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Fusion of spatial gray level dependency and fractal texture features for the characterization of thyroid lesions

U. Raghavendra [a,*], U. Rajendra Acharya [b,c,d], Anjan Gudigar [a], Jen Hong Tan [b], Hamido Fujita [e], Yuki Hagiwara [b], Filippo Molinari [f], Pailin Kongmebhol [g], Kwan Hoong Ng [h]

[a] Department of Instrumentation and Control Engineering, Manipal Institute of Technology, Manipal University, Manipal 576104, India
[b] Department of Electronics and Computer Engineering, Ngee Ann Polytechnic, Clementi 599489, Singapore
[c] Department of Biomedical Engineering, School of Science and Technology, SIM University, Clementi 599491, Singapore
[d] Department of Biomedical Engineering, Faculty of Engineering, University of Malaya, Kuala Lumpur 50603, Malaysia
[e] Iwate Prefectural University (IPU), Faculty of Software and Information Science, Iwate, Japan
[f] Department of Electronics and Telecommunications, Politecnico di Torino, Italy
[g] Department of Radiology, Faculty of Medicine, Chiang Mai University, Chiang Mai, 50200, Thailand
[h] Department of Biomedical Imaging, University of Malaya, Kuala Lumpur, Malaysia

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ABSTRACT

Thyroid is a small gland situated at the anterior side of the neck and one of the largest glands of the endocrine system. The abrupt cell growth or malignancy in the thyroid gland may cause thyroid cancer. Ultrasound images distinctly represent benign and malignant lesions, but accuracy may be poor due to subjective interpretation. Computer Aided Diagnosis (CAD) can minimize the errors created due to subjective interpretation and assists to make fast accurate diagnosis. In this work, fusion of Spatial Gray Level Dependence Features (SGLDF) and fractal textures are used to decipher the intrinsic structure of benign and malignant thyroid lesions. These features are subjected to graph based Marginal Fisher Analysis (MFA) to reduce the number of features. The reduced features are subjected to various ranking methods and classifiers. We have achieved an average accuracy, sensitivity and specificity of 97.52%, 90.32% and 98.57% respectively using Support Vector Machine (SVM) classifier. The achieved maximum Area Under Curve (AUC) is 0.9445. Finally, Thyroid Clinical Risk Index (TCRI) a single number is developed using *two* MFA features to discriminate the two classes. This prototype system is ready to be tested with huge diverse database.

1. Introduction

Thyroid cancer is the seventh most common cancer in women and fifteenth most common cancer in men [1]. According to the National Cancer Institute, there are about 56,000 new cases of thyroid cancer in the US each year [2]. Thyroid gland plays a vital role in the growth and development of human body, as it secretes hormones that regulates body's metabolism. Hence, it is referred as personality hormone. The two important hormones produced by thyroid glands are levothyroxine (T4) and tri-iodothyronine (T3), which are responsible for protein generation, body temperature regulation and overall energy production [3]. Anomaly in thyroid gland leads to either hypothyroidism or hyperthyroidism [4]. An under active thyroid gland produces hormone in deficient amount causing hypothyroidism. An over active thyroid glands produces hormone in excess, leading to hyperthyroidism. Doctors can suggest Thyroid-Stimulating Hormone (TSH) test to identify the thyroid disorder even before the commencement of symptoms [5]. Abnormal cell growth in the thyroid gland leads to benign or malignant nodules. The proper diagnosis of thyroid disease helps in suggesting accurate choice of drug treatment [6]. Ultrasound is one of the low-cost and effective imaging modality which helps to study the internal organs and blood flow in the human body [7]. The important characteristics of ultrasound is that, it creates different echoes for healthy and malignant tissues [7]. Computer Aided Diagnosis (CAD) using ultrasound images can assist radiologists in confirming lesions and avoid unnecessary biopsy [7].

1.1. State-of-the-art

The CAD systems are getting more and more popular as it reduces the possible errors by clinicians during their routine diagnosis. Thyroid has different stages of cancer and hence it is a

* Corresponding author.
E-mail address: raghavendra.u@manipal.edu (U. Raghavendra).

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classification problem [6]. The choice of different feature extraction methods and machine learning algorithms have been investigated to build an efficient CAD system.

In [8] thyroid disease is diagnosed using neural network and achieved a maximum accuracy of 88.3%. The Artificial Immune Recognition System (AIRS) in [9] achieved an accuracy of 81%. In [10], directional patterns of the thyroid ultrasound images are extracted and obtained overall classification accuracy of 89.4%. In 2008, neuro fuzzy classifier is used to diagnose thyroid lesions and achieved an accuracy of 95.33% [11]. Erol et al. [6] have experimented a method using Multilayer Perceptron Neural Network (MLPNN) and Radial Basis Function Neural Network (RBFNN) and concluded that RBFNN is the suitable classifier for thyroid disease identification. Kodaz et al. [12] have developed Information Gain based Artificial Immune Recognition system (IG-AIRS) and tested on thyroid disease data set and achieved an accuracy of 95.90%. System developed using combination of Principal Component Analysis (PCA) and Support Vector Machine (SVM) system reached an accuracy of 97.67% [13]. An expert system developed using generalized discriminant analysis and wavelet support vector machine obtained a classification accuracy of 91.86% [14]. To get the new feature space for thyroid disease, PCA is used with extreme learning machine classifier in [5] and attained *mean* accuracy of 97.73%. The parameters of the SVM classifier are optimized using Particle Swarm Optimization (PSO) technique and obtained an average accuracy of 97.49% [4]. The application of Fuzzy K-Nearest Neighbor (FKNN) classifier found in [15], by specifying its parameter adaptively achieved a *mean* accuracy of 98.82%. Acharya et al. [16] have developed texture feature based method and achieved maximum accuracy of 100%. The same group [17] used combination of Discrete Wavelet Transform (DWT) and texture features with AdaBoost classifier for thyroid lesion classification. They have reported an accuracy, sensitivity and specificity of 100%. They also incorporated single number index, which can be used in the clinical practice. Azar et al. [18] have compared different soft and hard fuzzy clustering techniques for thyroid disease classification using different scalar validity measures. The clustering results are visualized using Sammon mapping method and recommended various improvements to choose the optimal number of clusters for efficient classification.

The grayscale features based on entropy, Gabor wavelet, moments, image texture, and higher order spectra also shown good classification accuracy [19]. Acharya et al. [20] have also developed a CAD system for Hashimoto Thyroiditis using stationary wavelet transform with fuzzy classifier. They have achieved a maximum accuracy, sensitivity, and specificity of 84.6%, 82.8%, and 87.0% respectively. Recently, Acharya et al. [21] have developed a CAD system using Gabor transform features and Locality Sensitive Discriminant Analysis (LSDA). They have reported a maximum accuracy of 94.3% using C4.5 decision tree classifier. Table 1 shows the previous studies conducted on automated classification of thyroid lesions.

It can be observed from the literature that, most of the existing CAD systems used different textural features and machine learning algorithms (for classification). Various parameter optimization techniques are used to get better classification accuracy.

The novelty of this paper is the feature fusion based CAD tool for thyroid lesion diagnosis. It can be noted from the above table that none of the methods tried to understand the structure of data points in the feature space which resulted in decrease in the performance as the number of subjects increased. Moreover, it is challenging to get high classification performance for this unbalanced data with minimum number of features. Thyroid clinical risk index is developed to discriminate the two classes immediately with higher accuracy. Also, the performance of this study is enhanced by approximately 3.5% using only two features as compared to the results reported in Acharya et al. [21].

Initially, spatial gray level dependence texture features along with segmentation based fractal textures are explored. These texture features are fused to explore the intrinsic structure of abnormality present in the ultrasound images. Then, these extracted features are subjected to graph based marginal fisher analysis (MFA). Further, to enhance the overall performance, significant MFA features are ranked. These ranked features are fed to different classifiers to choose the best performing classifier. Fig. 1 illustrates the flow of the proposed approach.

2. THEORETICAL BACKGROUND OF THE PROPOSED METHODOLOGY

2.1. Data acquisition

During 1st December 2009 to 30th April 2015, Chiang Mai university hospital collected the ultrasound images of 242 subjects who were clinically confirmed to have thyroid benign or malignant

Table 1
Summary of related works reported on thyroid lesion characterization.

Authors	No. of subjects	Method/classifier	Accuracy
Lale Ozyilmz and Tulay Uldirim [8]	215	MLP, RBF and CSFNN	88.3%, 81.69% and 85.92%
Savelonas et al. [22]	66	Radon transform features/SVM	89.4%
Polat et al. [9]	215	AIRS	81%
Savelonas et al. [10]	66	Radon transform features/SVM	89.4%
Keles et al. [11]	215	Neuro fuzzy classifier	95.33%
Kodaz et al. [12]	215	IG-AIRS	95.90%
Tsantis et al. [23]	85	Morphological and wavelet-based features/SVM	AUC: 0.96
Dogantekin et al. [13]	215	PCA + SVM	97.67%
Ma et al. [24]	98	k-means clustering/PCA/SVM	87.8%
Chang et al. [25]	61	Significant texture features/SVM	100%
Iakovidis et al. [26]	200	Fusion of fuzzy local binary patterns and fuzzy gray-level histogram features/SVM	97.5%
Dogantekin et al. [14]	215	Discriminant analysis and wavelet support vector machine	91.86%
Chen et al. [4]	215	PSO + SVM	97.49%
Liu et al. [15]	215	Fuzzy k-nearest neighbor	98.82%
Ding et al. [27]	125	Hard area ratio and textural features/SVM	93.6%
Legakis et al. [28]	142	Textural and shape feature vectors/SVM	AUC: 0.93
Nikita Singh and Alka Jindal [29]	13	GLCM/SVM	84.62%
Keramidas et al. [30]	118	Noise resilient image features/SVM	95.2%
Acharya et al. [16]	10	Texture feature with SVM	100%
Acharya et al. [17]	10	Discrete wavelet transform and texture features with AdaBoost	100%
Acharya et al. [21]	242	Gabor transform with LSDA and C4.5 decision tree classifier	94.3%