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De-speckle Filtering in Ultrasound Imaging of the Carotid Artery

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Abstract- **The main objective of this paper is to evaluate the classification performance of de-speckle filtering on ultrasound imaging of the carotid atherosclerotic plaque. The following procedure was investigated on 230 images (recorded from 115 symptomatic, and 115 asymptomatic subjects): (i) six different de-speckle filters were used based on first order and higher order local statistics, anisotropic diffusion, and geometric properties; (ii) nine different texture feature sets were extracted, and (iii) the k-nearest neighbor classifier was used to classify a plaque as symptomatic or asymptomatic. The de-speckle filters based on higher order statistics, anisotropic speckle diffusion, and geometric properties gave a slightly higher percentage of correct classifications score than the original images.**

***Keywords*- de-speckle filtering, texture analysis, carotid plaque**

I. INTRODUCTION

There are indications that the morphology of atherosclerotic carotid plaques, obtained by high-resolution ultrasound imaging, has prognostic implications [1]. Smooth surface, echogenicity and a homogenous texture are characteristics of stable plaques, whereas irregular surface, echolucency and a heterogenous texture are characteristics of potentially unstable plaques. Computer-aided classification of carotid plaques will contribute towards a more standardized and accurate methodology for the assessment of carotid plaques. An automated system should be able, based on extracted texture feature, to classify plaques into one of the following types: (i) symptomatic because of ipsilateral hemispheric symptoms, and (ii) asymptomatic because they were not connected with ipsilateral hemispheric events. The aim is to identify patients at risk of stroke. Previous work [1] has shown that it is possible to identify a group of patients at risk of stroke based on texture features extracted from the ultrasound images of carotid plaques.

Speckle noise affects the quality of the ultrasound images and may therefore alter the correctness of the extracted texture features [2]. In recent work [3], based on statistical analysis of the extracted texture features after de-speckle filtering, we have shown that some improvement in class separation (between symptomatic and asymptomatic plaques) was evident. The objective of the current work is to investigate the actual improvement in classification success rate, using the image speckle reduction filtering as a preprocessing step.

II. METHODOLOGY

A total of 230 carotid plaque images (115 symptomatic + 115 asymptomatic) were processed. The plaque segments were outlined manually by the expert physician and were used for speckle reduction filtering, texture feature extraction and classification.

A. Speckle Reduction Filtering

Speckle is a form of multiplicative noise, which corrupts medical ultrasound imaging making visual observation difficult and therefore should be filtered out. In this work, six de-speckle filters were implemented using the following speckle reduction techniques [2]-[4]:

(i) Local statistic filters (speckle, amnoise) using first order local statistics in a pixel neighborhood, such as the mean and the variance. Their working principle may be described by a weighted average calculation using sub-region statistics to estimate statistical measures over sliding pixel windows.

(ii) Speckle Anisotropic Diffusion (rtd, anisodif) utilizing anisotropic diffusion, and speckle anisotropic diffusion.

(iii) Local statistic filters (momente) utilizing higher statistical moments in a pixel neighborhood, such as the skewnes and kurtosis of the histogram.

(iv) Geometric filter (speck), a powerful nonlinear geometric filter that filters the multiplicative noise by utilizing the local statistics of the image.

B. Texture Feature Extraction

Texture contains important information, which is used by humans for the interpretation and the analysis of many types of images. Texture refers to the spatial interrelationships and arrangement of the basic elements of an image [5].

In this study, the following nine different texture feature sets (a total number of 56 features) were extracted from the manually segmented plaques:

(i) First Order Statistics (FOS): 1) Mean value, 2) Median value, 3) Standard Deviation, 4) Skewness, 5) Kurtosis.

(ii) Spatial Gray Level Dependence Matrices (SGLDM) [6]: 1) Angular second moment, 2) Contrast, 3) Correlation, 4) Sum of squares: variance, 5) Inverse difference moment, 6) Sum average, 7) Sum variance, 8) Sum entropy, 9) Entropy, 10) Difference variance, 11) Difference entropy, 12), 13) Information measures of correlation. For each feature the mean values and the range of values were computed, and were used as two different feature sets.

(iii) Gray Level Difference Statistics (GLDS) [7]: 1) Contrast, 2) Angular second moment, 3) Entropy, 4) Mean.

(iv) Neighborhood Gray Tone Differ. Matrix (NGTDM) [5]: 1) Coarseness, 2) Contrast, 3) Business, 4) Complexity, 5) Strength.

(v) Statistical Feature Matrix (SFM) [8]: 1) Coarseness, 2) Contrast, 3) Periodicity, 4) Roughness.

(vi) Laws Texture Energy Measures (TEM) [8]: 1) LL - texture energy (TE) from LL kernel, 2) EE - TE from EE kernel, 3) SS - TE from SS kernel, 4) LE - average TE from LE and EL kernels, 5) ES - average TE from ES and SE kernels, 6) LS - average TE from LS and SL kernels.
(vii) Fractal Dimension Texture Analysis (FDTA) [8]: $H^{(k)}$ parameter (Hurst coefficient) for resolutions k=1, 2, 3, 4.
(viii) Fourier Power Spectrum (FPS) [7]: 1) Radial sum, 2) Angular sum.

C. Classification

The statistical k-nearest-neighbor (KNN) classifier with k=7 was used, with the leave-one-out method for evaluating the performance of the classifier [9]. Because this is a comparative study it was important that the error rate was estimated efficiently and in an unbiased way. In the leave-one-out method, each sample is evaluated in relation to the rest of the data samples, characterized by no bias concerning the possible training and evaluation bootstrap sets. The KNN classifier was chosen because it is a simple to implement and computationally very efficient which was important in this work due to the many feature sets and filters tested.

III. Results

Table I tabulates the classification success rate obtained for the nine different feature sets, for the original speckled plaque images and for the images filtered with the six de-speckle filters. The filters that exhibited classification improvement compared to the classification success rate of the original images, were in average the filter *momente* (+3.2%), the *anisodif* (+1%), the *speckle* (+0.8%) and the *speck* (+0.2%). Feature sets which benefited mostly by the de-speckle filtering were the TEM, the SFM and the FOS, where in the case of the filter *momente* an improvement of 9.2%, 9.1% and 7.4% was observed. Less improved feature sets were the GLDS, SGLDM and NGTDM. The feature set FPS was improved by none of the examined filters.

Table I Classification success rate for KNN with K=7. The success rate is given for the original and the filtered plaque images, for the nine feature sets and when all 56 features were used for classification. Bolded values indicate improvement after filtering.

Feature set	*No of Feat.*	*Original*	*Speckle*	*Amnoise*	*Rtd*	*Anisodif*	*Momente*	*Speck*
FOS	5	57.8	**63.9**	**59.1**	**62.6**	**64.8**	**65.2**	57.4
SGLDMm	13	63.5	61.7	62.2	60.4	58.7	61.7	**64.3**
SGLDMr	13	67.0	65.7	66.5	64.8	66.1	**67.4**	**68.7**
GLDS	4	62.6	61.3	58.7	58.7	59.1	62.6	**63.5**
NGTDM	5	67.0	**67.4**	57.8	64.8	**69.1**	**67.4**	63.0
SFM	4	57.4	**61.7**	**59.6**	55.7	**61.3**	**66.5**	**60.4**
TEM	6	59.1	**67.0**	**63.0**	57.4	**67.4**	**68.3**	**60.0**
FDTA	4	61.3	60.4	53.0	**66.1**	**65.2**	**65.7**	**61.7**
FPS	2	61.7	54.8	55.2	57.4	54.3	61.3	60.0
Average		*61.9*	***62.7***	*59.5*	*60.9*	***62.9***	***65.1***	***62.1***
All 56	56	67.0	67.0	61.3	65.7	64.3	**67.4**	**67.8**

The feature set FDTA was significantly improved by the filters *rtd* (+4.8%), *momente* (+4.4%), and *anisodif* (+3.9%). When all 56 features were used as a single feature vector, no significant improvement was observed.

Individual features which were improved after de-speckle filtering [3] based on statistical analysis were the contrast, busyness, complexity, sum of square variance and standard deviation.

IV. Concluding Remarks

In this study the effect of speckle reduction filtering in improving the classification of atherosclerotic carotid plaques is investigated. Based on the classification results some improvement was shown, especially in the case of feature sets based on statistical measures like the TEM, the SFM and the FOS. Less improvement was recorded on the more complex feature sets like the GLDS, SGLDM and NGTDM, which were also the feature sets that performed best in general. Best performing filter was *momente*, which is based on higher statistical moments.

The findings in this work show some promise and future work will further investigate variations of the best performing filters, and the effect of the number of iterations a filter is applied to the image. In addition, the use of de-speckle filtering as a pre-processing step in a system for the automated segmentation of ultrasound carotid plaque images will be examined.

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