CONTENT-BASED IMAGE RETRIEVAL FOR CAROTID PLAQUE ULTRASOUND IMAGES

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Abstract: The retrieval of similar medical images from a database of digital images with a known symptom outcome can be very useful for a better assessment of disease and treatment. In high-resolution ultrasound imaging of atherosclerotic carotid plaques the extraction of features characterizing the plaque morphology and structure can be used for the retrieval of similar plaques and the identification of individuals with asymptomatic carotid stenosis at risk of stroke. In this work a content-based image retrieval system is implemented using texture, histogram, shape and correlogram features and the SOM neural and the KNN statistical classifiers reaching a correct retrieval rate of 73%.

Introduction

The huge amount of medical and other digital images made available in the recent days necessitate content-based image retrieval (CBIR) systems in order to effectively and efficiently use the information that is intrinsically stored in these image databases. A critical step for achieving this goal is the automated extraction of features characterizing the image. There was a lot of work in the last years for the construction of CBIR systems [1], [2]. In [3] Nezamabadi-pour and Kabir used histogram for image retrieval whereas in [4] Laaksonen et al used the SOM classifier and different feature distributions for comparing different classes and different feature representations of the data in the context of the PicSOM CBIR system. In a recent work, Amores and Radeva [2] present a CBIR system for intravascular ultrasound images using a generalization of correlograms in order to extract local, global and contextual image features.

The objective of this work was to develop a CBIR system that will facilitate the automated retrieval of similar carotid plaque ultrasound images based on the following features: (i) texture, (ii) histogram, (iii) shape, (iv) correlogram. The aim was to identify plaque images with similar structure and based on their clinical history and known symptoms to decide the course of treatment for the test plaque/subject. The ultimate task was to identify individuals with asymptomatic carotid stenosis at risk of stroke [5]. Stroke is the third leading cause of death in the western world and the major cause of disability in adults.

Material

Ultrasound scans of carotid plaques were performed using duplex scanning and color flow imaging. A total of 230 carotid plaque ultrasound images (115 symptomatic and 115 asymptomatic) obtained from 209 subjects, were analysed. For training the system 80 symptomatic and 80 asymptomatic plaques were used, whereas for evaluation of the system the remaining 35 symptomatic and 35 asymptomatic plaques were used. The carotid plaques were labeled as symptomatic after one of the following symptoms was identified: Stroke, Transient Ischemic Attack or Amaurosis Fugax.

Feature Extraction

The following texture (i-viii) [6]-[11], histogram (ix) shape (x), and correlogram (xi) [2] feature sets were extracted from the segmented plaque images:

(i) Statistical Features (SF): The following statistical features were computed: 1) Mean value, 2) Median value, 3) Standard Deviation, 4) Skewness, and 5) Kurtosis.

(ii) Spatial Gray Level Dependence Matrices (SGLDM): The spatial gray level dependence matrices as proposed by Haralick et al. [6] 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 [6] 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, i.e. 3x3 matrices) and for angles $\theta = 0^o, 45^o, 90^o$ and 135^o 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.

(iii) Gray Level Difference Statistics (GLDS): The GLDS algorithm [7] 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) Homogeneity

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2) Contrast, 3) Angular second moment, 4) Entropy, and 5) Mean. The above features were calculated for displacements $\delta = (0, d), (d, d), (d, 0), (d, -d)$, where $\delta \equiv (\Delta x, \Delta y)$, and their mean values were taken. In this work the parameter $d=1$ was used.

(iv) Neighborhood Gray Tone Difference Matrix (NGTDM): Amadasun and King [8] proposed the Neighborhood Gray Tone Difference Matrix in order to extract textural features, which correspond to visual properties of texture. The following features were extracted, for a neighborhood size of $(2d+1)x(2d+1)$ where $d=1$ was chosen: 1) Coarseness, 2) Contrast, 3) Busyness, 4) Complexity, and 5) Strength.

(v) Statistical Feature Matrix (SFM): The statistical feature matrix [9] 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. The constants L_r, L_c which determine the maximum intersample spacing distance were set $L_r=L_c=4$.

(vi) Laws Texture Energy Measures (TEM): For the Laws TEM extraction [10], [11], 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 edge detector and S acts as 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.

(vii) Fractal Dimension Texture Analysis (FDTA): The Hurst coefficient $H^{(k)}$ [11] was computed for image resolutions $k=1, 2, 3$. A smooth surface is described by a large value of the parameter H whereas the reverse applies for a rough surface.

(viii) Fourier Power Spectrum (FPS): The radial sum and the angular sum of the discrete Fourier transform [11] were computed in order to describe texture.

(ix) Histogram: The histogram of the plaque images was computed for 30 equal width bins and was used as a second feature set. Histogram despite its simplicity provides a good description of the plaque structure.

(x) Shape: The following shape features were calculated from the plaque images: 1) X - coordinate maximum length, 2) Y - coordinate maximum length, 3) Area, 4) Perimeter, and 5) Perimeter^2/Area. The idea was to investigate whether the size and complexity of the shape of the segmented plaque had any diagnostic value.

(xi) Correlogram: Correlograms are histograms which measure not only statistics about the features of the image, but also take into account the spatial distribution of these features [2]. The proposed correlogram implemented in this work was calculated as the distribution of the pixels' gray level values from the center of the image. For each pixel the distance from the image center was calculated and for all pixels with the same distance their histograms were computed. In order to make the comparison between images of different sizes feasible, the correlograms were normalized into 30 possible distances from the center by dividing the calculated distances with *maximum_distance/30*. The resulting correlograms were matrices 30x253 (gray level values over 253 were set to be the white area surrounding the region of interest and were not consider for the calculation of the features).

The texture and the shape features were normalized before use by subtracting their mean value and dividing with their standard deviation whereas the histogram and correlogram features were used with their original values.

Image Classification / Retrieval

For the retrieval of similar plaque images the neural self-organizing feature map (SOM) classifier and the statistical K-nearest neighbor (KNN) classifier were used.

(i) The SOM Classifier: The SOM was chosen because it is an unsupervised learning algorithm where the input patterns are freely distributed over the output node matrix [12]. The weights are adapted without supervision in such a way, so that the density distribution of the input data is preserved and represented on the output nodes. This mapping of similar input patterns to output nodes, which are close to each other, represents a discretisation of the input space, allowing a visualization of the distribution of the input data. The output nodes are usually ordered in a two dimensional grid and at the end of the training phase, the output nodes are labeled with the class of the majority of the input patterns of the training set, assigned to each node.

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 an RxR neighborhood window centered at the winning node, were considered. The number of the input patterns in the neighborhood window for the two classes $m=\{1, 2\}$, (1=symptomatic, 2=asymptomatic), was computed as:

$$SN_m = \sum_{i=1}^{L} W_i N_{mi} \tag{1}$$

where L is the number of the output nodes in the RxR neighborhood window with $L=R^2$ (e.g. $L=9$ using a 3x3 window), and N_{mi} is the number of the training patterns of the class m assigned to the output node i. $W_i=1/(2\ d_i)$, is a weighting factor based on the distance d_i of the output node i to the winning output node. W_i gives the output nodes near to the winning output node a greater weight than the ones farther away (e.g. 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, etc). The evaluation input pattern was classified to the class m of the SN_m with the greatest value, as symptomatic or asymptomatic.

(ii) The KNN Classifier: The statistical k-nearest neighbor (KNN) classifier [13] was also used for the classification of the carotid plaques. In the KNN algorithm, in order to classify a new input pattern, its k nearest neighbors from the training set are identified. The new pattern is classified to the most frequent class among its neighbors based on a similarity measure that is usually the Euclidean distance. In this work the KNN carotid plaque classification system was implemented for different values of k and it was tested using for input the different feature sets.

For the SOM CBIR system, the retrieved images were assigned to the same output node with the test plaque or in the neighborhood of the winning node in the case that no plaques were assigned to the winning node. In the KNN system the k most similar images using the Euclidean distance as the similarity measure were retrieved. The evaluation of how successful was the retrieval, was based on the classification of the retrieved plaques into two types: (i) symptomatic, or (ii) asymptomatic. If the type of the reference test plaque was the same with the type of the majority of the retrieved images, then the retrieval was considered successful.

Results

Table 1 tabulates the success rates of correct retrievals for all cases.

Table 1: The success rate of correct retrievals in % for the SOM and KNN CBIR systems, using as input: (i) the texture, (ii) histogram, (iii) shape feature sets, (iv) the above three feature sets combined, (v) the correlogram features. For the SOM a 10x10 matrix was used whereas for the KNN the results for k=5 are given.

Feature set	SOM	KNN	Average
Texture	68.1	70.0	69.1
Histogram	69.5	67.1	68.3
Shape	61.4	58.6	60.0
Combined	70.0	72.9	71.5
Correlogram	67.1	70.0	68.6
Average	*67.2*	*67.7*	*67.5*

Using the 56 extracted texture features as input vector yielded about 68.1% correct retrievals for the SOM CBIR system with a SOM 10x10 output nodes architecture, whereas the KNN yielded 70.0% with k=5. Using as input the histogram of the image with 30 bins yielded 69.5% correct retrievals for the SOM and 67.1% for the KNN respectively. The shape parameters performed worse with 61.4% correct retrievals for the SOM and 58.6% for the KNN system. Furthermore all the above 91 features were combined and used as one input vector to the classifiers. In this case the histogram parameters were also normalized by subtracting their mean value and dividing with their standard deviation. Using all 91 features combined slightly improved the percentage of correct retrievals for the SOM system up to 70.0% and for the KNN up to 72.9%. The correlogram features performed also well and gave results comparable to the texture and histogram features, with 67.1% correct retrievals for the SOM and 70.0% for the KNN system. The correlogram features were not combined with the other features due to their large vector size (30x253=7590).

In Figure 1 an example is given with the five more similar plaques to the reference plaque shown at the top left side of the figure. Below each plaque its label as symptomatic or asymptomatic is given. In Figure 1 the SOM classifier was used with the 56 texture features used as input. As seen from the labels of the retrieved images, 4 out 5 of the retrieved images are labeled as symptomatic and their label coincides with the label of the reference plaque. Figures 2 and 3 show the retrieved images for the same reference plaque using the SOM with the histogram and the shape features. Figures 4, 5, and 6 illustrate the same example using the KNN classifier and the texture, histogram and the shape features respectively. Figure 7 shows the retrieved plaques when all 91 features were used combined as one input vector with the SOM classifier, whereas figure 8 shows the same example with the KNN classifier. Figure 9 shows the correlogram for the reference image and figures 10 and 11 show the retrieved images using as input the correlogram features for the SOM and the KNN classifiers respectively.

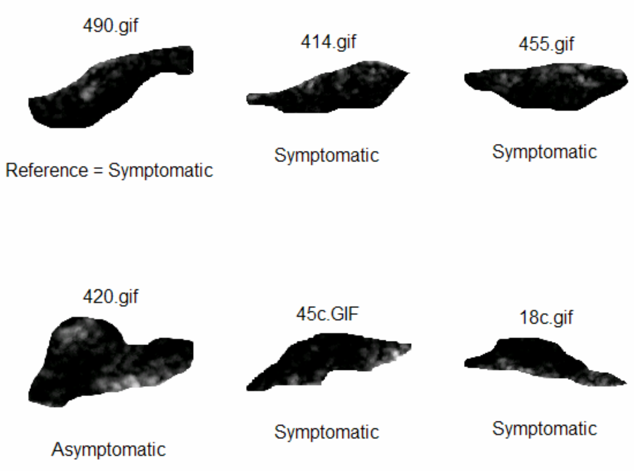

Figure 1: Image retrieval using the SOM classifier and the texture features

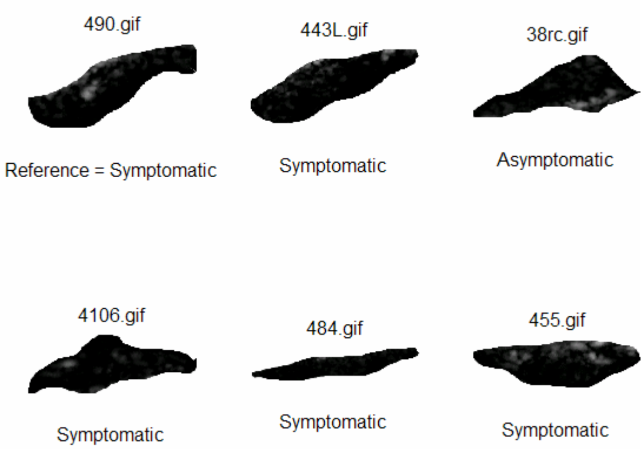

Figure 2: Image retrieval using the SOM classifier and the histogram parameters

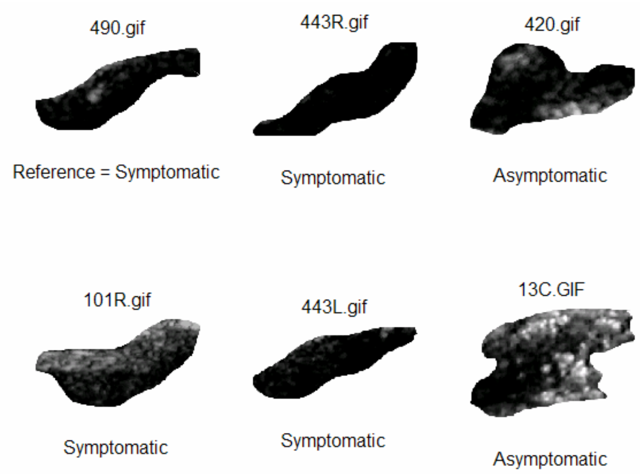

Figure 3: Image retrieval using the SOM classifier and the shape parameters

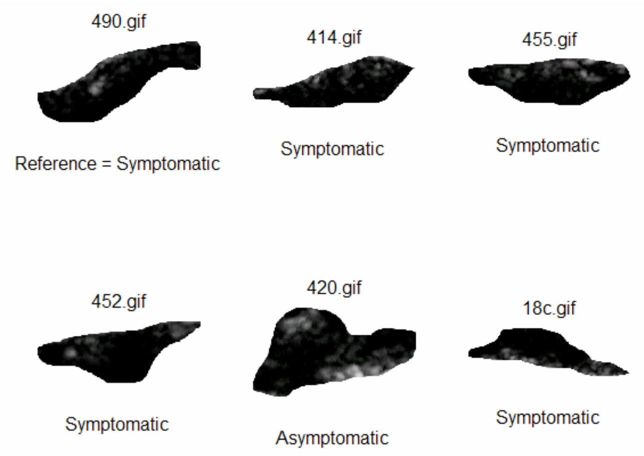

Figure 4: Image retrieval using the KNN classifier and the texture features

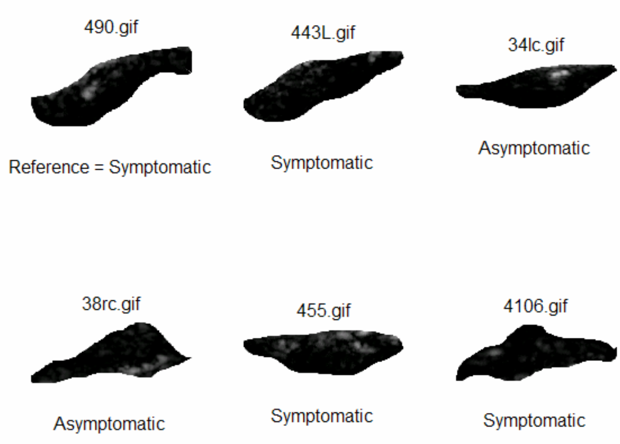

Figure 5: Image retrieval using the KNN classifier and the histogram parameters

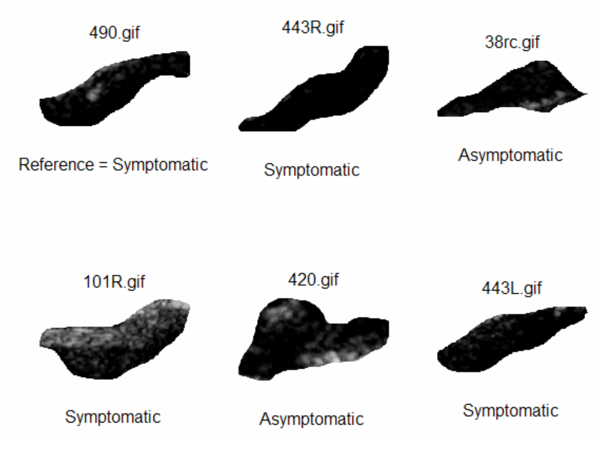

Figure 6: Image retrieval using the KNN classifier and the shape parameters

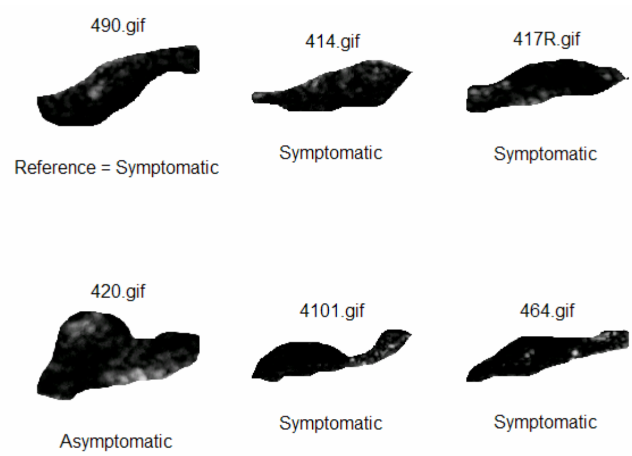

Figure 7: Image retrieval using the SOM classifier and all features combined

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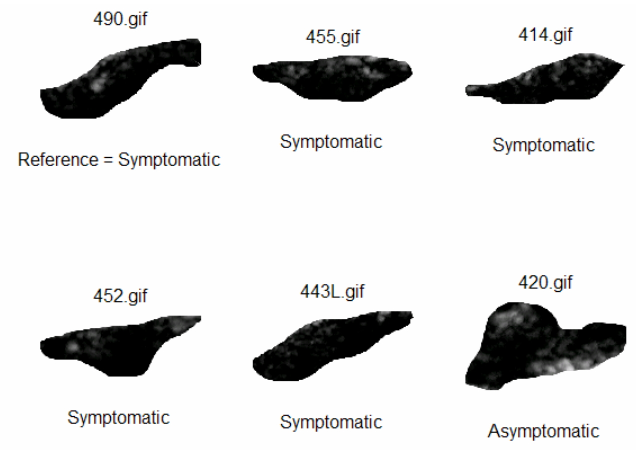

Figure 8: Image retrieval using the KNN classifier and all features combined

Figure 9: The correlogram matrix 30x253 of the reference image 490.gif

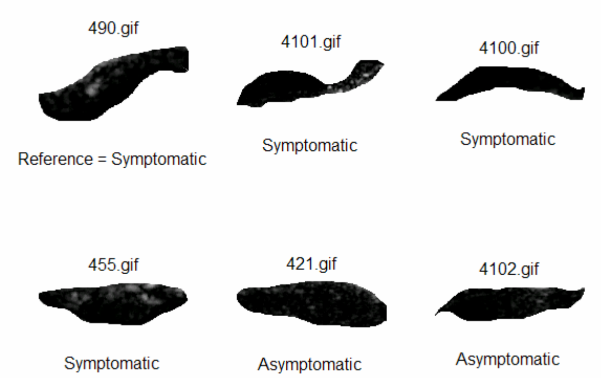

Figure 10: Image retrieval using the SOM classifier and the correlogram features

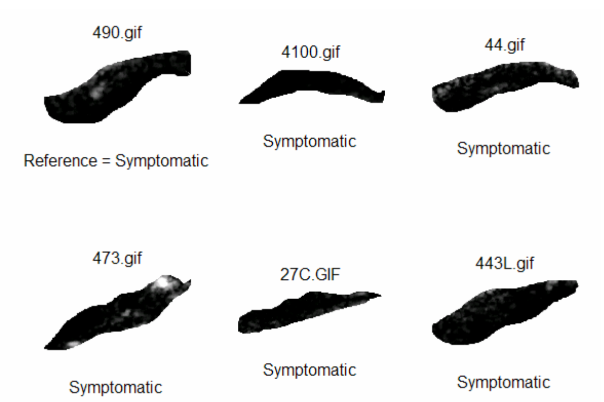

Figure 11: Image retrieval using the KNN classifier and the correlogram features

Concluding Remarks

In this work an image retrieval system for carotid plaque ultrasound images is presented using as input texture, histogram and shape features, based on the neural SOM and the statistical KNN classifiers. Best feature results were obtained when using the texture features with an average percentage of correct retrievals for both systems of 69.1%, followed closely by the correlogram and the histogram features with 68.6% and 68.3%. The simple shape features computed, based on the dimensions and the area of the plaque, performed worse and provided an average correct retrievals rate of 60.0% for both systems. When the texture, shape and histogram were combined the success rate was increased to 71.5% in average. Best individual result was obtained by the KNN CBIR system with the combined features as input, with 72.9% correct retrievals.

The performance of the KNN and the SOM classifiers was very similar. However the simpler statistical KNN classifier made it easier to track back and repeat the results than the more complex neural SOM classifier, which required separate training and evaluation phases.

Feature work will focus in developing an automated CBIR system, which through a user-friendly interface will provide to the physician not only the label of the retrieved plaques but also all the information about the original ultrasound images, the clinical data and the history of the similar cases. This will help the physician to decide the course of treatment and may spare patients from an unnecessary endarterectomy.

In conclusion the results in this work show that content-based image retrieval for carotid plaque images is feasible and that texture, correlogram and histogram features can be used successfully for the identification of cases with similar symptoms output.

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