# Carotid plaque stroke risk assessment using multiscale AM-FM analysis based on DoG filterbanks

Kyriacos P. Constantinou
*Dept. of Computer Science*
*University of Cyprus*
Nicosia, Cyprus
csp7ck1@ucy.ac.cy

Ioannis P. Constantinou
*Istognosis Ltd*
Nicosia, Cyprus
ioannis@istognosis.com

Marios S. Pattichis
*Dept. of Electrical and Computer Engineering*
*University of New Mexico*
Albuquerque NM, USA
pattichi@unm.edu

Efthyvoulos Kyriacou
*Dept. of Electrical Engineering, Computer Engineering and Informatics*
*Cyprus University of Technology*
Limassol, Cyprus
efthyvoulos.kyriacou@cut.ac.cy

Constantinos S. Pattichis
*Dept. of Computer Science*
*University of Cyprus*
Nicosia, Cyprus
pattichi@ucy.ac.cy

***Abstract*—The objective of this work was the investigation of multiscale Amplitude Modulation - Frequency Modulation (AM-FM) analysis based on Difference of Gaussians (DoG) filterbanks representations in order to predict the risk of stroke by analysing carotid plaques ultrasound images of individuals with asymptomatic carotid stenosis. We computed the instantaneous amplitude, instantaneous phase and the magnitude of instantaneous frequency to extract histogram features on each plaque region. The Support Vectors Machine classifier was implemented to classify asymptomatic versus symptomatic plaques. A dataset of 100 carotid plaque images (50 asymptomatic and 50 symptomatic) were tested, and showed that the AM-FM features based on DoG filterbanks and simple histograms performed better than the traditional AM-FM features. Best results were obtained when an eight scale filterbank with a combination of scales was used reaching the accuracy of 75%.**

***Index Terms*—mplitude Modulation - Frequency Modulation (AM-FM)mplitude Modulation - Frequency Modulation (AM-FM)A, Difference of Gaussians, Carotid plaque, Classification, Ultrasound imaging.**

## I. Introduction

It is very important to predict the risk of stroke for individuals with asymptomatic carotid plaque based on an objective quantitative methodology allowing risk-benefit assessment of endarterectomy in high-risk cases [1]. It has also been reported that individuals with echolucent atherosclerotic plaques have an increased risk of ischemic cerebrovascular events [2]. Additionally, plaque echolucency can be used to predict stroke [3]. It has also been reported that plaques that are more echolucent and heterogeneous are often associated with higher cerebrovascular risk and the development of ipsilateral neurological symptoms [4]. However, homogeneous hypoechoic and hyperechoic plaques usually remain asymptomatic without signs of ulceration.

Over the years, AM-FM representations have been used in a wide variety of medical image analysis applications based on a vastly reduced number of features that can be easily learned by simple classifiers [5]. More specifically, on AM-FM models, decompose images into AM-FM components where the instantaneous frequency provides a descriptor of local texture, the instantaneous amplitude captures slowly-varying brightness variations, while the instantaneous phase provides for a powerful descriptor of location, generalizing the traditionally important role of phase in the Fourier Analysis of images [6]. Previous work based on multiscale AM-FM analysis using a Gabor filterbank was reported by Christodoulou et al. [7], to classify carotid plaque ultrasound images of asymptomatic versus symptomatic cases with satisfactory results.

This paper describes the first study where multiscale AM-FM representations are computed using a filterbank based on Difference of Gaussians (DoG). In addition, the new methodology is used to separate asymptomatic from symptomatic cases based on ultrasound images of the atherosclerotic plaques. A fundamental advantage of the use of DoG filterbanks is that the new scales are completely invariant to rotations of the image. We computed the ultrasound plaque AM-FM feature sets based on histograms of: (i) instantaneous amplitude, (ii) instantaneous phase and (iii) magnitude of instantaneous frequency. We note that we expect that there is a relationship between AM-FM features and carotid plaque types. More generally, the relationship between texture features and plaque types has been previously explored in [8], [9].

979-8-3503-3959-8/23/$31.00 ©2023 IEEE

## II. Material & Methods

### A. Image Acquisition and Processing

We analysed a total of 100 carotid plaque ultrasound images (50 asymptomatic and 50 symptomatic). Symptomatic plaques were labelled with a follow-up of 6–96 months (mean 48 months) for the cases of stroke, transient ischemic attacks and amaurosis fugax. Asymptomatic plaques were never associated with symptoms [4]. Bilateral carotid duplex scanning was performed on admission to the study. Plaques were segmented by expert physicians using the "Plaque Texture Analysis software" version 3.2 (Iconsoft International Ltd, Greenford, London, U.K.) [4]. We performed image intensity and image resolution standardization. Image intensity normalization is performed using the image intensity values for blood (mapped to 0) and adventitia (mapped to 190) as described in [4]. Image resolution was standardized at 20 pixels per mm.

### B. Multiscale AM-FM

An input image $I(x,y)$ is expressed as a sum of AM-FM components as given by:

$$I(x,y) = \sum_{n=1}^{n=M} \alpha_n(x,y)\cos(\phi_n(x,y)) \tag{1}$$

where $n$ denotes the different AM-FM components, $\alpha_n(x,y)$ the Instantaneous Amplitude (IA) functions and $\phi_n(x,y)$ the instantaneous phase (IP) functions.

The analytic image extension can be computed effectively through the application of the 1D Hilbert-transform along each row as given by [10]:

$$I_{AS}[k_1,k_2] = I[k_1,k_2] + j\mathcal{H}_{1D}\{I[k_1,k_2]\} \tag{2}$$

$$\approx \sum_{n=1}^{K} \alpha_n[k_1,k_2]\exp(j\varphi_n[k_1,k_2]). \tag{3}$$

We note that the AM-FM decomposition is not expected to hold exactly because the underlying multiscale filterbank will not perfectly cover the entire 2D frequency spectrum. Nevertheless, the scales are designed to approximately cover the entire 2D frequency spectrum. Thus, the resulting AM-FM decomposition will provide a nice approximation to the input image.

The extended analytic image is then processed through a filterbank to produce:

$$I_{AS,i}[k_1,k_2] = g_i[k_1,k_2] * I_{AS}[k_1,k_2] \tag{4}$$

where $g_i$ denotes the impulse response of the $i$-th filter in the filterbank.

We then calculate the instantaneous amplitude, the instantaneous phase and the instantaneous frequency using [11]:

$$\alpha_i[k_1,k_2] = \frac{|I_{AS,i}[k_1,k_2]|}{|G_i(\nabla\varphi[k_1,k_2])|}, \tag{5}$$

$$\varphi_i[k_1,k_2] = \arctan\left(\frac{\text{imag}(I_{AS,i}[k_1,k_2])}{\text{real}(I_{AS,i}[k_1,k_2])}\right), \tag{6}$$

$$\nabla\varphi_i[k_1,k_2] = \text{real}\left(-j\frac{\nabla I_{AS,i}[k_1,k_2]}{I_{AS,i}[k_1,k_2]}\right), \tag{7}$$

Dominant component analysis can be applied over different scales and Combination of Scales (CoS) can be used to generate AM-FM channel estimates:

$$a_{c,i}, \phi_{c,i}, \nabla\phi_{c,i}, \quad i = \{\text{low, medium, high}\}.$$

At every pixel, we select the filter that gives the maximum instantaneous amplitude (IA). The dominant IA is given by the $P$-th channel. We then select $a_{c,P}, \phi_{c,P}, \nabla\phi_{c,P}$ as the estimates associated with the dominant component.

### C. Difference of Gaussians (DoG) Filterbanks

The DoG filter is created by subtracting two Gaussian functions of different widths. The result is a band-pass filter that removes high frequency components representing noise, and also some low frequency components representing the homogeneous areas in the image. It is assumed to be associated with the edges in an image.

The DoG equation is as follows [12]:

$$DoG(x,y) = \frac{1}{2\pi\sigma^2}\exp\left(\frac{-(x^2+y^2)}{2\sigma^2}\right) - \frac{1}{2\pi\kappa^2\sigma^2}\exp\left(\frac{-(x^2+y^2)}{2\kappa^2\sigma^2}\right) \tag{8}$$

where $\sigma^2$ is the variance, and $\kappa$ is a constant multiplicative factor. The DoG filterbank used in this study for AM-FM analysis is given in Table I and plotted in Fig. 1. AM-FM analysis was implemented as documented in equation (8). The DoG AM-FM feature sets are given in Table II.

TABLE I: DoG filterbank setup where $\sigma_0 = \sqrt{2}/2$ and $\kappa = \sqrt{2}$ (plotted in Fig 1).

| Scale | $\sigma$ | $\kappa\sigma$ |
|---|---|---|
| 1 | $8\sqrt{2}\sigma_0$ | $16\sigma_0$ |
| 2 | $8\sigma_0$ | $8\sqrt{2}\sigma_0$ |
| 3 | $4\sqrt{2}\sigma_0$ | $8\sigma_0$ |
| 4 | $4\sigma_0$ | $4\sqrt{2}\sigma_0$ |
| 5 | $2\sqrt{2}\sigma_0$ | $4\sigma_0$ |
| 6 | $2\sigma_0$ | $2\sqrt{2}\sigma_0$ |
| 7 | $\sqrt{2}\sigma_0$ | $2\sigma_0$ |
| 8 | $\sigma_0$ | $\sqrt{2}\sigma_0$ |

### D. DoG Filterbanks and Histogram Based AM-FM Feature Sets (see Table II)

Feature sets (FS1) were computed for all the scales of multiscale DoG filterbanks and for each combination of scales as follows: 8 bin histograms of instantaneous amplitude $\alpha_{c,i}$,

TABLE II: AM-FM Analysis Feature Sets

| Feature Set | Features | Number of Scales | Component Selection | Combination of Scales | | | Total Number of Features |
|---|---|---|---|---|---|---|---|
| | | | | Low | Medium | High | |
| FS1 | $\alpha_{c,i}$ 8 bins<br>$\phi_{c,i}$ 4 bins<br>$\lvert\nabla\phi_{c,i}\rvert$ 4 bins | 4<br>6<br>8 | - | - | - | - | (8+4+4)×4=62<br>(8+4+4)×6=96<br>(8+4+4)×8=128 |
| FS1cs | $\alpha_{c,i}$ 8 bins<br>$\phi_{c,i}$ 4 bins<br>$\lvert\nabla\phi_{c,i}\rvert$ 4 bins | 8 | DCA | VVL-VL | L-ML-M | MH-H-VH | (8+4+4)×3=48 |

VVL: Very Very Low, VL: Very Low, L: Low, ML: Medium Low, M: Medium, MH: Medium High, H: High, VH: Very High.

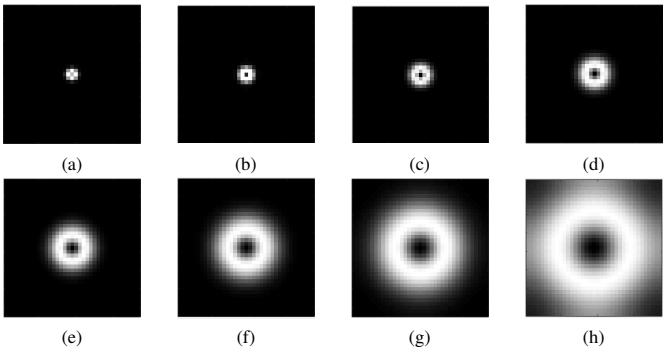


Fig. 1: An 8 scale DoG filterbank in the frequency domain based on Table I. Scales starting from: (a) Very Very Low (VVL), (b) Very Low (VL), (c) Low (L), (d) Medium Low (ML), (e) Medium (M), (f) Medium High (MH), (g) High (H) and (h) Very High (VH).

4 bins histogram of instantaneous phase $\phi_{c,i}$ and 4 bins histogram of the magnitude of instantaneous frequency $|\nabla\phi_{c,i}|$. The 8 scale DoG filtenbank feature set (FS1cs) was computed using a combination of scales as shown in Table II. For each combination of scales, dominant component analysis was applied.

### *E. Statistical Analysis*

The features extracted were statistically analysed to select significantly different features. A Mann-Whitney U-test was used with the statistical significance set to 0.05.

### *F. The SVM Classifier*

A Support Vector Machines (SVM) classifier was trained to classify the feature sets (FS) investigated into two classes: 1) asymptomatic plaques or 2) symptomatic plaques (the plaques that caused stroke including transient ischemic attacks).

The SVM models were investigated using Gaussian radial basis function (RBF) kernels $k(x_i, x_j) = \exp(-\|x_i - x_j\|^2)$ where $x_i$ and $x_j$ were data points; this was decided as the rest of the kernel functions could not achieve satisfactory results.

For the classification performance, a 10-fold cross validation method was used. The data were divided randomly into a training set consisting of 90% of the cases, with the remaining 10% of the cases as an evaluation set.

## III. Results

DoG based AM-FM analysis was carried out as introduced in section II-D. Four, 6 and 8 scale DoG filterbanks were used

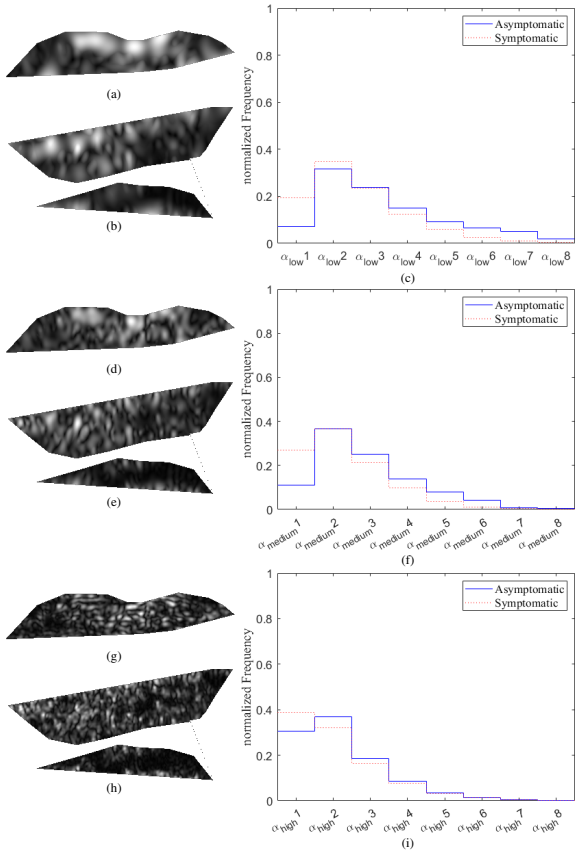


Fig. 2: Multiscale AM-FM analysis based on an 8 scales DoG filterbank. Instantaneous amplitude features of FS1cs feature set were derived from demodulations using combination of scales and dominant component analysis (see Table II): (a) Asymptomatic $\alpha_{low}$, (b) Symptomatic $\alpha_{low}$, (c) Histogram $\alpha_{low}$, (d) Asymptomatic $\alpha_{medium}$, (e) Symptomatic $\alpha_{medium}$, (f) Histogram $\alpha_{medium}$, (g) Asymptomatic $\alpha_{high}$, (h) Symptomatic $\alpha_{high}$, (i) Histogram $\alpha_{high}$.

and the FS1 and FS1cs feature sets were computed (see Table II). For the FS1cs feature set an 8 scale DoG filterbank was used with a combination of scales and dominant component analysis as given in Table I.

Multiscale AM-FM analysis based on the 8 scale DoG filterbank of Table I on an asymptomatic plaque and a symptomatic plaque with the extracted AM-FM features for instantaneous amplitude (IA) and instantaneous phase (IP), are illustrated in Fig. 2 and Fig. 3 respectively. Analysis was carried out

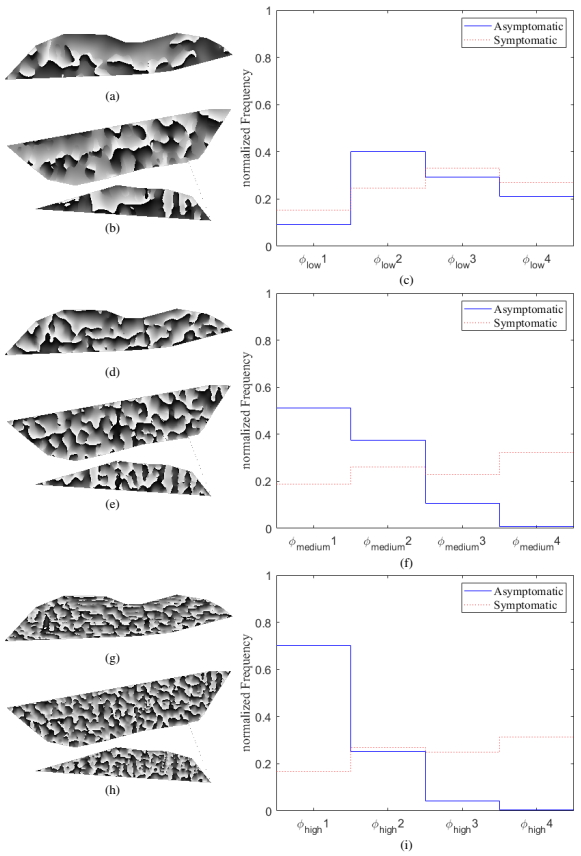


Fig. 3: Multiscale AM-FM analysis based on an 8 scales DoG filterbank. Instantaneous phase features of FS1cs feature set were derived from demodulations using combination of scales and dominant component analysis (see Table II): (a) Asymptomatic $\phi_{low}$, (b) Symptomatic $\phi_{low}$, (c) Histogram $\phi_{low}$, (d) Asymptomatic $\phi_{medium}$, (e) Symptomatic $\phi_{medium}$, (f) Histogram $\phi_{medium}$, (g) Asymptomatic $\phi_{high}$, (h) Symptomatic $\phi_{high}$, (i) Histogram $\phi_{high}$

using histogram based features with combination of scales and dominant component analysis feature set (FS1cs), as shown in Table II. The difference in the AM-FM histogram features between the asymptomatic plaque and the symptomatic plaque are shown.

Table III tabulates the classification results for the feature sets (see Table II). When using FS1, the highest average classification accuracy was 74%, achieved using an 8 scale DoG filterbank. The best overall average classification accuracy was achieved for the FS1cs feature set and it was 75% with an average sensitivity of 76% and an average specificity of 75% when an 8 scale DoG filterbank with combination of scales was used.

The overall classification accuracy is similar to what has been achieved with standard texture features (e.g., [1]). Nevertheless, the achieved accuracy is slightly higher than what was previously achieved with standard AM-FM Gabor filterbanks (see [7]). We believe that this improvement is due to the perfect rotation invariance of the DoG filterbank.

TABLE III: Classification results of asymptomatic versus symptomatic carotid plaque ultrasound images using multiscale AM-FM analysis with DoG frequency sampling (for the feature set description see Table II).

| Scales | Feature Set | Accuracy | Sensitivity | Specificity | AUC |
|---|---|---|---|---|---|
| 4 | | 69 | 72 | 66 | 0.75 |
| 6 | FS1 | 72 | 75 | 70 | 0.78 |
| **8** | | **74** | **74** | **73** | **0.8** |
| **8** | **FS1cs** | **75** | **76** | **75** | **0.81** |

## IV. CONCLUSIONS

The multiscale AM-FM analysis based on DoG filterbanks and derived representations provided new feature sets, that demonstrated successful classification of asymptomatic versus symptomatic carotid ultrasound plaque images. This work gave slightly higher classification accuracy when compared to other studies carried out on the same problem using AM-FM [7] feature sets extracted via Gabor filterbanks. Moreover, the results of this study are similar to studies carried out based on classical feature sets and clinical feature sets [1].

## ACKNOWLEDGMENT

This work is supported by the project 'AtheroRisk' Excellence/0421/0292, Research and Innovation Foundation, the Republic of Cyprus.

## REFERENCES

[1] E. C. Kyriacou, S. Petroudi, C. S. Pattichis, M. S. Pattichis *et al.*, "Prediction of high-risk asymptomatic carotid plaques based on ultrasonic image features," *IEEE Trans. Inf. Technol. Biomed.*, vol. 16, no. 5, pp. 966–973, 2012.

[2] E. B. Mathiesen, K. H. Bønaa, and O. Joakimsen, "Echolucent plaques are associated with high risk of ischemic cerebrovascular events in carotid stenosis: the tromsø study," *Circ. J.*, vol. 103, no. 17, pp. 2171–2175, 2001.

[3] R. Topakian, A. King, S. Kwon, A. Schaafsma *et al.*, "Ultrasonic plaque echolucency and emboli signals predict stroke in asymptomatic carotid stenosis," *Neurology*, vol. 77, no. 8, pp. 751–758, 2011.

[4] A. N. Nicolaides, S. K. Kakkos, E. Kyriacou, M. Griffin *et al.*, "Asymptomatic internal carotid artery stenosis and cerebrovascular risk stratification," *J. Vasc. Surg.*, vol. 52, no. 6, pp. 1486–1496, 2010.

[5] K. P. Constantinou, I. P. Constantinou, C. S. Pattichis, and M. S. Pattichis, "Medical image analysis using AM-FM models and methods," *IEEE Rev. Biomed. Eng.*, vol. 14, pp. 270–289, 2021.

[6] K. P. Constantinou, "AM-FM medical image analysis," PhD dissertation, University of Cyprus, 2022.

[7] C. I. Christodoulou, C. S. Pattichis, V. Murray, M. S. Pattichis, and other, "AM-FM representations for the characterization of carotid plaque ultrasound images," in *IFMBE Proc.* Springer Berlin Heidelberg, 2009, pp. 546–549.

[8] M. B. Griffin, E. Kyriacou, C. Pattichis, D. Bond *et al.*, "Juxtaluminal hypoechoic area in ultrasonic images of carotid plaques and hemispheric symptoms," *J. Vasc. Surg.*, vol. 52, no. 1, pp. 69–76, 2010.

[9] L. Saba, S. S. Sanagala, S. K. Gupta, V. K. Koppula *et al.*, "Multimodality carotid plaque tissue characterization and classification in the artificial intelligence paradigm: A narrative review for stroke application," *Ann. Transl. Med.*, vol. 9, no. 14, 2021.

[10] J. P. Havlicek, "AM-FM image models," Ph.D. dissertation, University of Texas at Austin, 1996.

[11] V. Murray, P. Rodriguez, and M. S. Pattichis, "Multiscale AM-FM demodulation and image reconstruction methods with improved accuracy," *IEEE Trans. Image Process.*, vol. 19, no. 5, pp. 1138–1152, May 2010.

[12] D. G. Lowe, "Distinctive image features from scale-invariant keypoints," *Int. J. Comput. Vis.*, vol. 60, no. 2, pp. 91–110, 2004.