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Optimized Gabor features for mass classification in mammography

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ABSTRACT

Gabor filter bank has been successfully used for false positive reduction problem and the discrimination of benign and malignant masses in breast cancer detection. However, a generic Gabor filter bank is not adapted to multi-orientation and multi-scale texture micro-patterns present in the regions of interest (ROIs) of mammograms. There are two main optimization concerns: how many filters should be in a Gabor filter band and what should be their parameters. Addressing these issues, this work focuses on finding optimizing Gabor filter banks based on an incremental clustering algorithm and Particle Swarm Optimization (PSO). We employ an SVM with Gaussian kernel as a fitness function for PSO. The effect of optimized Gabor filter bank was evaluated on 1024 ROIs extracted from a Digital Database for Screening Mammography (DDSM) using four performance measures (i.e., accuracy, area under ROC curve, sensitivity and specificity) for the above mentioned mass classification problems. The results show that the proposed method enhances the performance and reduces the computational cost. Moreover, the Wilcoxon signed rank test over the significance level of 0.05 reveals that the performance difference between the optimized Gabor filter bank and non-optimized Gabor filter bank is statistically significant.

1. Introduction

Breast cancer is the most common form of cancer which affects women all over the world and stands next to lung cancer in mortality among women [1,2]. A computer-aided diagnosis (CAD) system based on mammograms can assist the radiologists in detecting breast cancer. A CAD system for masses involves two main stages for mass extraction and processing: detection and segmentation, false positive reduction, and discrimination between benign and malignant masses. In the first stage, potential mass regions of interests (ROIs) are detected and segmented from the mammogram image. The detected ROIs represent not only masses but also dense breast parenchyma, which appear as white regions like masses in mammograms and result in false positives. The false positive reduction stage classifies the detected ROIs into mass and normal ROIs. The mass ROIs are further classified as benign and malignant.

Different efforts have been made so far for reducing false positives and increasing benign-malignant classification accuracy. Texture descriptors have been shown to represent masses more accurately [3]. Since texture microstructures appear at different orientations and scales, they can be represented more effectively using Gabor filters. Gabor filters have been used for this purpose (e.g., see Refs. [2,6] and references therein) and give better performance for false positive reduction and benign-malignant discrimination [6]. However, a Gabor filter bank is not adopted to multi-orientation and multi-scale texture microstructures present in mammograms. To address this issue, we propose to tune and optimize the filters in a Gabor filter bank in order to extract the local texture descriptors that characterize texture micro-patterns (e.g., edges, lines, spots and flat areas) more effectively. There are two main optimization concerns; first, how many filters are appropriate to be used in the bank (filter selection problem) and second, what should be the parameter values of each Gabor filter included in the bank (filter design problem). Clearly, both of these problems are application oriented and a general setting of a Gabor filter bank (see e.g., Refs. [8,9]) does not perform well in different application scenarios. In this work, we proposed a systematic approach that unifies the filter selection and design processes using Particle Swarm Optimization (PSO) and an incremental clustering algorithm. In particular, PSO, a global optimization technique, is used to search for optimal

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parameters of Gabor filters to address the filter design problem. In addition, an incremental clustering algorithm removes redundant Gabor filters from the bank by combining similar filters (in parameter space), thus addressing the filter selection problem. Filters in the same cluster are represented with a single filter which is the centroid of the cluster. The strategy helps in two ways; first, the recognition accuracy is improved and second, the computational cost is reduced (discussed in Section 4). This idea was initially presented in Ref. [7].

The key idea is optimizing the parameters of Gabor filters such that they respond stronger to features that best discriminate between normal and abnormal tissue, improving the performance of breast cancer recognition. The main contribution of this paper is a strategy based on PSO and incremental clustering for optimizing a Gabor filter bank that responds stronger to multi-scale and multi-orientation texture micro-patterns in a mammogram and enhances the classification rate. For the evaluation of the effect of the optimized Gabor filter bank on the mass classification problems, it is applied on overlapping blocks of the ROIs to collect moment-based features (i.e., mean, standard deviation, skewness) from the magnitudes of Gabor responses.

The rest of this paper is organized as follows. In the next section, we review related research. In Section 3, we present the proposed methodology in detail. Subsequently, in Section 4, we present our experimental results and discuss the effectiveness of the proposed technique. Finally, Section 5 concludes our work and presents directions for future research.

2. Related work

Mass detection has attracted the attention of many researchers, and many detection techniques have been proposed. A detailed review of these methods can be found in Refs. [10–13]. Next, we give an overview of the most related recent mass classification methods.

Most of the existing methods differ in the types of features that are used for mass representation and the way these features are extracted. Different types of features such as texture, gradient, grey-level, and shape [10] features have been employed for mass representation. Texture descriptors have been very effective in detecting normal and lesion regions in mammograms [14–16]. Wei et al. [17] extracted multiresolution texture features from wavelet coefficients and used them for the discrimination of masses from normal breast tissue in mammograms. They used Linear Discriminant Analysis (LDA) for classifying the ROIs as mass or non-mass. This method was tested on 168 ROIs containing biopsy-proven masses and 504 ROIs containing normal parenchyma, resulting in Az (Area under ROC curve) equal to 0.89 and 0.86 for the training and test data sets.

If texture is described accurately, then texture descriptors can perform better than other descriptors [3]. Lladó et al. [3] used a spatially enhanced Local Binary Pattern (LBP) descriptor, to represent textural properties of masses and to reduce false positives; this method achieved an overall Az equal to 0.94 ± 0.02 on 512 ROIs (256 normal and 256 masses) extracted from mammograms from the DDSM database. The LBP-based method outperforms other CAD methods for mass classification. However, the LBP descriptor builds statistics on local micro-patterns (dark/bright spots, edges, and flat areas etc.) and it is not robust to noise. The scheme proposed by Sampaio et al. [18] used geo-statistic functions for extracting texture features and SVM for classification, yielding Az of 0.87.

Oliveira et al. [19] addressed the problem of the classification of mammogram regions as mass and non-mass and proposed a method using texture features and SVM. The texture features in this method are computed using the taxonomic diversity index and the taxonomic distinctness. This method gives an average accuracy of 98.88% on DDSM database. The method developed by Nguyen et al. [20] for the classification of suspicious ROIs into masses and non-masses employs texture features extracted using Block Variance of Local Coefficients (BVLC) and SVM. This method achieved AUC of 0.93 on MIAS database. Junior et al. [21] presented a method for false positive reduction problem using texture features extracted as several diversity indices from ROIs and SVM. This method is reported to achieve 100% accuracy on DDSM database. Reyad et al. [22] compared first order statistics, LBP and multiresolution analysis features for the classification of mass and non-mass. They used SVM classifier and showed that the combination of first order statistics and LBP gives the best accuracy (98.63%) for mass regions from DDSM. Hussain [23] used multi-scale spatial Weber Law Descriptor (WLD) and SVM to propose a method for false positive reduction in mammograms. The accuracy rate of this method was 98.93% for the classification of mass and non-mass ROIs from DDSM database.

Rouhi et al. [24] used intensity, textural, and shape features, genetic algorithm (GA) for feature selection, and artificial neural network (ANN) to develop a method for the classification of benign and malignant masses. The accuracy of this method on DDSM using 10-fold cross validation is 82.06%. Nanni et al. [25] compared three texture descriptors (Local Ternary Pattern (LTP), local phase quantization (LPQ)) for the discrimination of mammogram tissues as benign and malignant. They used SVM for classification and claimed to achieve an AUC of 0.97, but Li et al. [26] compared their method with this method and showed that this method achieved classification accuracy rates of 64.62 (LTP) and 62.3 (LPQ) on 114 mass regions (52 benign and 62 malignant) from DDSM database using 5-fold cross validation. Li et al. [26] proposed a method for the discrimination of benign and malignant masses using texton analysis with multiple sub-sampling strategies. K-nearest Neighbor (KNN) classifier is used for each sub-sampling strategy and majority-vote is used for final decision from all KNN classifiers. This method achieved an accuracy rate of 85.96% on 114 mass regions (52 benign and 62 malignant) from DDSM database.

Gabor filters have been extensively used for texture description in various image processing and analysis approaches [27,28]. They decompose an image into multiple scales and orientations making the analysis of texture patterns more straightforward. Mammograms contain a lot of texture, and as such, Gabor filters are suitable for texture analysis of mammograms [29,30]. Different texture description techniques using Gabor filters differ in the way that the texture features are extracted [31]. Hussain [2] employed Gabor filters to create 20 Gabor images, which were then used to extract a set of edge histogram descriptors. He used KNN along with fuzzy c-means clustering as a classifier. The method was evaluated on 431 mammograms (159 normal cases and 272 containing masses) from the DDSM database using tenfold cross validation. This method achieved a true positive (TP) rate of 90% at 1.21 false positives per image. The data set used for validation is biased towards abnormal cases, which favors the mass cases. It should be mentioned that this method extracts edge histograms which are holistic descriptors, and do not represent the local textures of masses.

Lahmiri and Boukadoum [32] used Gabor filters along with Discrete Wavelet Transform (DWT) for mass classification. They applied Gabor filters at different frequencies and spatial orientations on the HH high frequency sub-band image obtained using DWT, and extracted statistical features (i.e., mean and standard deviation) from the Gabor images. For classification, they used SVM with polynomial kernel. Their method was tested on 100 mammograms from the DDSM database using tenfold cross validation, achieving an accuracy of 98%. Although the detection accuracy achieved was good, the size of the dataset used for testing was relatively small. Costa et al. [33] explored the use of Gabor filters along with Principal Component Analysis (PCA) for feature extraction,