

AN INTEGRATED SYSTEM FOR THE ASSESSMENT OF ULTRASONIC IMAGING ATHEROSCLEROTIC CAROTID PLAQUES

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ABSTRACT

The objective of this work is to develop a system that will facilitate the automated characterization of ultrasonic imaging carotid plaques for the identification of individuals with asymptomatic carotid stenosis at risk of stroke. A total of 166 images were collected which were classified into: symptomatic because of ipsilateral hemispheric symptoms, or asymptomatic because they were not connected with ipsilateral hemispheric events. Ten different texture feature sets were extracted: first order statistics, spatial gray level dependence matrices, gray level difference statistics, neighbourhood gray tone difference matrix, statistical feature matrix, Laws texture energy measures, fractal dimension texture analysis, Fourier power spectrum and shape parameters. A modular neural network classifier was developed composed of self-organizing map (SOM) classifiers, achieving an overall diagnostic yield of 76.4%. The results of this work show that it is possible to identify a group of patients at risk of stroke based on texture features.

1. INTRODUCTION

There is evidence that carotid endarterectomy in patients with asymptomatic carotid stenosis will reduce the incidence of stroke. However, a large number of patients is operated unnecessarily. Therefore it is necessary to identify patients at high risk which will be considered for carotid endarterectomy, and patients at low risk which will be spared from an unnecessary, expensive and often dangerous operation. There are indications that the morphology of atherosclerotic carotid plaques, obtained by high resolution ultrasound imaging, has prognostic implications [1], [2]. 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. The objective of this work is to develop a computer-aided system that will facilitate the automated characterization of carotid plaques for the identification of individuals with asymptomatic carotid stenosis at risk of stroke.

2. FEATURE EXTRACTION

In this study, a total of 61 texture features and shape parameters were extracted from 166 manually segmented ultrasound images (see Fig. 1) (76 symptomatic and 90 asymptomatic) using the following algorithms:

(a) First Order Statistics (FOS)

The following FOS features were computed [3]: 1) Mean, 2) Median, 3) Standard Deviation, 4) Skewness, and 5) Kurtosis.

(b) Spatial Gray Level Dependence Matrices (SGLDM)

The spatial gray level dependence matrices as proposed by Haralick et al. [4] are based on the estimation of the second-order joint conditional probability density functions that two pixels (k,l) and (m,n) with distance d in direction specified by the angle θ , have intensities of gray level i and gray level j . Based on the probability density functions the following texture measures [4] were computed: 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, and 12), 13) Information measures of correlation. For a chosen distance d (in this work $d=1$ was used) and for angles $\theta = 0^\circ, 45^\circ, 90^\circ$ and 135° we computed four values for each of the above 13 texture measures. In this work, the mean and the range of these four values were computed for each feature, and they were used as two different feature sets.

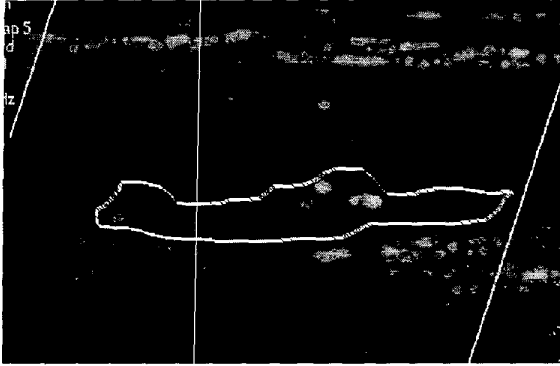


Fig. 1 An ultrasound image of a manually segmented (closed white contour) atherosclerotic carotid plaque.

(c) *Gray Level Difference Statistics (GLDS)*

The GLDS algorithm [5] uses first order statistics of local property values based on absolute differences between pairs of gray levels or of average gray levels in order to extract the following texture measures: 1) Contrast, 2) Angular second moment, 3) Entropy, and 4) Mean.

(d) *Neighbourhood Gray Tone Difference Matrix (NGTDM)*

Amadasun and King [6] proposed the Neighbourhood Gray Tone Difference Matrix in order to extract textural features which correspond to visual properties of texture. The following features were extracted: 1) Coarseness, 2) Contrast, 3) Business, 4) Complexity, and 5) Strength.

(e) *Statistical Feature Matrix (SFM)*

The statistical feature matrix [7] measures the statistical properties of pixel pairs at several distances within an image which are used for statistical analysis. Based on the SFM the following texture features were computed: 1) Coarseness, 2) Contrast, 3) Periodicity, and 4) Roughness.

(f) *Laws Texture Energy Measures (TEM)*

For the Laws TEM extraction [8], [9], vectors of length $l=7$, $L=(1,6,15,20,15,6,1)$, $E=(-1 -4,-5, 0, 5,4,1)$ and $S=(-1 -2, 1, 4, 1 -2 -1)$ were used, where L performs local averaging, E acts as an edge detector and S acts as a spot detector. If we multiply the column vectors of length l by row vectors of the same length, we obtain Laws lxl masks. In order to extract texture features from an image, these masks are convoluted with the image and the statistics (e.g. energy) of the resulting image are used to describe texture. The following texture features were extracted: 1) LL - texture energy from LL kernel, 2) EE - texture energy from EE kernel, 3) SS - texture energy from SS kernel, 4) LE - average texture energy from LE and EL kernels, 5) ES - average texture energy from ES and SE

kernels, and 6) LS - average texture energy from LS and SL kernels.

(g) *Fractal Dimension Texture Analysis (FDTA)*

Mandelbrot [10] developed the fractional Brownian motion model in order to describe the roughness of natural surfaces. The Hurst coefficient $H^{(k)}$ [10] was computed for image resolutions $k=1, 2, 3, 4$. A smooth surface is described by a large value of the parameter H whereas the reverse applies for a rough surface.

(h) *Fourier Power Spectrum (FPS)*

The radial sum and the angular sum of the discrete Fourier transform [5] were computed in order to describe texture.

(i) *Shape Parameters*

The following shape parameters were calculated from the segmented plaque image: 1) X - coordinate maximum length, 2) Y - coordinate maximum length, 3) Area, 4) Perimeter, and 5) Perimeter²/Area.

In order to identify the best features for the classification of the carotid plaques the distance between the two classes for each feature was computed as

$$dis = 1 - \frac{\sigma_1 + \sigma_2}{|m_1 - m_2|} \quad (1)$$

where m_1 and m_2 are the mean values and σ_1 and σ_2 are the standard deviations of the two classes. The maximum possible distance value is 1, whereas negative values indicate overlap of the two classes. The best features are the ones with the greatest distance.

3. PLAQUE CLASSIFICATION

Following the feature extraction, feature classification was implemented based on a modular neural network architecture [11]. The self-organizing map (SOM) classifier [12] was used for the classification of the carotid plaques into symptomatic or asymptomatic. The ten features sets were used as input to the classifiers as described in the previous section. All features were normalised by division with their mean values before use.

In the evaluation phase, a new input pattern was assigned to the winning output node with the weight vector closest to the new input vector. In order to classify the new input pattern, the majority of the labels of the output nodes in a 3×3 neighbourhood window centered at the winning node, were considered. The number of the input patterns in the neighbourhood window for the two classes $m=\{1, 2\}$, ($1=\text{symptomatic}, 2=\text{asymptomatic}$), was computed as:

$$SN_m = \sum_{i=1}^L W_i N_{m_i} \quad (2)$$

where L is the number of the output nodes in the $R \times R$ neighbourhood window with $L=R^2$ ($L=9$ using a 3×3

window), and N_{mi} is the number of the training patterns of the class m assigned to the output node i . W_i is a weight factor giving to the output nodes near to the winning output node a greater weight than the ones farther away (in a 3x3 window, for the winning node $W_i=1$, for the four nodes perpendicular to the winning node $W_i=0.5$ and for the four nodes diagonally located $W_i=0.3536$). The evaluation input pattern was classified to the class m of the SN_m with the greatest value, as symptomatic or asymptomatic.

Beyond the classification result, a confidence measure on how reliable the classification result was computed as:

$$conf = 2(\max\{SN_1, SN_2\}) / (SN_1 + SN_2) - 1 \quad (3)$$

If the plaque was classified as symptomatic then the computed confidence measure was multiplied with -1. The confidence measure has a range of values from -1 (symptomatic) to 1 (asymptomatic). Values close to zero mean low confidence of the correctness of the classification result whereas values close to -1 or 1 indicate a high confidence. Figure 2 shows the distribution of the 116 carotid plaques of the training set on a 12x12 SOM using as input the GLDS feature set and gives an example on the confidence measure calculation.

In this work, a modular neural network system composed of ten SOM classifiers was developed. The ten different SOM classifiers were trained and evaluated using as input each one of the feature sets given in section 2. The ten classification results were combined using: 1) majority voting where the input pattern was assigned to the class with the greatest number of votes, and 2) with weighted averaging based on the confidence measure. In this case, the final classification result was the average of the ten confidence measures computed as described in Eq. 2. If the final result value was negative, then the plaque was classified as symptomatic, otherwise if it was positive as asymptomatic. The confidence measure decided the contribution of each feature set to the final result.

4. RESULTS AND DISCUSSION

A total of 166 (76 symptomatic and 90 asymptomatic) ultrasound images of carotid atherosclerotic plaques were analysed. Ten different texture feature sets and shape parameters (a total of 61 features) were extracted from the manually segmented plaque images as described in section 2. For each feature set, the mean and standard deviation for the symptomatic and asymptomatic classes were computed, as well as the distance (as given in Eq. 1) between the two classes. A high degree of overlap between the values of the two classes was obtained. The best texture features using the distance given by Eq. 1 as criterion, were found to be: the coarseness of NGTDM, the entropy, the range of values of the angular second

moment of SGLDM, the median gray level value, the mean values of the inverse difference moment of SGLDM, the fractal value H1, and the roughness and the periodicity of SFM. In general, texture in symptomatic plaques tends to

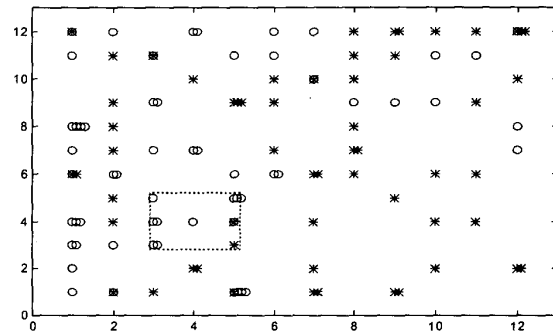


Fig. 2 Distribution of 116 carotid plaques of the training set (58 symptomatic and 58 asymptomatic) on a 12x12 SOM using as input the GLDS feature set which gave in average the highest diagnostic yield (* = symptomatic, o = asymptomatic). Similar plaques are assigned to neighbouring output matrix nodes. (A plaque assigned at node (4,4) will be classified as asymptomatic since the majority of the labels in the 3x3 window are asymptomatic (10:2). In this case the confidence measure will be calculated as given in Eq. 2: $2*(1+3*0.5+6*0.3536)/(1+4*0.5+7*0.3536)-1=0.69$).

be more dark, with higher contrast, more heterogeneous, more rough and less periodical, whereas in asymptomatic plaques texture tends to be brighter, with less contrast, more homogeneous, more smooth, with large areas with small gray tone variations, and more periodical. This confirms the original assumption [1], [2] that smooth surface, echogenicity and a homogenous texture are characteristics of stable plaques, whereas irregular surface, echolucency and a heterogeneous texture are characteristics of potentially unstable plaques.

For the classification task, the unsupervised neural SOM classifier was implemented with a 12x12 output node architecture and it was trained for 5000 learning epochs. For training the classifier, 58 symptomatic and 58 asymptomatic plaques were used, whereas for evaluation of the system the remaining 18 symptomatic and 32 asymptomatic plaques were used. In order to verify the correctness of the classification results a bootstrapping procedure was followed. The system was trained and evaluated using five different bootstrap sets where in each set 116 different plaques were selected at random for training and 50 different plaques for evaluation. Different neighbourhood window sizes were evaluated for computing the confidence measure, where the 3x3 window size proved to give in average the best results.

Table I tabulates the average diagnostic yield obtained for the 10 different feature sets, with a 3x3 neighbourhood window size. This corresponds to a neighbourhood of 9 output nodes on the 12x12 SOM. Best feature set was the GLDS with 68.8%, followed closely by the FOS with 68.4%, the Laws TEM with 66.0%, and the SGLDM (mean values) with 65.2%. Worst feature set was the shape parameters with diagnostic yield only 51.6%, which means that they contain little diagnostic information. The combination of the classification results significantly improved the average diagnostic yield for the ten feature sets from 62.4% up to 70.4% when combined with majority voting, and up to 76.4% when combined with the confidence measure. Figure 2 illustrates the distribution of 116 carotid plaques of the training set on a 12x12 SOM, using as input the GLDS feature set which gave in average the highest diagnostic yield. In addition the diagnostic yield was calculated for the 15 best features which were computed as described in Eq. 1 and tabulated in Table I. Using the 15 best features, an average 66.8% diagnostic yield was obtained. This was better than the average diagnostic yield of the individual feature sets but worse than the diagnostic yield of the best feature sets, and much worse than the overall diagnostic yield of the combiner.

Combining the classification results of the ten different feature sets with the use of a confidence measure, improved the classification results obtained by the individual feature sets, reaching an average diagnostic

Table I Mean and standard deviation of the diagnostic yield (DY), for the evaluation set, for five bootstrap sets, for the SOM classifier for a 3x3 neighbourhood window size.

Feature Set	Size	SOM DY%
FOS	5	68.4 ± 7.1
SGLDM (mean)	13	65.2 ± 6.0
SGLDM (range)	13	62.8 ± 8.5
GLDS	4	68.8 ± 7.1
NGTDM	5	61.2 ± 4.3
SFM	4	63.2 ± 4.1
TEM	6	66.0 ± 4.6
FDTA	4	63.6 ± 7.1
FPS	2	53.6 ± 4.3
Shape parameters	5	51.6 ± 6.7
Average		62.4 ± 6.0
Combine the ten feature sets with majority voting		70.4 ± 7.7
Combine by averaging the ten confidence measures		76.4 ± 6.0
15 best features	15	66.8 ± 5.2

yield of 76.4% for the evaluation set. The benefits of combining are more obvious in the case where there are no dominant best feature sets or best classifiers, as was the case with the features extracted from the carotid plaque images in this study.

The statistical KNN classifier was also implemented for the classification of carotid plaques. The overall diagnostic yield for the KNN system was 72.8%, and it was lower than the 76.4% achieved with the SOM system.

In conclusion, the results in this work show that it is possible to identify a group of patients at risk of stroke based on texture features extracted from high resolution ultrasound images of carotid plaques. This group of patients will benefit from a carotid endarterectomy whereas other patients will be spared from an unnecessary operation.

5. REFERENCES

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