Thyroid Ultrasound Images Classification using the Shearlet Coefficients and the Generic Fourier Descriptor

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Abstract: To ameliorate the classification accuracy of the thyroid ultrasound imaging computer-aided diagnosis (CAD) system based on feature extraction, we used the Shearlet Transform (ST) to extract texture features, and the Generic Fourier Descriptor (GFD) to extract shape feature descriptor based on contours information. The ST supplies a rotation invariant descriptor at various scales. The GFD descriptor is autonomous, robust, and has no redundant features. Then, we applied a feature selection method on the extracted shearlet descriptor to build up the performance metrics. Finally, we used the objective metrics(sensitivity, specificity, and accuracy) to validate the performance of the proposed method. Experimentally, we apply our novel methods on a public dataset and we use the Support Vector Machine(SVM) and Random Forest (RF) as classifier. The obtained results prove the superiority of the proposed method.

1 INTRODUCTION

Thyroid nodule is an abnormal growth of cancerous lumps in the thyroid gland, it is the accumulation of malignant cells in thyroid gland tissues. It is one of the most leading cause of cancer deaths. In 2017, 56,870 new patients in the United States have been reported to have involved nearly thyroid cancer (Abbasian Ardakani et al., 2018). Generally, the most of thyroid nodules diseases are benign.

Currently, thyroid ultrasound imaging has been the most used tools for early thyroid nodules detection and diagnosis. It is inexpensive, radiation-free imaging tool, and provides the benefits information needed for medical diagnosis (Abbasian Ardakani et al., 2018; Zhang and Lu, 2002). However, the diagnosis of thyroid ultrasound image depends greatly on personal experience and skills. Thus, many benign and malignant nodules have similar visual characteristics. Hence, experienced radiologists have a high good diagnosis rate than beginner radiologists. Thyroid ultrasound Computer Aided Diagnosis (CAD) system becoming progressively a crucial tool, that assists to offers an objectivity evaluation diagnostic and a better decision accuracy. In general, the thyroid ultrasound CAD system is constituted of four steps, containing image preprocessing, image segmentation, feature extraction and selection, and classification. Feature extraction is one of the crucial stages in thyroid ultrasound CAD. The extracted features are usually classified into textural and shape (morphological) features. Latterly, many researches are focused on the feature extraction and selection steps. Usually, the thyroid nodules classification problems depend on the extracted features. Also, the textural features are commonly used in thyroid ultrasound CAD.

Usually, the textural features descriptors are calculated using a diversity of statistical and structural approaches, such as Grey Level Co-occurrence Matrix (GLCM), autocorrelation-based approaches, Local Binary Pattern, and auto-covariance coefficients. These methods can describe the statistical features of grey level variation in a Region of Interest (ROI). The popular advantage of these methods is they are easy to implement, but the extracted textural features by these methods are mostly from the special domain and ignore the frequency features, which are very important in the classification step. Moreover, the multiscale properties of an image not evaluated in these methods. The Multiscale Geometric Analysis (MGA) grants complete features analysis using different scales.

Recently, image analysis based on transform approaches has been widely used in the image feature extraction. The transform approaches is the represen-

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tation of an image in the frequency and scale space; when the features description and interpretation are related on this special coordinate. The MGA is applied in different fields. One common field is the texture feature extraction in thyroid ultrasound images. The shearlet transform is a powerful spatial frequency analysis method. Shearlet provides sufficient tools to exactly detect the orientations, the scales and the positions of pixels (Easley et al., 2008a). Shearlet transform has been fully utilized in image processing, Edge and Ridge Detection and Analysis, image separation, and image denoising(**?**). Despite, a limited research used the shearlet transform on the textural features extraction.

Also, thyroid nodules analysis based on the shape description is very important. Shape features can be categorized into two principal groups: region-based features and contour-based features. The contour-based description method explores the boundary information and ignores the internal content of the shape, so the versatility is not high. The region-based description method uses the internal pixel information shape. Contour-based Descriptors can be described by the fourier descriptor, the wavelet descriptor, and the shapes signatures. In many existing shape feature descriptors, the Generic Fourier Descriptor (GFD) has several desirable features, such as low computational complexity, sharpness to fine description, which makes it a popular descriptor. The GFD is one of the boundary feature extraction techniques. GFD is obtained by applying the 2D Fourier Transform in polar image and it extracts the spectral features in radial and circular direction.

In this paper, we use the ST to extract textural feature and the GFD to explore shape descriptor features. To achieve better classification performance, we propose a hybrid approach combining ST and GFD for ultrasound thyroid nodules classification. The rest of paper is organized as follows. In section 2, we interpret the related work. The proposed method is described in section 3. The section 4 represents the obtained results and discussion. Finally, conclusion with some feature works idea is given in section5.

2 RELATED WORKS

The calcification and detection of thyroid nodules in ultrasound images was evolved in many studies. Different Computer-Aided Diagnosis was developed using a variety of features and classifiers for the classification of thyroid nodules. The most studies has proven the potentiality and the importance of textural and morphological features on the diagnostic of nodules. Many CAD has developed for thyroid diseases classification. The neural networks has used by Ozyilmaz et al.(Ozyilmaz and Yildirim, 2002) for the diagnosis of thyroid nodules, they are applied different architectures on their database (13, 2017). The proposed method attained 88.3% as maximal accuracy value. Also, Keles et al.(Keleş and Keleş, 2008), developed a CAD system based on neuro fuzzy classification testing on the similar dataset (13, 2017), it attaining 95.33% accuracy value. Iakovidis et al.(Iakovidis et al., 2010), proposed a method based on textural and echogenicity features, focused on image analysis. In this work, they used the fuzzy local binary pattern to represent the texture feature. The proposed method used 250 thyroid ultrasound images, achieving 97.5% as the best ROC AUC, utilizing polynomial kernel SVM as classifier. Acharya et Al.(Acharya et al., 2011), proposed a system for the diagnosis and classification of malignant thyroid nodules using 20 contrast enhancement images(CEUS). They used the Discrete Wavelet Transform (DWT) and texture parameters for feature extraction. The DWT detects the small variations in malignant and benign nodules. The accuracy values achieve 98% using KNN classifier. In another study(Acharya et al., 2012), the same author combined a Fourier Descriptor (FD), local binary patterns, fractal dimensions and Law's texture energy to detect features from 20 images. The highest accuracy value is of 100% using SVM and fuzzy classifier. On other lately studies, in (Raghavendra et al., 2017) authors used the Binary Stack Decomposition (BSD) algorithm and Two-Threshold Binary Decomposition algorithm to extract 120 features from 242 images. In this case, a 97.52% accuracy value was attained using SVM classifier. The higher number of extracted features decreases the performance and the exactitude of the impact of these features. So, they have applied the fisher analysis (MFA) to select and reduce the features sets. MFA based on the fuse of existing features and the created features. Chi et al(Chi et al., 2017), proposed a recently study published on 2017; they used a deep learning features extraction method using a GoogLeNet model. In this approach, 1024 features was extracted and used to classify the nodules using Random Forest classifier. They used two dataset in the evaluation of their method, the accuracy value attained 98.29% of the first dataset (357); and 96.34% for the second dataset (164 images). The obtained results improves that deep learning offer a good results.

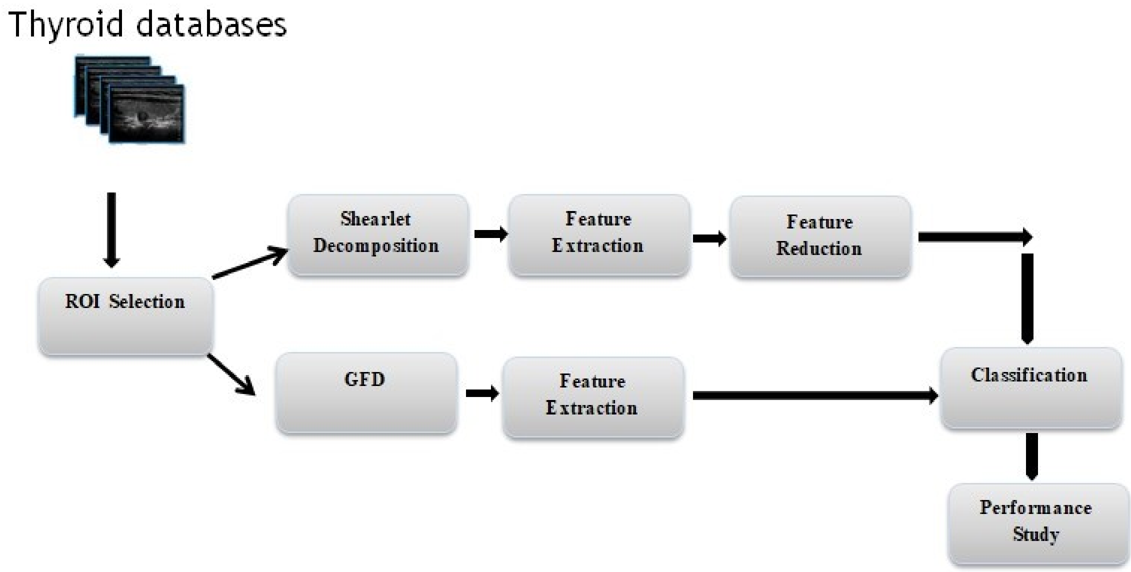

Figure 1: Diagram of the proposed method.

3 MATERIALS AND METHODS

The proposed method is composed of three steps: ROI selection, Shearlet Transform and GFD decomposition feature extraction, feature selection, and classification based on SVM and RF. The proposed approach was presented in figure 1.

3.1 Data Collection

In our experiment, a total of 447 thyroid ultrasound images with benign and malignant thyroid nodules were used to evaluate the performance of the proposed method. Thyroid ultrasound images used in this work are acquired from the laboratory CIM @ LAB of the National University of Colombia and the medical diagnostic institute. Each image involves one or more nodules (attached with XML file ready by expert and contain annotation and patient's information). The ROI was selected using the position denoted in the XML file. The original image had a resolution of 546*410. These extracted nodules are grouped into two classes: benign and malign. In this work, out of 447 thyroid nodules, 372 nodules are malignant and 75 nodules are benign. An example of thyroid benign and malign is presented in figure2 respectively.

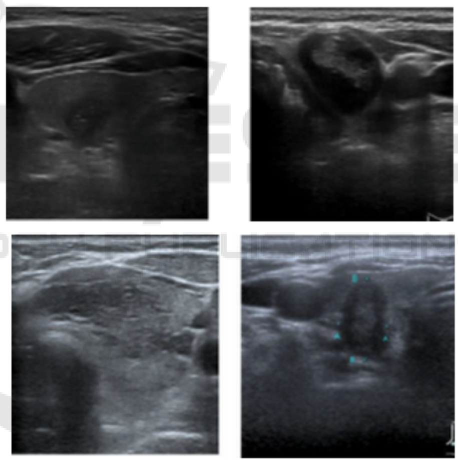

Figure 2: Example of benign and malign thyroid nodules.

3.2 Feature Extraction

3.2.1 Shearlet-based Texture Feature Descriptors

The textural feature are extracted using the Shearlet Transfrom (ST) , it is briefly defined as follows: Shearlet systems were first introduced by K. Guo, G. Kutyniok, D. Labate, W.-Q Lim and G. Weiss in (Guo et al., 2006; Labate et al., 2005). ST is a multiscale directional transform method which allows efficient encoding of anisotropic features, based on directional filter followed by Laplacian pyramid (LP). Shearlet Transform provides an effective tool for combining the multi-scale and the invariance notation. This multi-scale decomposition improves the robustness multi-directional and multi-scale analysis and the representation of the data image. It represent the image in the frequency space where the texture description is closely related to this coordinate. ST used to identify directional features in images (Easley et al., 2008b; Guo et al., 2006). It is generated by applying a set of operators to a single function. The most important advantage of the ST is not sensitive with scales and orientations variations, and it is more powerful in understanding the geometry of images. Recently, ST constitute one of the most successful methods for the efficient representation of multidimensional data and in the understanding the geometry of images. Like that, it is only connected with two parameters, the scaling parameter a and the translation parameter t. For the input image f, continuous Shearlet Transform is described by:

$$f \longrightarrow SH_{\psi} f(a,s,t) = \langle f, \psi_{a,s,t} \rangle \tag{1}$$

Where:
ψ: is the generating function;
a : is the scaling parameter;
$s \in \mathbb{R}$: shear parameter;
$t \in \mathbb{R}$:translation parameter;
and $\psi_{a,s,t}$:shearlet basis functions.
Important properties of shearlets are they are well localized, they follow parabolic scaling law, they have high directional sensitivity, and they are optimally sparse.

In the proposed method, ultrasound thyroid nodule is decomposed by ST into three layers, therefore the textural features descriptors were extracted from these layers. The contrast, correlation, energy, homogeneity, entropy, skewness, variance, mean, standard-deviation of each sub-bands are extracted from these three layers for the horizontal and vertical cone and are used as directional features. Shearlet can capture directional features like orientations in images, which are in fact one of the most discriminating features. By practicing the ST to an image, a number of decomposition levels and directional subbands are produced.

3.2.2 Fourier Feature Descriptors

In this study, we have utilized the generic Fourier descriptor (GFD) for efficient shape representation. Most of the actual shape descriptors are non-robust. GFD is proposed to crucify the disadvantages of the current shape representation methods that independent, easy to implement, less sensitive to noise, and robust. GFD introduced by Zhang(Zhang and Lu, 2002). It is a contour-based shape descriptor for image classification. To obtain invariance to rotation, the image is first converted to polar coordinates then we use a 2D Fourier transform on a polar image. GFD uses the modified polar Fourier transformation (MPFT) of a region shape to the polar coordinate system. So, the coordinates of all pixels of the initial images are converted into polar coordinates. It detects spectral feature in both radial and circular direction. The determination of the number T and R for the description of the forms is physically feasible, because the shape characteristics are usually extracted by the low frequencies. Finally, the GFD has the following expression:
For an shape image

$$I = \{f(x,y); 0 \leq x < M, 0 \leq N\} \tag{2}$$

$$pf(\rho,\psi) = \sum_{r=0}^{\mathcal{R}} \sum_{i=0}^{\mathcal{T}} f(r,\theta_i)^{j2\pi(\frac{r}{R}\rho + \frac{2\pi i}{T}\psi)} \tag{3}$$

Where:
T : is the angular resolution;
R : is the radial resolution;
The Fourier coefficients obtained are translation invariant. So to realize scaling and rotation invariance, the following normalization is calculated:

$$GFD = \{|\frac{pf(0,0)}{aire}, |\frac{pf(0,1)}{pf(0,0)}, ..., |\frac{pf(0,n)}{pf(0,0)}, ..., |\frac{pf(m,n)}{pf(0,0)}\} \tag{4}$$

Where:
area : symbolize the area of the border circle in which the polar image exists;
and$n$= max (angular frequencies);
m = max (radial frequencies).

In this paper, we have used the Generic Fourier Fescriptor (GFD) as shape descriptor. For efficient shape description, only a small number of GFD features are selected for shape representation. In our implementation, 36 GFD features reflecting 4 radial frequencies and 9 angular frequencies are selected to index the shape. The selected GFD features form a feature vector which is used for indexing the shape. Therefore, the online matching is efficient and simple. The extracted features with GFD are no redundant and it grants a multi-resolution feature analysis in radial and angular directions. The GFD feature vector is introduced by the following expression: GFD(0, 0),GFD(0, 1), . . . ,GFD(0, n), . . . ,GFD(m, 0). . . ,GFD(m, n).

3.3 Feature Selection

Feature selection is a dimensionality reduction method which aims to select a subset of relevant and informative features from the initial features set by eliminating irrelevant and redundant features. It augments the classification performance, the efficiency in learning stage, and reducing the computation cost and the complexity. The total number of extracted texture feature was 207. Some of these are irrelevant and not significant in the differentiation between benign and malignant nodules and not appropriate for classification. The feature selection method utilized should be able to choose a subset of relevant and most representative features. In this study, we have applied the Reliable Attribute Selection Based on Random Forest (RASER)(Noura et al., 2016) to eliminate the non-informative features. The features results obtained after applying this feature selection method was used in the classification, and for construct SVM and RF models.

3.4 Classification Algorithm

In order to evaluate the performance of the proposed method, the extracted features were fed to the classifier for discriminating the malignant from the benign nodules. Machine Vector Support (SVM) and Random Forest (RF) were applied to measure the performance of these features. Concise descriptions of these two classifiers are given below.

3.4.1 Support Vector Machine

Support Vector Machine (SVM) is a supervised learning algorithm, SVM belongs to the class of linear classifiers (that use a linear separation of data). It is known for their strong theoretical guarantees, their great flexibility and their ease of use even without much knowledge of data. SVM is intended to separate data into classes using a boundary, so that the distance between the different groups of data and the boundary between them is maximum. SVM is based on the generation of hyperplanes to discriminate features categorizing to two different classes. In this study, a weighted SVM algorithm is used to equilibrate imbalance classes. Weighted SVM (W-SVM) solves the problem of having two classes with unequal training data. W-SVM sets the penalty parameter C in proportion to the size of the class. With regard to RF, the principal advantage of SVM is its simpler geometric interpretation and lower computational cost. The main advantages of SVM are its simpler interpretation and computation cost compared to Random Forest (RF).

3.4.2 Random Forest

Random Forest (RF) is a one of the ensemble methods of classification. The ensemble methods type is based on vote to predict the final decision. RF is constructs of a large number of decision trees based on averaging random selection of variables. RF is based on the idea of bagging and Random subspaces in the construction of decision trees. The randomness notion is in the subsampling of the training data and in the selection of the node tests, each tree is build using different subset. RF uses the majority votes in the classification case in the terminal leaf nodes. More than, RF has the ability to measure the importance of used the features.

3.4.3 Validation of Classifier

We have used the group 10 fold cross-validation on the evaluation of the proposed method. K-fold cross validation based on the random split of the dataset into k equal samples, and it guarantee that the same set of data not be selected in both testing and training sets. Between the k samples, one sample is used as test dataset and the remaining k-1 sets are used as training dataset. The accuracy, sensitivity, specificity were chosen as critical measure performance of the proposed method for both SVM and random forest classifiers. Their definitions are as follows:

$$Sensitivity = TP/(TP+FN) \tag{5}$$

$$Specificity = TN/(TN+FP) \tag{6}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{7}$$

where : TP represent the correct classification rate of malignant instances;
FN is the misclassification rate of malignant instances;
TN is the correct benign instances; and
FP indicates the misclassification rate of benign instances.

4 RESULTS AND DISCUSSION

In this paper, the thyroid nodules are classified into two classes: benign and malignant. The ROIs are extracted initiallly from the ultrasound images and then subjected to the shearlet transform and generic fourier descriptor. All nodules are decomposed with shearlet transform into three layers. The 9 textural features(contrast, correlation, energy, homogeneity, entropy, skewness, variance, mean,and standard-deviation) are extracted from each sub bands. In total,

Table 1: Classification performance for Shearlet feature using SVM and RF(unit: %).

Index	Without feature selection		With feature selection	
	SVM	RF	SVM	RF
Accuracy	93.3	94.65	94.59	96.64
Sensitivity	89.86	92.95	91.78	93.15
Specificity	91.6	95.79	93.11	95.98

Table 2: Classification performance for different features using SVM and RF (unit:%).

Index	Shearlet		GFD		Fusion feature	
	SVM	RF	SVM	RF	SVM	RF
Accuracy	94.59	96.64	97.74	95.9	96.55	98.51
Sensitivity	91.78	93.15	97.58	97.4	95.87	98.17
Specificity	93.11	95.98	98.11	89.2	97.11	96.08

207 features were extracted from the all sub bands. Further, these features were subjected to Reliable Attribute Selection Based on Random Forest (RASER) dimensionality reduction method to eliminite redundant and irrelivant features. Finally, relevant features were fed to SVM and RF classifier to test the proposed method based on 10 cross validation. The table 1 represents a comparison of the classification performance using SVM and RF classifier. The feature selection method provides also a good classification performance compared to the classification without feature reduction method.

It can be note that best accuracy, sensitivity and specificity values are 94.59%, 91.78%, and 93.11% for SVM and 96.64%, 93.15%, and 95.98% for RF after apply the feature selection. In rest of study, only the relevant shearlet coefficient are used. Unlike shearlet transform, GFD has no redundant features.
Table 2 represents the obtained evaluation metrics value between different feature type using SVM and RF classifiers, respectively. GFD achieves better classification compared to the Shearlet-based method. The accuracy value achieve 97.74%,96.64 % respectively for GFD using SVM and RF classifier, and 94.59%, 95.9% for the shearlet coefficient using SVM and RF.
Therefore, the quantitative results of classification accuracy, sensitivity, and specificity for different combination of texture features and classifiers are shown in table 2. They show that the contribution of the new descriptors improves the overall accuracy, sensitivity, and specifity. The classification accuracy of the fusion features is 96.55% and 98.51% using SVM and RF respectively, which are much higher than those of other methods.
Recently, several researchers have encouraged to propose new efficient method to diagnose thyroid cancer using ultrasound images. Table 3 summarizes the achieved results on thyroid nodule classification, we introduce the obtained performances by presenting the accuracy value. The compared methods are: Conic Section Function Neural Network (Ozyilmaz and Yildirim, 2002); neuro fuzzy Classification(Keleş and Keleş, 2008); fuzzy local binary pattern(Iakovidis et al., 2010); Discrete Wavelet Transform (DWT) and texture parameters(Acharya et al., 2011) that is based in the texture feature and the wavelet transform; Two-Threshold Binary Decomposition algorithm(Acharya et al., 2012); and deep learning features extraction(Chi et al., 2017). Really, we produced the accuracy value for the proposed method as well as for six relevant thyroid nodules classification methods from the state of the art. It can be clearly seen that the proposed method reaches a good performances and still better to other methods.

In this paper, we have proposed an efficient method for classification of thyroid nodules using the shearet transform, generic fourier descriptor and invariant texture features. Shearleat transform has some important properties, like multiresolution, multidirection and multiscale, which approve the uniqueness above different levels. At present, textural feature is commonly used in CAD system to classify the ultrasound thyroid nodules. The combination of statistical and transform based features improve the classification accuracy for thyroid nodules classification.

5 CONCLUSION

In conclusion, we proposed a new feature extraction method based on shearlet transform and generic fourier descriptor for characterizing thyroid nodules in ultrasound image. The comparative experiment results indicated that the combination of both shearlet-based texture and fourier based edge features have the best classification performance. The proposed method was tested on public thyroid database re-

Table 3: Evaluation of the proposed method comparatively to the other methods (unit: %).

	Methods	Accuracy
Ozyilmaz et al(2002)	Conic Section Function Neural Network	88.3
Keles et al(2008)	neuro fuzzy Classification	95.33
Iakovidis et al(2010)	fuzzy local binary pattern	97.5
Acharya et Al(2011)	Discrete Wavelet Transform (DWT) and texture parameters	98
Acharya et Al(2017)	Two-Threshold Binary Decomposition algorithm	97.52
Chi et al(2017)	deep learning features extraction	98.29
Proposed methods	Shearlet Transform and Generic Fourier Descriptor	98.51

quired from the laboratory CIM @ LAB. The classification performance of textural feature has also been optimized by the RASER dimensionality reduction method. A comparative study shows that the metrics performance is better with the application of feature selection step. In addition, GFD was used to extract the boundary information. Finally, the combination of texture feature obtained with shearlet decomposition and boundary information acquired using GFD give the highest classification performance.

Thus, in our future work, we want to propose an automated CAD system for detection and classification of thyroid nodules.We aim also to study and propose other feature selection methods.

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