Multiscale AM-FM Models and Instantaneous Amplitude Evaluation for Mammographic Density Classification

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Abstract

Breast cancer is the most common cancer in women and the number of incidences keeps rising. Mammographic breast density has been recognized as a very important breast cancer risk and can also mask abnormalities. Information regarding mammographic breast density may be used for planning individualized breast cancer screening and treatment. Thus, breast density is increasingly assessed as the limitations of a one-fits-all method of screening and Computer Aided Detection become more apparent. The presented work investigates the use of Amplitude-Modulation Frequency-Modulation (AM-FM) models in the evaluation of multiscale Instantaneous Amplitude (IA) features for the characterization of breast density. AM-FM models provide a meaningful and concise method to model digital images. The IA evaluated at different frequency scales is used to capture the relative variations in the breast tissue characteristic to the different breast density classes. Normalized histograms of the IA across the different frequency scales - estimated using multiscale Dominant Component Analysis - are used to model the breast density classes. Classification of a new mammogram into one of the density categories is achieved using the k-nearest neighbor method and the Euclidean distance metric. The method is evaluated using the Breast Imaging Reporting and Data System on the Medical Image Analysis Society mammographic database and the results are presented and compared to other methods in the literature. The presented method allows breast density classification accuracy reaching over 80%.

1 Introduction

Breast cancer is the second most commonly diagnosed cancer, and the most common cancer in women both in the developing and developed world. Mammography has been the modality of choice for breast cancer screening for early detection. Yet, the incidences of breast

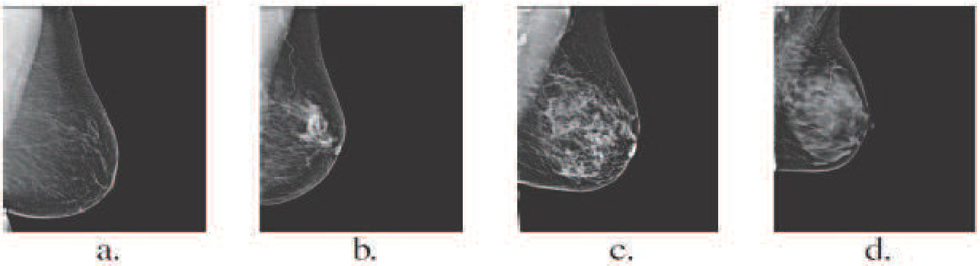

Figure 1: Examples of mammograms from the breast parenchymal density BI-RADS classes a) BI-RADS I, b) BI-RADS II, c) BI-RADS III, d) BI-RADS IV.

cancer continue to rise. Breast density has not only been shown to be one of the most important risks for developing breast cancer [3], but it also impacts the ability of the detection of breast cancer by masking abnormalities. Breast density assessment information can be used towards breast cancer screening personalization; as the basis for supplementary screening using other imaging techniques [11]. 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 [13]. The Breast Imaging Reporting and Data System (BI-RADS) Atlas produced by the American College of Radiology (ACR) [1] provides a mammographic breast density categorization that serves as a comprehensive guide and a classification system, important for peer review and quality assurance. The BI-RADS mammographic breast density categories descriptions are [1]: (I) the breast is almost entirely fatty, (II) there are scattered fibroglandular densities, (III) the breast is heterogeneously dense which may obscure small masses, and (IV) the breast is extremely dense, which lowers the sensitivity of mammography. The first two classes are low density, low risk and the last two are high density, higher risk. Examples of the four BI-RADS mammographic breast density classes can be seen in Fig. 1.

The new requirements regarding reporting breast density in place, the global increase in breast cancer and the high inter- and intra- observer variability in breast density classification [6] necessitate the development of accurate mammographic breast density classification algorithms. A review can be found in [9]. Petroudi et al. [10] proposed a scheme that uses texture models to capture the mammographic appearance: parenchymal density patterns are modeled as a statistical distribution of clustered, rotationally invariant filter responses in a low dimensional space. More recently He et al. [5] calculated different texture features on the intensity histograms to characterize different tissue types, using Bayes classifier for classification.

Amplitude-Modulation Frequency-Modulation (AM-FM) methods provide powerful and physically meaningful image decompositions that describe non-stationary content and capture local (instantaneous) variations in amplitude, frequency, and phase. AM-FM models characterize each pixel value as sampled from amplitude and frequency modulated orthogonally oriented signals. The AM components capture the local texture contrast whilst the FM components capture the local texture orientation and granularity. The extraction of such features is most relevant to the appearance of fibroglandular density patterns and thus AM-FM derived features may provide a strong basis for the development of density classification algorithms. AM-FM models have been used in different medical image applications and a recent review can be found in [8]. This paper presents an initial evaluation of the use of AM-FM features for breast density classification towards the development of a complete

Figure 2: The Gabor filterbank used.

Computer Aided Detection (CAD) system incorporating breast density. Multi-scale Instantaneous Amplitude (IA) AM-FM features are used to model mammographic density and classification is achieved using k-nearest neighbor (k-NN) with Euclidean distance.

2 Method

Initially the mammograms are pre-processed and normalized, and the breast region is segmented using the methodology in [10]. The AM-FM demodulation is evaluated on the preprocessed mammograms but only the values corresponding to the breast region mask are utilized for tissue characterization. Each segmented breast region is then represented by a set of normalized histograms of the evaluated AM-FM features, one for each frequency scale. Finally, the k-NN method is used to classify mammograms to the corresponding density class with the leave one woman out cross-validation method.

AM-FM methods model an image as a function of spatially local amplitude and frequency modulations. An image can be decomposed to a sum of AM-FM components using:

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

In the AM-FM expansion $I(.)$ is the input image, $a_n(x,y)\cos(n\varphi(x,y))$ is the collection of M AM-FM component signals used to model the essential image modulation structure [7], and $n = 1,2,\ldots,M$ denote the different frequency scales. Each scale is defined in terms of a collection of bandpass filters that share similar magnitude range. $a_n(x,y)$ denote the instantaneous amplitude (IA) functions, and $\varphi_n(x,y)$ denote the instantaneous phase functions (IP). The IA amplitude reflects local image intensity variations, e.g. edges, with different spatial scale variations reflected in different frequency scales. There are different AM-FM demodulation methods that can be used for the estimation of the different AM-FM components. The multiscale approach introduced by Murray et al. [7] is used here. Very briefly, given the real input image $I(x,y)$ the 2-D extended analytic signal associated with $I(x,y)$ is computed by:

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

where H_{2d} denotes the $2-D$ extension of the $1-D$ Hilbert transform operator [7]. The resulting I_{AS} is processed through a filterbank. For each bandpass filter output I_{AS_n}, it is possible to estimate the IA with:

$$a_n(x,y) \approx |I_{AS_n}(x,y)| \tag{3}$$

Unlike [7] the Gabor filterbank using eight orientations and six different frequency scales is applied [2] (see Fig. 2). Image characterization is achieved using multiscale Dominant Component Analysis (mDCA). The filterbank channels are grouped into scales from very

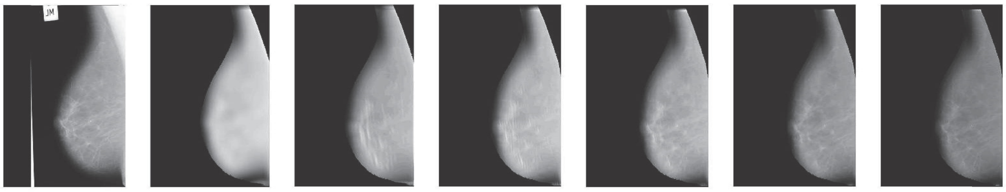

Figure 3: The maximum IA representation for all scales ranging from the very very low frequencies to the very high for a BI-RADS1 mammogram. The first image is the original mammogram.

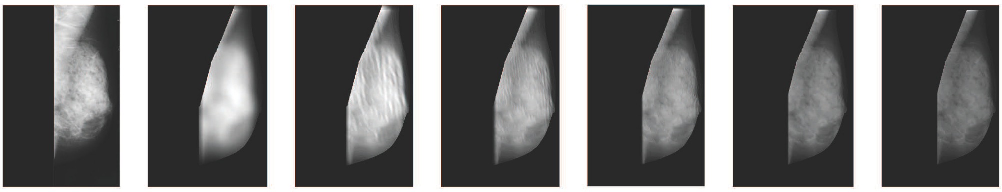

Figure 4: The maximum IA representation for all scales for a BI-RADS4 mammogram.

very low frequencies to very high frequencies [2] and the maximum IA is evaluated across all orientations for each scale, and used to characterize each pixel in the breast region. Examples can be seen in figures 3 and 4. For each scale, for each mammogram, the normalized histogram of the IA is evaluated. Normalized histograms from different frequency scales are concatenated and used to characterize the corresponding mammogram and in turn the different mammographic density classes.

The k-NN method is used to classify mammograms to the corresponding density class using the Euclidean distance measure. k is set to 5 after empirical evaluation. Despite k-NN being a quite simple classification method - for this stage of the algorithm development it works quite well. The method is developed and quantitatively evaluated using the 206 mammograms with no abnormalities present in the Medical Image Analysis Society (MIAS) mammogram database [12]. The mammograms are classified into one of the four BI-RADS density classes - as classified for [9]. The performance of the presented method is evaluated using the leave one woman out validation model on the normalized histograms of the presented AM-FM texture features.

3 Results - Discussion

The algorithm is evaluated on the mammograms that do not include any abnormalities from the MIAS mammographic database [12]. The classification accuracy using k-NN on the different density classes is shown in Table 1. The agreement with the density annotations provided with the MIAS database, when all the mammograms from all different classes are used for classification, is 80.00%. 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.

The presented work has demonstrated that AM-FM features can help differentiate be-

Table 1: Classification accuracy results for the MIAS breast density characterization using a k-NN classifier with IA AM-FM features

MIAS BI-RADS Class	BI-RADS 1	BI-RADS 2	BI-RADS 3	BI-RADS 4	TOTAL
IA AM-FM	89%	85%	69%	77%	80%

tween the different breast density classes. So far, only histograms of the IA have been used which capture the contrast in the texture of the images. In addition, the value of IA reflects the extend of the presence of frequency components from that particular scale in the image. Figures 3 and 4 provide examples of the IA for the 6 scales and it can be seen that the AM-FM features can capture differences in the mammographic appearance of fibroglandular tissue e.g homogeneity vs heterogeneity that characterize different mammographic density variations or lack thereof. This was also investigated by classifying the images using the IA histogram from each frequency scale separately, which resulted in different classification accuracies for the different classes e.g. the very low frequency scale captured the homogeneity present in very high density breasts providing the best single scale classification accuracy for BI-RADS 4 at 71%. Depending on the application, different AM-FM decompositions using different frequency coverage can provide for higher classification accuracy, and so can the incorporation of IF and IP. Moreover, the use of all concatenated values may negatively affect the results because it can affect the evaluation of the measure distance. The next step will be dimensionality reduction using Principal Component Analysis and other dimensionality reduction methods. The presented methodology did not involve any processing or reduction of the IA features. Still, the resulting classification accuracy of 80% into one of the four BI-RADS classes compares very favorably with other methods in the literature. Petroudi et al. [10] evaluated texton histograms using chi-square distance and achieved a classification accuracy of 76% but on a different database. Oliver et al. [9] extracted morphological and texture features from the segmented breast areas and used a Bayesian combination of a number of classifiers, achieving 84% BI-RADS classification accuracy on the same dataset. Chen et al. [4] achieved a classification density of 76% on the MIAS database with BI-RADS classification using a topographic representation, saliency and shape. The achieved classification accuracy from the evaluation of the IA warrants further investigation of AM-FM texture features to help establish a best feature selection for each density class.

4 Conclusion

The evaluation of the IA from AM-FM provides a characterization of the contrast of texture at different frequency scales for an image. Thus, it may be used to capture different characteristics in the appearance of mammographic breast density for BI-RADS density classification. The method builds on the AM-FM demodulation method presented in [7] but with the use of a Gabor filterbank. The normalized histogram of the maximum IA across all frequencies for each scale is used to characterize the breast density for each mammogram. The histograms are concatenated to characterize each image and classification is achieved by comparing the corresponding distribution to the rest using k-NN and Euclidean distance. The achieved classification accuracy of 80% on the MIAS [12] database for BI-RADS classification is high and comparable to other methods in the literature. Future work will involve use of additional AM-FM features, dimensionality reduction and investigation of other classification methods.

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