_i)$ which measures the similarity between x_k and $v_i$and when x_k is an outlier i.e., x_k is far from the other data points, then $K(x_k,v_i)$ will be very small, so the weighted sum of data points shall be more strong. The full explanation of KFCM algorithm is as follows:

KFCM Algorithm:
Step 1: Select initial class prototype $\{v_i\}_{i=1}^{c}$
Step 2: Update all memberships u_{ik} with 7.
Step 3: Obtain the prototype of clusters in the forms of weighted average with (8).
Step 4: Repeat step 2-3 till termination. The termination criterion is.$\|V_{new} - V_{old}\| \leq \epsilon$
Where $\|\cdot\|$ is the Euclidean norm. V is the vector of cluster centres & $\in$ is a small number that can be set by user (here $\in = 0.01$).

6. RESULTS AND DISCUSSIONS

The proposed method of speckle reduction eliminates only the speckled pixels without affecting the good pixels. The performance of the proposed method studied for longitudinal section images of the carotid artery shown in tables 1 and 2. The denoising is performed as a preprocessing step before segmentation of the longitudinal sections of the carotid artery for finding the intima and media layers in diagnosing plaque. As the plaque portion need not be altered in property by the denoising filter its segmentation by two methods are studied to validate the performance.

Table.1 Performance Of Filters For Normal Carotid Artery

FILTERS	PSNR for Variance			
	0.01	0.02	0.04	0.06
Wavelet filter	30.86	30.07	28.53	27.30
Anisotropic diffusion filter	32.53	29.54	26.49	24.74
Fourth order PDE filter	32.23	31.15	29.46	28.21
Frost filter	30.92	30.93	30.75	30.54
Median filter	32.98	31.84	30.31	29.06
Bayes shrink filter	32.30	29.43	26.44	24.71
Wavelet Bayes filter	32.51	29.53	26.49	24.74

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Hybrid median filter	32.74	29.77	29.06	28.55
Relaxed median filter	32.76	31.65	30.09	29.01
Mean filter	28.64	28.48	28.12	27.70
Nonlinear mean filter	33.06	32.61	31.74	30.95

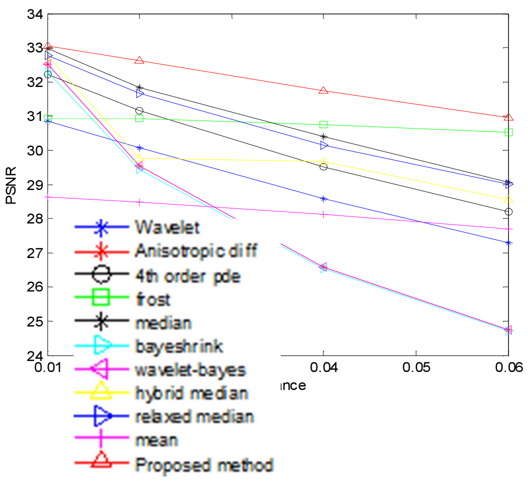

Fig.1. Performance Of Filters For Normal Carotid Artery

Table.2 Performance Of Filters For Abnormal Carotid Artery

FILTERS	PSNR for Variance			
	0.01	0.02	0.04	0.06
Wavelet filter	32.81	31.55	29.52	28.11
Anisotropic diffusion filter	33.59	30.60	27.54	25.84
Fourth order PDE filter	35.21	33.54	31.35	29.87
Frost filter	33.17	33.07	32.88	32.61
Median filter	36.14	34.50	32.40	30.94
Baye shrink filter	33.51	30.56	27.52	25.83
Wavelet Bayes filter	33.59	30.60	27.54	25.84
Hybrid median filter	34.92	33.13	31.16	29.92
Relaxed median filter	35.84	34.16	32.12	30.70
Mean filter	30.15	29.96	29.56	29.19
Nonlinear mean filter	35.84	35.16	34.00	33.04

From the figures 1 and 2 it is found that the nonlinear mean filter perform better compared with the existing filters and it is validated by the segmentation methods.

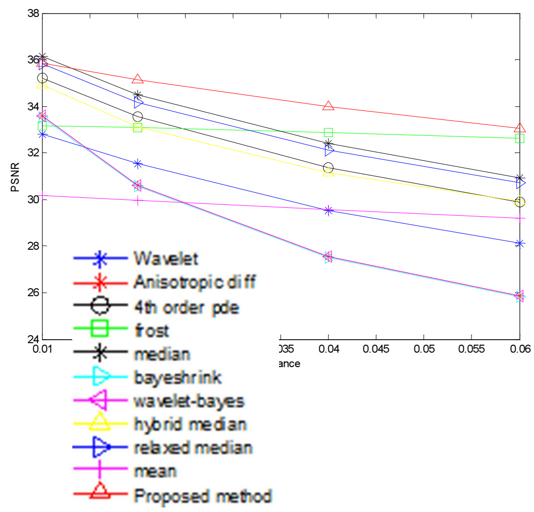

Fig.2 Performance Of Filters For Abnormal Carotid Artery

For segmentation the original ultrasonic image was partitioned into sub images by KFCM. Here the segmented images in figure 3b and 3c shows the active contour based and KFCM based segmentation results of longitudinal section of normal carotid artery respectively that is given in figure 3a.

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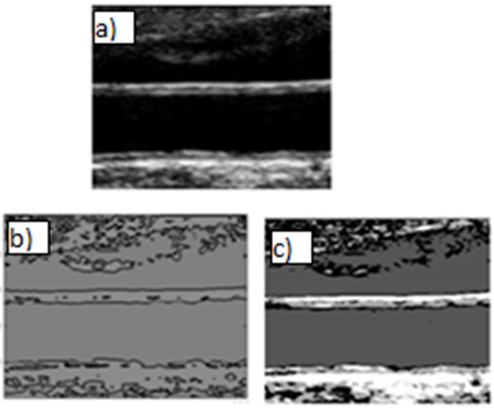

Fig.3.A) Original Image Of Longitudinal Sections Of Normal Carotid Artery Images B) Segmented Images Using Active Contour C) Segmented Images Using KFCM Clustering

The segmented images in figure 4b and 4c shows the active contour based and KFCM based segmentation results of longitudinal section of diseased carotid artery respectively that is given in figure 4a. The segmented images in figure 5b and 5c shows the active contour based and KFCM based segmentation results of cross sectional view of diseased carotid artery respectively that is given in figure 5a.

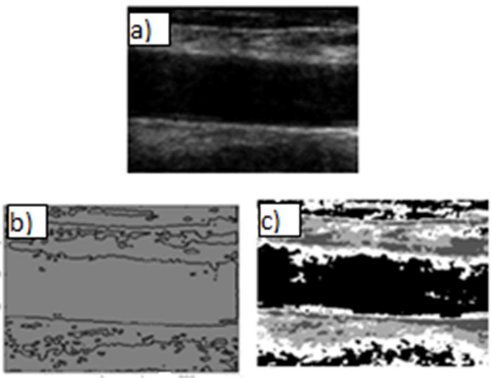

Fig.4.A) Original Image Of Longitudinal Sections Of Abnormal Carotid Artery Images B) Segmented Images Using Active Contour C) Segmented Images Using KFCM Clustering

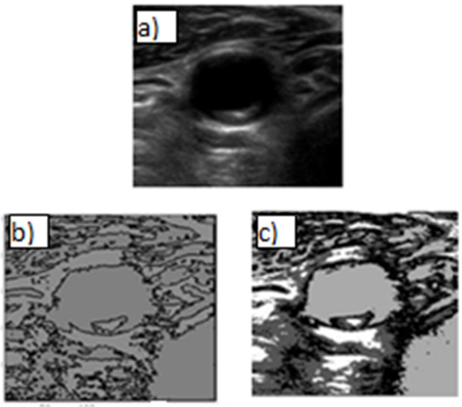

Fig.5.A) Original Image Of Cross Section Of Carotid Diseased Artery B) Segmented Image Using Active Contour C) Segmented Image Using KFCM Clustering

From the results it is clearly observed that the adventitia to intima wall layers segmentation in the far wall of the carotid artery is better in KFCM based method than the active contour based method of segmentation. It is also clear that the KFCM based segmentation of the diseased artery shows breaks in the intima layer due to the presence of plaque materials that leads to atherosclerosis which is not clear in active contour method. The cross sectional image in 5c clearly shows the atherosclerotic plaque region that reduces the lumen diameter that in turn reduces the blood flow to the brain causing stroke.

7. CONCLUSIONS

In this paper, a new method for speckle reduction is proposed and used kernel-induced new metric to replace the Euclidean norm in fuzzy c-means algorithm in the original space and then derived the alterative kernel-based fuzzy c-means algorithm for segmenting the carotid artery wall layers. The results of this paper confrmed that the combination of proposed nonlinear mean filtering and KFCM based segmentation are able to segment the adventitia to intima wall layers in the far wall of carotid artery and helps the physiscian in diagnosing the diseased artery from the normal artery. The method has the advantage of automation with reduced number of iterations. The algorithm was verified on longitudinal and cross sectional images of normal and diseased carotid artery and the results can be used for clinical purposes.

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