Classification of Microcalcification based on Wave Atom Transform

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Abstract - Mammography is commonly used for early cancer detection in women breast. The presence of microcalcification clusters in the digital mammograms is the significant indication of breast cancer and their nature is not necessarily malignant. It is very difficult task to distinguish between benign and malignant clusters. Computer-Aided Diagnosis (CADx) designed to help phatologists determine the type of microcalcification in a mammogram. Usually, it's consisting of two steps, feature extraction and classification. In our methodology, we proposed the use of wave atom transform as feature extraction technique and Support Vector Machine (SVM) as classifier. Here the proposed method is compared with wavelet transform. While comparing, our proposed method achieved good classification accuracy. However, some of the previous researches have shown better results than ours.

Key words: Microcalcification, support vector machine, Wave atom transform

I. INTRODUCTION

Breast cancer is the leading cause of cancer death in women in the world and second commonest cancer in India. Indian council for medical research reports that the incidence of breast cancer has doubled in the metropolitan cities in the past 24 years. There are many methods that can be used to classify the micro calcification in digital mammograms. A new feature extraction method based on discrete wavelet transform for the classification of digital mammograms is proposed in [1]. This method is based on maximizing the difference between the different classes. Euclidean distance measure is used to classify the given mammograms.

Classification of micro calcification based on dual-tree complex wavelet transform and Support Vector Machine (SVM) is proposed in [2]. It consists of two phases namely offline and online. At the offline phase, SVM training is conducted using some training data to find the support vectors. A two stage method based on wavelet transform for detecting and segmenting the micro calcification is developed in [3]. In the first stage the given mammogram is decomposed by un-decimated wavelet transform in order to get the sub-bands at full size. The detected pixels in the high frequency sub-bands are dilated and then weighted before taking inverse wavelet transform. The spatial decomposition property of the discrete wavelet transform is used for the detection of micro calcification in [4]. In order to trace out micro calcification in the mammographic images, the statistical features such as skewness and kurtosis is used.

A CAD system presented in [5] is able to extract features of the texture from the region of interest areas by statistical method and signal process method and then the system can classify the samples into two salubrious classes by using classifier based on Support Vector Machine (SVM). Curvelet transform based texture features are used for the classification of tissues is presented in [6]. From the each wedge, seven statistical features such as energy, entropy, mean, standard deviation, maximum probability, inverse difference moment and homogeneity are extracted and nearest neighbor classifier is used for the classification purpose. The classification accuracy is calculated by using 5-fold cross validation technique.

In recent years, the theory of the multi-resolution analysis based wavelet frames are widely used in image processing techniques. Tight wavelet frame systems are used to remove the motion blurring from the image by regularizing the sparsity of both the original image and the motion blur kernel is explained in [7]. The resulting minimization problem could be efficiently solved by the split Bregman method. Two framelet based de-convolution algorithms are proposed in [8]. A new hybrid fusion method based on the fast intensity-hue-saturation transform with a control parameter along with the framelet transform is proposed in [9].The radiance difference between panchromatic image and intensity image is minimized by the control parameter. The framelet transforms redundancy which is introduced into the wavelet system is mainly used to extract the detailed spatial information from the difference image.

In this paper, comparison for the classification of micro calcification in digital mammograms based on wave atom transform and wavelet transform is proposed.

II. METHODOLOGY

The classification of microcalcification system is based on wave atom transform, wavelet transform and SVM as classifier. In this following section the theoretical background of all the techniques are introduced.

2.1. Wave Atom Transform

Wave atom transform is presented by Demanet in 2007 . The transformation, obeying the parabolic scaling law, can be considered a variant of 2D wavelet packets. Wave atom transform have two very significant properties. First one is the ability to adapt to arbitrary local directions of a pattern. The second one is the ability to sparsely represent anisotropic patterns aligned with the axes. Wave atoms offer sharp frequency localization than other wave packets. It also has significant sparse expansion for oscillatory functions when compared with wavelets, curvelets and Gabor atoms.

The forms of wave packets, known as wavelets, Gabor, ridgelets, curvelets and wave atoms, are created using two parameters, which are α and β . These variables symbolize decomposition and directional ability for all wave forms. α and β values are 1/2 for wave atoms and Figure 1 shows wave packet's support in space and in frequency plane. Here, α corresponds to the multiscale structure of the transform and β corresponds to directional selectivity.

Actually, wave atoms are built from tensor products of 1D wave packets. One-dimensional wave packets can be represented as $\psi_{m,n}^{j}(X)$, where $j, m \geq 0$, and $n \in Z$. frequency restrictions are $\pm\omega_{j,m} = \pm\pi 2^{j} m$ *with* $C_1 2^{j} \leq m \leq C_2 2^{j}$. space restrictions is defined as

$$X_{j,n} = 2^{j} n \tag{1}$$

Two-dimensional wave atoms $\varphi_{\mu}(X1, X2)$ are constructed with subscript $\mu = (j, m, n)$, where $m = (m_1, m_2), n = (n_1, n_2)$. 2D ortho-normal basis is written as follows:

$$\varphi_{\mu}^{+}(X_1, X_2) = \psi_{m1}^{j}\left(X_1 - 2^{-j} n_1\right)\psi_{m2}^{j}\left(X_2 - 2^{-j} n_2\right) \tag{2}$$

$$\varphi_{\mu}^{-}(X_1, X_2) = H\psi_{m1}^{j}\left(X_1 - 2^{-j} n_1\right)H\psi_{m2}^{j}\left(X_2 - 2^{-j} n_2\right) \tag{3}$$

Where, H is Hilbert transform. The wave atom tight frame is formed by combination of (2) and (3).

$$\varphi_{\mu}^{(1)} = \frac{\varphi_{\mu}^{+} + \varphi_{\mu}^{-}}{2}, \varphi_{\mu}^{(2)} = \frac{\varphi_{\mu}^{+} - \varphi_{\mu}^{-}}{2}. \tag{4}$$

2.2. Support Vector Machine

Support vector machines (SVMs) are a set of related supervised learning methods that analyze data and recognize patterns, used for classification and regression analysis (Rejani and Selvi, 2009). The standard SVM is a non-probabilistic binary linear classifier, i.e. it predicts, for each given input, which of two possible classes the input is a member of. A classification task usually involves with training and testing data which consists of some data instances. Each instance in the training set contains one "target value" (class labels) and several "attributes" (features) (Gorgel et al., 2009). SVM has an extra advantage of automatic model selection in the sense that both the optimal number and locations of the basic functions are automatically obtained during training. The performance of SVM largely depends on the kernel.

SVM is essentially a linear learning machine. For the input training sample set

$$(x_i\ ,\ y_i\ ),\ i=1...n,\ x\in R^n\ ,\ y\in\{-1,+1\}$$

Let the classification hyper plane equation is to be

$$(\omega, x)+b=0 \tag{5}$$

Thus the classification margin is $2/|\omega|$. To maximize the margin, that is to minimize $|\ \omega\ |$, the optimal hyper plane problem is transformed to quadratic programming problem as follows,

$$\begin{cases}\min\phi(\omega)=1/2(\omega,\omega)\\ s,t,\ y_i((\omega.x)+b)\geq 1, i=1,2...l\end{cases} \tag{6}$$

After introduction of Lagrange multiplier, the dual problem is given by,

$$\begin{aligned}&\{\max Q(\alpha)=\sum_{i=1}^{n}\alpha_i-\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}y_i y_j\alpha_i\alpha_j K(x_i\ ,x_j\ )\\ &s.t\sum_{i=1}^{n}y_i\alpha_i\ =0,\alpha_i\ \geq 0, i=1,2...n\end{aligned} \tag{7}$$

According to Kuhn-Tucker rules, the optimal solution must satisfy

$$\alpha_i\,(y_i\,((w.x_i\,)+b-1=0, i=1,2,..n$$

That is to say if the option solution is

$$\alpha^*=(\alpha_1^*,\alpha_2^*,.....\alpha_i^*)^T,\ \ i=1,2,...n$$

Then

$$w^*=\sum_{i=1}^{n}\alpha_i^*\,y_i\,x_i \tag{8}$$

$$b^*=y_i-\sum_{i=1}^{n}y_i\alpha_i^*(x_i\,,x_j\,),\ j\in\{\,j\mid\alpha_i^*\rangle 0\}$$

For every training sample point x_i, there is a corresponding multiplier. And the sample points that are corresponding to $\alpha_i=0$ don't contribute to solve the classification hyper plane while the other points that are corresponding to $\alpha_i\rangle 0$ do, so it is called support vectors. Hence the optimal hyper plane equation is given by,

$$\sum_{x,\in SV}\alpha_i\,y_i\,(x_i.x_j\,)+b=0 \tag{9}$$

The hard classifier is then,

$$y=\mathrm{sgn}\left[\sum_{x,\in SV}\alpha_i\,y_i\,(x_i.x_j\,)+b\right] \tag{10}$$

For nonlinear situation, SVM constructs an optimal separating hyper plane in the high dimensional space by introducing kernel function $K(x, y) = \phi(x).\phi(y)$, hence the nonlinear SVM is given by,

$$\begin{cases} \min \phi(\omega) = 1/2(\omega, \omega) \\ s, t, y_i((\omega.\phi(x_i)) + b) \geq 1, i = 1,2...l \end{cases} \tag{11}$$

And its dual problem is given by,

$$\begin{aligned} &\max L(\alpha) = \sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} y_i y_j \alpha_i \alpha_j K(x_i.x_j) \\ &s.t. \sum_{i=1}^{n} y_i \alpha_i = 0, 0 \leq \alpha_i \leq C, i = 1,2,...,l \end{aligned} \tag{12}$$

Thus the optimal hyper plane equation is determined by the solution to the optimal problem.

2.3. Discrete Wavelet Transform

Nowadays, wavelets have been used quite frequently in image processing and used for feature extraction, denoising, compression, face recognition, and image super-resolution. The decomposition of images into different frequency ranges permits the isolation of the frequency components introduced by “intrinsic deformations” or “extrinsic factors” into certain sub-bands. This process results in isolating small changes in an image mainly in high frequency sub-band images.

The 2-D wavelet decomposition of an image is performed by applying 1-D DWT along the rows of the image first, and, then, the results are decomposed along the columns. This operation results in four decomposed sub-band images referred to as low–low (LL), low–high (LH), high–low (HL), and high–high (HH).

III. RESULTS AND DISCUSSIONS

Here we comparing the wave atom transform with wavelet transform, from the below mentioned table we come to know that the wave atom transform gives the better result than the wavelet transform. Table 1and 2 gives the output of wavelet transform with different wavelets like Bior3.7, db8, Sym8. Table 3 and 4 gives the output of the proposed method.

Table 1 Benign/ Malignant.

Level	Bior3.7		db8		Sym8	
	Benign	Malignant	Benign	Malignant	Benign	Malignant
2	91.78	36.80	100	31.45	97.30	42.04
3	94.50	42.11	94.50	36.56	91.77	42.11
4	91.89	52.69	83.56	57.77	98	31.56
5	91.78	52.66	81.19	73.65	83.45	57.76

Table 2. Normal/ Abnormal.

Level	Bior3.7		db8		Sym8	
	Normal	Abnormal	Normal	Abnormal	Normal	Abnormal
2	87.10	37.09	91.34	38.56	85.70	44.20

3	91.45	40	78.50	52.45	87.12	47.10
4	85.87	45.56	88.50	50	94.24	45.75
5	77.77	58.45	82.67	55.67	81.34	60

Table3. Success rates of SVM method for the classification of images as normal and abnormal.

Wave atom transform +SVM classifier(WAT+SVM)			
Scale	Accuracy	Sensitivity	Specificity
1	100	1	1
2	100	1	1
3	96	0.92	1
4	92	0.88	1

Table4. Success rates of SVM method for the classification of images as benign and malignant.

Wave atom transform +SVM classifier(WAT+SVM)			
Scale	Accuracy	Sensitivity	Specificity
1	100	1	1
2	90	0.90	0.90
3	78	0.76	0.70
4	66	0.63	0.63

IV. CONCLUSION

This paper describes a CAD system for recognizing breast cancer in ROIs of digital mammograms. The study also investigates the presentation of the system with wave atom transform, and SVM method. The proposed method is compared with the wavelet transform. These results demonstrate that wave atom transform and SVM are useful and prevailing methods to distinguish the mammographic images as normal, benign and malignant.

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