Investigation of AM-FM Methods for Mammographic Breast Density Classification

Styliani Petroudi, Ioannis Constantinou, Chrysa Tziakouri, Marios Pattichis and Constantinos Pattichis

***Abstract*—Breasts are composed of a mixture of fibrous and glandular tissue as well as adipose tissue and breast density describes the prevalence of fibroglandular tissue as it appears on a mammogram. Over the past few years, evaluation and reporting of breast density as it appears on mammograms has received a lot of attention because it impacts one's risk of developing breast cancer but also the capability of detecting breast cancer on mammograms. In addition, mammography fails in the identification of breast cancer in almost half of the women with dense breasts. Different image analysis methods have been investigated for automatic breast density classification. The presented method investigates the use of Amplitude-Modulation Frequency-Modulation (AM-FM) multi-scale feature sets for characterization of breast density as the first step in the development of a density specific Computer Aided Detection System. AM-FM decompositions use different scales and bandpass filters to extract the instantaneous frequencies (IF), instantaneous amplitude (IA) and instantaneous phase (IP) components from an image. Normalized histograms of the maximum IA across all frequencies and scales are used to model the different breast density classes. Classification of a new mammogram into one of the breast density classes is achieved using the k-nearest neighbor method with $k=5$ and the euclidean distance metric. The method is evaluated on the Medical Image Analysis Society (MIAS) mammographic database and the results are presented. The presented method allows breast density classification accuracy reaching over 84%. Future work will involve a new AM-FM methodology approach based on adaptive filterbank design and performance index decision.**

I. INTRODUCTION

Mammography has been the modality of choice for breast cancer screening for the early detection of breast cancer. Mammographic breast density refers to the amount of fibroglandular tissue in the breast, as it appears on a mammogram, first reported by Wolfe in 1976 [1]. Breast density is a most important risk factor that has received a lot of attention also in the legislation [2] as it may be deemed necessary to report to women their breast density so that they can make more informed decisions regarding their breast health. Breast density has not only been shown to be one of the most important risks for developing breast cancer [3], [4], [5], but it also impacts the ability of the detection of breast cancer by masking abnormalities. Better understanding of breast density and how it corresponds to a significant increase of breast cancer risk have led to the need of breast density assessment and use of the information for supplementary screening using other imaging techniques such as whole-breast ultrasound (US), [6], [7]. For women with dense breasts adjunct imaging such as US, breast Magnetic Resonance Imaging (MRI) and tomosynthesis can be used in addition to x-ray mammography for increased breast cancer detection sensitivity.

There is a number of different qualitative methods for breast density assessment, such as the Wolfe [1], the Six Class Category [4] and the Tabar classification [8]. Following Wolfe's mammographic breast parenchymal density categorization [1], the American College of Radiology proposed the Breast Imaging Reporting and Data System (BI-RADS) [9] mammographic parenchymal density classification.

Mammographic breast density is usually assessed by visual inspection by the radiologist. However, there is great inter- and intra- observer variability reported for both experienced and inexperienced readers [10],[11]. Lobbes *et al.* [10] reported a classification accuracy of under 60% for BI-RADS breast density classification for the experienced readers who tended to overestimated the density class whilst the inexperienced readers presented an even lower classification accuracy. The paper also reported moderate agreement between visual inspection and classification using semi-automated methods. Sukha *et al.* [11] reported that experienced readers showed higher inter-observer variability for two different visual assessment breast density methods with the greatest difference reported for the mammograms of mixed adipose-glandular appearance. Mammographic breast density is a powerful breast cancer risk factor that has considerable potential in risk stratification and in monitoring the effects of interventions in risk alteration. Yet, the need still exists to develop objective methods that provide precise, simple and reproducible density measures to achieve this [5].

Different computer aided techniques and methodologies have been developed for more objective and reproducible mammographic breast parenchymal density evaluation and classification. The method proposed by Byng et al. [12] that uses interactive thresholding of image intensity to segment the dense tissue as it appears on the mammograms, is the most widely used semi-automatic breast density classification. The method uses the percentage of the segmented region to establish the dense classification and is implemented in Cumulus^{TM} software. More recently Volpara^{TM} which uses a relative - rather than an absolute - physics model which reduces the need for accurate imaging physics data [13] provides objective

Styliani Petroudi is with the Department of Computer Science at the University of 1678 Nicosia, Cyprus. styliani@ucy.ac.cy

Ioannis Constantinou is with the Department of Computer Science at the University 1678 Nicosia, Cyprus. ikonst01@cs.ucy.ac.cy

Chrysa Tziakouri is with the Department of Radiology at the Nicosia General Hospital, Nicosia, Cyprus.

Marios Pattichis is with the Department of Electrical and Computer Engineering at the University of New Mexico, Albuquerque, NM, USA. pattichis@gmail.com

Constantinos Pattichis is with the Department of Computer Science at the University 1678 Nicosia, Cyprus. pattichi@ucy.ac.cy

978-1-4799-3163-7/13/$31.00 ©2013 IEEE

volumetric assessment of breast tissue density.

As breast density is evaluated on the 2D projection of the breast on the mammogram, and there is a number of factors that result in significant intensity variation in mammograms, a number of breast density classification methods have used different texture based features for density classification. One of the first works for breast density segmentation and classification was by Miller and Astley [14] who investigated texture-based discrimination between fatty and dense breast types applying granulometric techniques and Laws texture masks. Petroudi et al. [15] proposed a scheme that uses statistical based texton models to capture the mammographic appearance within the breast area. Kallenberg et al. [16] developed a breast density segmentation algorithm using a set of different features with information about location, intensity, texture and global context with a neural network for pixel classification intensity. Chen *et al.* [17] used topographic representation obtained using level sets with saliency and independency to detect shapes of interest and create a density map from where different features are extracted for breast density classification. Classification accuracy was over 76.01%. Most recently, Li *et al.* [18] have shown that texture features alone retain information for the assessment of breast cancer risk that is distinct from image intensity.

Amplitude-Modulation Frequency-Modulation (AM-FM) decompositions provide physically meaningful image texture measurements as they can capture local (instantaneous) variations in amplitude, frequency, and phase [19]. Significant texture variations are well represented in the frequency components. By using AM-FM components from different scales, one can produce multiscale features at pixel-level resolutions. Over the past decade, AM-FM has been used in different medical image applications including CAD systems, a review of which can be found in [20]. Maragos et al. [21] presented an application for ultrasound spectroscopy where Doppler ultrasound resolution was improved using AM-FM models. Multiscale AM-FM methods were applied to electromyographic signals [22], ultrasound images of the carotid artery [23], and other applications with very good results.

This paper investigates the development of an automatic mammographic breast density classification based on texture representation using multi-scale AM-FM models.

II. Method

For breast density characterization the mammograms are pre-processed and normalized as in [15] and the mammographic breast region is segmented. Following, different AM-FM features are evaluated on the segmented breast region. Each segmented breast region is then represented by a normalized histogram of the evaluated AM-FM features. The k-nearest neighbor (k-NN) method is used to classify mammograms to the corresponding density class with the leave one out cross-validation method.

AM-FM methods provide a way to model non-stationary image contents as a series of AM-FM component images in terms of amplitude and phase functions. Let

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

be the form of the AM-FM expansion where $I(.)$ is the input image, $a_n(x,y)\cos(n\varphi(x,y))$ the collection of M AM-FM component signals used to model the essential image modulation structure [19], and $n = 1,2,...,M$ denote the different frequency scales. Each scale is defined in terms of a collection of bandpass filters that share similar magnitude range. Frequency-modulated (FM) components $\cos(\varphi_n(x,y))$ are used to capture the fast-changing variability in image intensity [19]. $a_n(x,y)$ denote the instantaneous amplitude (IA) functions, and $\varphi_n(x,y)$ denote the instantaneous phase functions (IP). The instantaneous frequency (IF) functions $\nabla\varphi_n(x,y)$ are defined in terms of the phase gradient:

$$\nabla\varphi_n(x,y) = \left(\frac{\partial\varphi_n}{\partial x}(x,y), \frac{\partial\varphi_n}{\partial y}(x,y)\right). \tag{2}$$

Each frequency scale n is defined in terms of a collection of bandpass filters that share similar magnitude range.

There are different AM-FM demodulation methods that can be used for the estimation of the different AM-FM components: IA, IP and IF. For the work presented here AM-FM demodulation is based on the multi-scale approach introduced by Murray et al. [19]. However, instead of using flat passband filters, in our application, we consider a six-scale Gabor filterbank that sample 8 orientations (see Fig. 1).

To summarize the method, given the real input image $I(x,y)$ the 2-D extended analytic signal associated with $I(x,y)$ is computed as follows:

$$I_{AS}(x,y) = I(x,y) + jH_{2d}[I(x,y)]. \tag{3}$$

where H_{2d} denotes the $2-D$ extension of the $1-D$ Hilbert transform operator [19]. The resulting I_{AS} is processed through filterbank. For each bandpass filter output I_{AS_n}, it is possible to estimate the IA, and the IP using:

$$a_n(x,y) \approx |I_{AS_n}(x,y)| \tag{4}$$

$$\varphi_n(x,y) \approx \arctan\left(\frac{imag(I_{AS_n}(x,y))}{real(I_{AS_n}(x,y))}\right) \tag{5}$$

For computing the AM-FM decomposition, the filterbank is based on the Gabor filterbank using eight orientations and six different scales [24]. Image characterization is achieved using the maximum IA component from Dominant Component Analysis (DCA). The maximum evaluated IA across all frequencies and scales is used to characterize each pixel in the breast region and the 256 bin normalized histogram (pdf) of the estimated maximum IA is used to characterize each image. Over all image scales, at all image pixels, DCA constructs an AM-FM image representation, by using AM-FM estimates from the channel with the maximum instantaneous amplitude response.

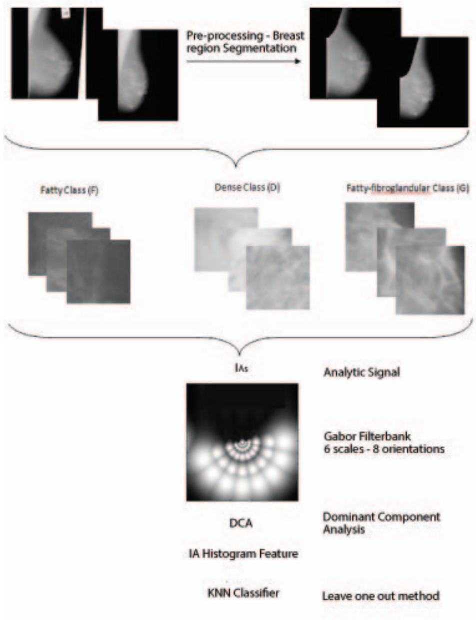

Fig. 1. Breast density classification presented methodology.

Mammographic breast density classification is achieved using the k-NN method with $k = 5$. Different values of k ranging from $k = 1$ to $k = 7$ where evaluated and as $k = 5$ and $k = 7$ resulted to the same lowest error rate, $k = 5$ was chosen. Despite k-NN being a quite simple classification method - it works by finding the k closest training points according to some metric and using majority vote to assign the instance to a class - it works quite well. k-NN is evaluated using Euclidean distance. The method is developed and quantitatively evaluated using the Medical Image Analysis Society (MIAS) mammogram database [25]. The MIAS database contains 161 cases and thus 322 mammograms. It also provides breast density classification as the mammograms in the database are classified to three different density classes, fatty, fatty-glandular and dense glandular. Thus for the purposes of this work, the mammograms are automatically classified to one of these three classes. The performance of the presented method is evaluated using the leave one out validation model on the normalized histograms of the presented AM-FM texture features - actually two and not one mammograms are left out when both mammograms of a woman in the MIAS database belong to the same density class.

III. Results

The algorithm is evaluated on a set of mammograms from the MIAS mammographic database [25]. However, as the database includes not only normal mammograms but also cases where there are abnormalities present and there is a different representation of the three classes in the database, only 62 mammograms are chosen per density class. The classification accuracy using kNN on the different density classes is shown in Table I. The agreement with the density annotations provided with the MIAS database when all the mammograms from all different classes are used for classification was 84.00%. Accuracy is calculated as the percentage of correctly classified mammograms in a breast parenchymal density category over the ground truth total number of mammograms in that category.

TABLE I
CLASSIFICATION ACCURACY RESULTS FOR THE MIAS BREAST DENSITY CHARACTERIZATION USING kNN CLASSIFIER WITH AM-FM TEXTURE FEATURES

MIAS Density Classification	Accuracy%
Fatty	81.25%
Fatty-Glandular	83.87%
Dense-Glandular	86.49%
All Density Classes	84.00%

IV. Discussion

This paper presents an initial investigation of the use of AM-FM texture features for the automatic classification of mammograms on breast parenchymal density classes. The classification accuracy using only IA reaches over 84%. Histograms of IA and IF have been effectively used for content-based image retrieval using short feature vectors [26] and the achieved classification testifies to this. For the work presented here only the IA component has been investigated. The comparatively high classification accuracy can be attributed to the fact that AM-FM decompositions provide for physically meaningful texture measurements [26] over multiple scales, at a pixel-level resolution. The work presented here used the more classical Gabor Filterbank for decomposition. Depending on the application different AM-FM decompositions using different frequency coverage can provide for higher breast density classification, as does the incorporation of IF and IP.

The presented method compares favorably with other methods presented in the literature. Petroudi et al. [15] evaluated texton histograms using chi-square distance achieved a classification accuracy of 76% but on a different database. It should be noted that recently Liasis et al. [27] achieved a classification accuracy of 93%. However, this resulted as a combination of different texture features - textons, Local Binary Patterns (LBP) and Scale-Invariant Feature Transform (SIFT) - using a Support Vector Machine (SVM) classifier. The SVM classification accuracy was much lower when each feature set was evaluated separately, where LBP reached a classification accuracy of 82.7%. Also, that method was more computationally expensive. Chen et al. [17] achieved a classification density of 76% on the MIAS database with BI-RADS classification using a topographic representation, saliency and shape. Oliver et al. [28] extracted morphological and texture features from the segmented breast areas and used a Bayesian combination of a number of classifiers, but also achieved 84% accuracy for BI-RADS classification on the same dataset.

The classification accuracy achieved here warrants further investigation of AM-FM texture features for establishing a best feature selection for each density class.

V. Conclusion

This paper presents an investigation of the use of AM-FM texture features for the characterization of mammographic parenchymal density. The method builds on the AM-FM demodulation method presented in [19]. The normalized histogram of the maximum IA across all frequencies and scales is used to characterize the breast density for each mammogram. Classification is achieved by comparing the corresponding distribution to the rest using kNN and Euclidean distance. The achieved results - a classification accuracy of 84% on the MIAS [25] database- are quite promising, especially when one takes into account that only the normalized histogram of the maximum IA component estimated for each pixel was used. Further evaluation using additional features, different filterbanks as well as different demodulation methods can result in higher classification rates, and these will form the basis of future work.

VI. ACKNOWLEDGMENTS

This work was funded through the project Development of a Breast Cancer Density Specific Computer Aided Detection System, ΤΠΕ/ΟΡΙΖΟ/0311(ΒΙΕ)/029, 2/2013-2/2015 of the Program for Research and Technological Development 2007-2013 of the Cyprus Research Promotion Foundation

References

[1] J. Wolfe, "Breast patterns as an index of risk for developing breast cancer," *American Journal of Roentgenology*, vol. 126, pp. 1130–1139, 1976.

[2] C. I. Lee, L. W. Bassett, and C. D. Lehman, "Breast density legislation and opportunities for patient-centered outcomes research," *Radiology*, vol. 264, no. 3, pp. 632–636, 2012.

[3] K. Kerlikowske, "The mammogram that cried wolfe," *New England Journal of Medicine*, vol. 356, pp. 297–300, 2007.

[4] N. Boyd, J. Byng, R. Jong, E. Fishell, L. Little, A. Miller, G. Lockwood, D. Tritchler, and M. Yaffe, "Quantitative classification of mammographic densities and breast cancer risk: Results from the canadian national breast screening study," *Journal of the National Cancer Institute*, vol. 87, no. 9, pp. 670–675, 1995.

[5] V. Assi, J. Warwick, J. Cuzick, and S. W. Duffy, "Clinical and epidemiological issues in mammographic density," *Nature Reviews Clinical Oncology*, vol. 9, pp. 33–40, 2012.

[6] F. Schaefer, A. Waldmann, A. Katalinic, C. Wefelnberg, M. Heller, W. Jonat, and I. Schreer, "Influence of additional breast ultrasound on cancer detection in a cohort study for quality assurance in breast diagnosisanalysis of 102,577 diagnostic procedures," *European Radiology*, vol. 20, no. 5, pp. 1085–1092, 2010.

[7] R. Highnam, N. Sauber, S. Destounis, J. Harvey, and D. McDonald, "Breast density into clinical practice," in *Breast Imaging*, ser. Lecture Notes in Computer Science, A. Maidment, P. Bakic, and S. Gavenonis, Eds. Springer Berlin / Heidelberg, 2012, vol. 7361, pp. 466–473.

[8] I. T. Gram, E. Funkhouser, and L. Tabar, "The tabar classification of mammographic parenchymal patterns," *European Journal of Radiology*, vol. 24, no. 2, pp. 131 – 136, 1997.

[9] *Illustrated Breast Imaging Reporting and Data System (BI-RADS)*, 3rd ed. American College of Radiology, 1998.

[10] M. Lobbes, J. Cleutjens, V. Lima Passos, C. Frotscher, M. Lahaye, K. Keymeulen, R. Beets-Tan, J. Wildberger, and C. Boetes, "Density is in the eye of the beholder: visual versus semi-automated assessment of breast density on standard mammograms," *Insights into Imaging*, vol. 3, no. 1, pp. 91–99, 2012.

[11] A. Sukha, M. Berks, J. Morris, C. Boggis, M. Wilson, N. Barr, and S. Astley, "Visual assessment of density in digital mammograms," in *Digital Mammography*, ser. Lecture Notes in Computer Science, J. Mart, A. Oliver, J. Freixenet, and R. Mart, Eds. Springer Berlin / Heidelberg, 2010, vol. 6136, pp. 414–420.

[12] J. W. Byng, N. F. Boyd, E. Fishell, R. A. Jong, and M. J. Yaffe, "The quantitative analysis of mammographic densities," *Physics in Medicine and Biology*, vol. 39, no. 10, p. 1629, 1994.

[13] R. Highnam, S. Brady, M. Yaffe, N. Karssemeijer, and J. Harvey, "Robust breast composition measurement - volpara^{TM}," in *Digital Mammography*, ser. Lecture Notes in Computer Science, J. Mart, A. Oliver, J. Freixenet, and R. Mart, Eds. Springer Berlin / Heidelberg, 2010, vol. 6136, pp. 342–349.

[14] P. Miller and S. Astley, "Classification of breast tissue by texture and analysis," *Image and Vision Computing*, vol. 10, pp. 277–282, 1992.

[15] S. Petroudi, T. Kadir, and M. Brady, "Automatic classification of mammographic parenchymal patterns: A statistical approach," in *Proceedings of EMBC, International Conference on Engineering in Medicine and Biology*. IEEE, 2003, pp. 798–801.

[16] M. G. J. Kallenberg, M. Lokate, C. H. van Gils, and N. Karssemeijer, "Automatic breast density segmentation: an integration of different approaches," *Physics in Medicine and Biology*, vol. 56, no. 9, pp. 2715–2729, 2011.

[17] Z. Chen, A. Oliver, E. Denton, and R. Zwiggelaar, "Automated mammographic risk classification based on breast density estimation," in *Pattern Recognition and Image Analysis*, ser. Lecture Notes in Computer Science. Springer Berlin Heidelberg, 2013, vol. 7887, pp. 237–244.

[18] X.-Z. Li, S. Williams, and M. J. Bottema, "Background intensity independent texture features for assessing breast cancer risk in screening mammograms," *Pattern Recognition Letters*, vol. 34, no. 9, pp. 1053 – 1062, 2013.

[19] V. Murray, P. Rodriguez, and M. Pattichis, "Multiscale am-fm demodulation and image reconstruction methods with improved accuracy," *Image Processing, IEEE Transactions on*, vol. 19, no. 5, pp. 1138–1152, 2010.

[20] V. Murray, M. Pattichis, E. Barriga, and P. Soliz, "Recent multiscale am-fm methods in emerging applications in medical imaging," *EURASIP Journal on Advances in Signal Processing*, vol. 2012, no. 1, p. 23, 2012.

[21] P. Maragos, T. Loupas, and V. Pitsikalis, "Improving doppler ultrasound spectroscopy with multiband instantaneous energy separation," *Proc 14th International Conference on Digital Signal Processing*, vol. 2, pp. 611–614, 2002.

[22] C. Christodoulou, P. Kaplanis, V. Murray, M. Pattichis, C. Pattichis, and T. Kyriakides, "Multi-scale am-fm analysis for the classification of surface electromyographic signals," *Biomedical Signal Processing and Control*, vol. 7, no. 3, pp. 265 – 269, 2012.

[23] C. Loizou, V. Murray, M. Pattichis, I. Seimenis, M. Pantziaris, and C. Pattichis, "Multiscale amplitude-modulation frequency-modulation texture analysis of multiple sclerosis in brain mri images," *Information Technology in Biomedicine, IEEE Transactions on*, vol. 15, no. 1, pp. 119–129, 2011.

[24] A. Bovik, N. Gopal, T. Emmoth, and A. Restrepo, "Localized measurement of emergent image frequencies by gabor wavelets," *Information Theory, IEEE Transactions on*, vol. 38, no. 2, pp. 691–712, 1992.

[25] J. Suckling, J. Parker, D. Dance, S. Astley, I. Hutt, C. Boggis, I. Ricketts, E. Stamatakis, N. Cerneaz, S. Kok, P. Taylor, D. Betal, and J. Savage, "The mammographic image analysis society digital mammogram database," in *Second International Workshop on Digital Mammography*, vol. 1069, 1994, pp. 375–378.

[26] M. Pattichis, "Multidimensional am-fm models and methods for biomedical image computing," in *Engineering in Medicine and Biology Society, 2009. EMBC 2009. Annual International Conference of the IEEE*, 2009, pp. 5641–5644.

[27] G. Liasis, C. Pattichis, and S. Petroudi, "Combination of different texture features for mammographic breast density classification," *2012 IEEE 12th International Conference on Bioinformatics and Bioengineering*, pp. 732–737, 2012.

[28] A. Oliver, J. Freixenet, R. Marti, J. Pont, E. Perez, E. Denton, and R. Zwiggelaar, "A novel breast tissue density classification methodology," *Information Technology in Biomedicine, IEEE Transactions on*, vol. 12, pp. 55 –65, 2008.