# Survey of Computer-Aided Diagnosis

**of Thyroid Nodules in Medical Ultrasound Images**

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**Abstract.** In medical science, diagnostic imaging is an invaluable tool because of restricted observation of the specialist and uncertainties in medical know- ledge. A thyroid ultrasound is a non-invasive imaging study used to understand the anatomy of thyroid gland which is not possible with other tech- niques. Various classifiers are used to characterize thyroid nodules into benign/malignant based on the extracted features to make correct diagnosis. Current classification approaches are reviewed with classification accuracy for thyroid ultrasound image applications. The aim of this paper is to review exist- ing approaches for the diagnosis of Nodules in thyroid ultrasound images.

**Keywords:** Thyroid Nodule, TIRADS, Ultrasound Images, Computer-Aided Diagnosis, Feature extraction, Classification.

## Introduction

Thyroid nodules are swells that appear in the thyroid gland and can be due to the growth of thyroid cells. The nationwide relative frequency of thyroid cancer among all the cancer cases is 0.1%-0.2%. As per this statistics, it is concluded that thyroid related cancer is a serious disease which can lead to death, with increasing incidence rates every year. Hence, early detection is important for effective diagnosis. For diag- nosing thyroid diseases, Ultrasound (US) and Computer Tomography (CT) are two of the most popular imaging modalities. US imaging is inexpensive, non-invasive and easy to use. However, US image contains echo perturbations and speckle noise, which

could make the diagnostic task harder. The boundary of malignant tumor often merged with the surrounding tissues. Therefore, some Computer-Aided Diagnosis (CAD) system is necessary to increase reliability and reduce invasive operations in order to delineate nodules, classifying benign/malignant and estimating the volumes of thyroid tissues.

Generally, CAD systems are consisting of various stages like pre-processing, seg- mentation, feature extraction and classification. The boundaries of the tumors in US images are unclear and hard to distinguish due to artifacts such as speckle, reverbera- tion echo, acoustic shadowing and refraction. Thus, it is necessary to suppress speckle noise before segmentation. Image segmentation plays an important role for automatic

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delineation of important regions used for analyzing anatomical structure, tissue types and pathological regions. Accuracy of segmentation is important because many cru- cial features for discriminating benign and malignant lesions are based on the contour, shape and texture of the lesion. These features can be effectively extracted after the lesion boundary is correctly detected. Thus, an accurate segmentation method is es- sential for a correct diagnosis. Segmentation of thyroid nodule in ultrasound images is given in [9-12].

The rest of this paper is organized in following sections. Section 2 describes the Feature Extraction and Selection for identification of thyroid nodules in ultrasound images. The classification techniques are explained in Section 3 and conclusions are given in Section 4.

## Feature Extraction and Selection

Feature extraction is used to find a feature set of tissue that can accurately distinguish lesion/non-lesion or benign/malignant. Recently, various feature extraction methods were proposed from which lot of features from medical images can be obtained. However, it is difficult to select significant features from the extracted features. There is no single feature that can accurately determine whether a nodule is benign or ma- lignant. In addition to features that can be derived from the inside of the nodule, the tissue texture around the margin of the nodule is also important. The growth of malig- nant tumors tends to distort the surrounding tissue texture, while benign nodules tend to have smooth surfaces with more uniform texture around them. Different shapes and margins have different likelihoods of malignancy. Thus, texture features have the potential to capture characteristics that are diagnostically important but are not easily visually extracted. Feature selection is a process of feature reduction by removing irrelevant, redundant or noisy data and has an immediate effect on application by accelerating the classification algorithm. A typical feature selection process consists of four basic steps: namely, subset generation, subset evaluation, stopping criterion and result validation. The feature space could be very large and complex, so extract- ing and selecting the most effective features are very important.

In literature, different authors have extracted different types of features from thyroid tissue. In [12], six textural features are extracted from the selected ROIs. These textural features including Haar wavelet features, homogeneity feature, histogram feature, Block Difference of Inverse Probabilities (BDIP) and Normalized Multi-Scale Intensi- fy Difference (NMSID) will be used in the RBF neural network to classify the thyroid region. In [23], two features associated with the Rayleigh distribution parameter, four wavelet energy coefficients, four radon transform parameters are computed for each rectangular window. These features are also combined with the longitudinal mid- distance measure for each thyroid gland. This distance corresponds to the vertical distance measured between the borders of the thyroid at its middle section.

In [24], the features such as mean, variance, Coefficient of Local Variation Fea- ture, Histogram Feature, NMSID Feature, and Homogeneity are extracted and are used to train the classifiers such as ELM and SVM.

**Table 1.** Feature Extraction Approaches For Thyroid Ultrasound Image Analysis

REF. FEATURE EXTRACTION APPROACH

[42][43][44] Grey Level Histogram

[45] Muzzolini ’S Features [42][45] Co-Occurrence Matrix

[11] Radon Transform

1. Local Binary Patterns
2. Fuzzy Local Binary Pattern

[7] Mean, Variance, Coefficient Of Local Variation Feature, Histogram Feature,

Normalized Multi Scale, Intensity Different NMSID Feature, Homogeneity

[48] Statistical Pixel Level Features

[14] Morphology And Tissue Reflectivity

[11] Intensity And Statistical Textural Feature

[48] Textural Features

In [46,47], texture patterns appearing in US images can be represented by a fuzzy distribution of Local Binary Patterns, referred to as Fuzzy Local Binary Patterns (FLBP) features [8]. The original approach of Local Binary Pattern (LBP) [12] has been proven to be sensitive to small variations of the pixel intensities usually caused by noise. The FLBP is an enhanced extension of the LBP approach, capable of better coping with speckle noise [8], a common characteristic of all US images [13]. In US images a substantial amount of information concerning the pathology of the examined tissue is contained in image echogenity [11]. Several studies on US medical images have been using echogenity features based on grey-level histograms (GLH) and Fuzzy grey-level histograms (FGLH). Morphological features describe the shape and the boundary regularity of each nodule and comprised several 1st order statistics of the boundary radius along with area, smoothness, concavity, and symmetry and fractal dimension [12].

In [21],a set of twenty morphological features (Mean radius, Radius entropy, Ra- dius standard deviation, Perimeter, Area Circularity Smoothness Convex hull mean radius Concavity Number of concave points Symmetry Fractal dimension) and wave- let local maxima (first order histogram, Mean value, entropy, central moment 3rd de- gree, kurtosis, skewness, variance, standard deviation) are extracted from segmented nodule. The various feature extraction approaches for thyroid nodule in ultrasound images are summarized in Table 1.

## Classification

The suspicious regions will be classified as lesion/non-lesion or benign/malignant based on the selected features by various classification methods. The Thyroid Imag- ing Reporting and Data System (TIRADS) is a standardized US characterization and

reporting data system of thyroid lesions for clinical management. The TIRADS is based on the concepts of the Breast Imaging Reporting Data System (BIRADS) of the American College of Radiology [2]. The categories are as follow: TIRADS 1: normal thyroid gland, TIRADS 2: benign conditions (0% malignancy), TIRADS 3: probably benign nodules (< 5% malignancy), TIRADS 4: suspicious nodules (5–80% malig- nancy rate). A subdivision into 4a (malignancy between 5 and 10%) and 4b (malig- nancy between 10 and 80%) was optional, TIRADS 5: probably malignant nodules (malignancy>80%), TIRADS 6: included biopsy proven malignant nodules.

There are different neural networks used in image segmentation such as Back Propagation neural network, Hopfield neural networks and Self-Organizing Maps (SOM). Various previous studies based on classifiers used to identify the malignancy in the thyroid lesion are mentioned in [15,16]. Many machine learning techniques such as Linear Discriminant Analysis (LDA), Support Vector Machine (SVM) and Artificial Neural Network (ANN) have been studied for thyroid lesion classification. The classification accuracy of various classifiers for thyroid nodule in ultrasound images are summarized in Table 2.

**Table 2.** Accuracy of Thyroid Classifiers

|  |  |  |  |
| --- | --- | --- | --- |
| Publication year | Ref. | Method | Accuracy |
|  |  |  | (%) |
| 1984 | [42] | FA FA+C4.5 (Pruned) | 94.38 |
|  |  | FAFA+C 4.5 (Rules) | 94.38 |
|  |  | Einstein | 91.91 |
|  |  | FAF A+Einstein | 93.34 |
| 1997 | [40] | A Fuzzy Classifier with Ellipsoidal Regions | 93.34 |
| 1997 | [41] | MLP | 36.74 |
|  |  | LVQ | 81.86 |
|  |  | RBF | 72.09 |
|  |  | PPFNN | 78.14 |
| 1999 | [39] | k-NN method | 96.90 |
|  |  | EACH method | 95.60 |
|  |  | RPA method | 96.10 |
| 2002 | [30] | 3NN-Par | 94.20 |
|  |  | FED IC-Plain | 96.10 |
| 2006 | [31] | EDA | 98.06 |
|  |  | WEDA | 98.00 |
| 2006 | [32] | HMM method | 87 .91 |
|  |  | SOM method | 88.84 |
| 2006 | [33] | LDA | 93 .44 |
|  |  | SVM | 94.44 |
|  |  | GPC-EP (s-soft) | 96.75 |
|  |  | GP C-EP(m-soft) | 97.23 |

**Table 2.** (*continued*)

|  |  |  |  |
| --- | --- | --- | --- |
| 2007 | [29] | AIRS | 81 |
|  |  | AIRS with fuzzy weighted pre-processing | 85 |
| 2008 | [12] | MLNN with LM | 92.96 |
|  |  | PNN | 94.43 |
|  |  | LVQ | 89.79 |
| 2008 | [27] | AIRS | 94.82 |
|  |  | IG-AIRS | 95.90 |
| 2009 | [26] | PNN with GA Feature selection | 96.8 |
|  |  | SVM with GA Feature selection | 99.05 |
| 2009 | [18] | BPA | 92 |
|  |  | RBF | 80 |
|  |  | LVQ | 98 |
| 2011 | [25] | GDA–WSVM Expert System | 91.86 |
| 2011 | [24] | SVM | 84.78 |
|  |  | ELM | 93.56 |
|  |  | Radon- based approach | 90.9 |

FED IC-Plain: Feature Extraction for Dynamic Integration of Classifiers MLP with bp: multi layer perceptron with back-propagation.

MLP with fbp: multi layer perceptron with fast back-propagation. DIMLP: DIMLP with two hidden layers and default learning parameters. PNN with GA: Probabilistic Neural Network with Genetic Algorithm MLNN with LM: Multilayer neural network Levenberg–Marquardt

IG-AIRS : Information Gain based Artificial Immune Recognition System

GDA–WSVM : Generalized Discriminant Analysis and Wavelet Support Vector Machine Sys- tem WEDA: Wrapped Evolutionary discriminate analysis PLS-QDA: Partial Least Squares Discriminant Analysis-Quadratic Discriminant Analysis CSFNN: Adaptive Conic Section Function Neural Network SOM: Self Organizing map PPFNN: Probabilistic Potential Function Neural Network PWC : Pairwise Classification ESTDD: Expert system for thyroid diseases diagnosis RBF: Radial Basis Function HOFDA: High order Fisher discriminate analysis Par : Parametric Approach

C4.5-1: C4.5 with default learning parameters C4.5-2: C4.5 with parameter c equal to 5. C4.5-3: C4.5 with parameter c equal to 95. FAFA: Function attribute finding algorithm EDA: Evolutionary discriminate analysis NEFCLASS-J: Neuro Fuzzy Classification SMC: Single-model multigroup classifiers LDA: Linear Discriminant Analysis

GPC-EP: Gaussian Process Classifier RPA: Recursive Partition Averaging LVQ: Learning Vector Quantizer BPA : Back propagation algorithm DPM : Decision pathway modeling ELM: Extreme Learning machine HMM: Hidden Markov Model OAC: One-Vs-All Classification

In [17] the thyroid disease are diagnosed by training a neural network on the basis of signs and symptoms that outperforms human physicians especially in the presence of noise. In [10], the potential of boundary descriptors for the assessment of thyroid nodules on US images is investigated according to malignancy risk. The diagnosis of thyroid producing thyroid disorders using ANNs is presented in [18]. The best

accuracy of LVQ Network for diagnosis is 98%. In [19] RBF, Probabilistic Neural Network (PNN) and Linear Vector Quantizer (LVQ) and SVMs are used for diagnos- ing thyroid diseases. The overall accuracy of diagnosis system is range from near 96% to 99%. A comparative thyroid disease diagnosis realized by multilayer, proba- bilistic, and learning vector quantization neural networks is presented in [13]. The results showed that Probabilistic Neural Network has given the best classification accuracies for thyroid disease dataset. An approach for differentiating benign and malignant thyroid nodules based on SVM with biased penalties is presented by [20]. The results showed that the method is able to get 90.1% with the sensitivity of 93.8% and the specificity of 86.6%. In [21] a computer-based image analysis system is pro- posed employing the SVM classifier for the automatic characterization of 120 verified thyroid nodules. Here the accuracy of SVM in classifying the low and high risk no- dules is 96.7% where QLSMD classifier is 92.5% and QB classifier is 92%. In [22], five support vector machines (SVM) were adopted to select the significant textural features and to classify the nodular lesions of thyroid.

In [8] the computational characterization of thyroid tissue is investigated using su- pervised classification of directionality patterns in thyroid US images. The overall classification accuracy obtained by the application of the proposed Radon-based ap- proach was 89.4%. In [22], the thyroid disease with a new hybrid machine learning method was diagnosed. The classification accuracy of 81 % was obtained with AIRS classification system. In [14] feature selection is argued as an important problem via diagnosis and demonstrate that GAs (Genetic Algorithms) provide a simple, general and powerful framework for selecting good subsets of features leading to improved diagnosis rates. In [23], a biometric system based on features extracted from the thy- roid tissue accessed through 2D US was proposed. Using leave-one-out cross- validation method the identification rate was up to 94%. In [24] an automatic system is developed that classified the thyroid images and segmented the thyroid gland using machine learning algorithms. In [25], a Generalized Discriminant Analysis and Wavelet Support Vector Machine System (GDA\_WSVM) method is presented for diagnosis of thyroid diseases.

## Conlusions

Thyroid nodules are categorized according to the pathology as the enlarged follicles, the follicular cells with follicles, the papillary cells with follicles, the follicular cells with fibrosis, the papillary cells with fibrosis and the fibrosis. Many physicians are confused about the nature of various echo patterns of thyroid nodules because of low resolution of ultrasound. Various techniques are applied by different researchers to process Thyroid US as many of the structures are hardly visible due to noise ambigui- ty, vagueness and uncertainty**.** Thus, the utilization of new and more efficient classifi- ers could improve the accuracy performance towards classifying thyroid nodule as benign/malignant. In order to detect the abnormal structure, intuitive ways must be found out to interpret and describe the inherent ambiguity and vagueness in the US image using (intuitionistic and neutrosophic) fuzzy set theory. Therefore, this research

would definitely be an aid, even to experienced radiologists, by providing a second opinion for the characterization of nodules. Moreover, it could be used as a valuable tool in follow-up diagnosis (such as thyroid cancer) where the validity of conclusions drawn by radiologist depends on the classification accuracy. Such techniques will help to aid the diagnosis process by automatically detecting the nodules in thyroid images and consequently lead to reduction of false diagnosis related thyroid diseases. Thyroid volume estimation from the segmented thyroid region and classification of thyroid nodules based on malignancy risk factor in ultrasound images could also in- volve in the future work.

## References

* 1. Unnikrishnan, A.G., Menon, U.V.: Thyroid disorders in India: An epidemiological perspective. Indian Journal of Endocrinology and Metabolism 15, 78–81 (2011)
  2. Horvath, E., Majlis, S., Rossi, R., Franco, C., Niedmann, J.P., Castro, A.: An ultrasono- gram reporting system for thyroid nodules stratifying cancer risk for clinical manage- ment. J. Clin. Endocrinol Metab, 748–751 (2009)
  3. Baskin, H.J.: Thyroid Ultrasound and Ultrasound-Guided FNA, 2nd edn. Springer (2008)
  4. Sharma, N., Aggarwal, L.M.: Automated medical image segmentation techniques. Jnl. of Medical Physics / Association of Medical Physicists of India 35(1), 3–14 (2010)
  5. Pal, S.K.: A review on image segmentation techniques. Pattern Recg., 1277–1294 (1993)
  6. Noble, J.A., Boukerroui, D.: Ultrasound image segmentation: A survey. IEEE Trans. on Medical Imaging 25, 987–1010 (2006)
  7. Ma, J., Luo, S., Dighe, M., Lim, D., Kim, Y.: Differential Diagnosis of Thyroid No- dules with Ultrasound Elastography based on Support Vector Machines. In: IEEE Int. Ultrasonics Symp. Proc, pp. 1372–1375 (2010)
  8. Savelonas, M., Maroulis, D., Iakovidis, D., Karkanis, S.: A VBAC Model for Automatic Detection of Thyroid Nodules in Ultrasound Images, pp. 1–4. IEEE (2005)
  9. Savelonas, M.A., Iakovidis, D.K., Dimitropoulos, N., Maroulis, D.: Computational Cha- racterization of Thyroid Tissue in the Radon Domain. In: IEEE International Sympo- sium on Computer-Based Medical Systems, pp. 1–4 (2007)
  10. Savelonas, M.A., Maroulis, D.E., Iakovidis, D.K., Dimitropoulos, N.: Computer-Aided Malignancy Risk Assessment of Nodules in Thyroid US Images Utilizing Boundary Descriptors. In: Panhellenic Conf. on Informatics, pp. 156–160. IEEE (2008)
  11. Savelonas, M.A., Iakovidis, D.K., Legakis, I., Maroulis, D.: Active Contours Guided by Echogenicity and Texture for Delineation of Thyroid Nodules in Ultrasound Images. IEEE Transactions on Information Technology in Biomedicine 13, 519–527 (2009)
  12. Chang, C., Lei, Y., Tseng, C., Shih, S.: Thyroid Segmentation and Volume Estimation in Ultrasound Images. In: IEEE Int. Conf. on Systems, Man and Cybernetics, pp. 3442– 3447 (2008)
  13. Temurtas, F.: A comparative study on thyroid disease diagnosis using neural networks. Expert Systems with Applications 36, 944–949 (2009)
  14. Saiti, F., Naini, A.A., Shoorehdeli, M.A., Teshnehlab, M.: Thyroid Disease Diagnosis Based on Genetic Algorithms using PNN and SVM, pp. 1–4. IEEE (2009)
  15. Cai, J., Liu, Z.Q.: Pattern recognition using Markov random field models. Patt. Recog., 725–733 (2002)
  16. Cheng, H.D., Shan, J., Ju, W., Guo, Y., Zhang, L.: Automated breast cancer detection and classification using ultrasound images: A survey. Pattern Recognition 43, 299–317 (2010)
  17. Zhang, G., Berardi, V.L.: An investigation of neural networks in thyroid function diag- nosis. Health Care Management Science 1, 29–37 (1998)
  18. Shukla, A., Kaur, P., Tiwari, R., Janghel, R.R.: Diagnosis of Thyroid Disorders using Artificial Neural Networks. In: IEEE Int. Advance Computing Conf., pp. 1016–1020 (2009)
  19. Rouhani, M., Mansouri, K.: Comparison of several ANN architectures on the Thyroid diseases grades diagnosis. In: Int. Comp. Science and IT- Spring Conf., pp. 526–528. IEEE (2009)
  20. Ma, J., Luo, S., Dighe, M., Lim, D., Kim, Y.: Differential Diagnosis of Thyroid No- dules with Ultrasound Elastography based on Support Vector Machines. In: IEEE Int. Ultrasonics Symp. Proc., pp. 1372–1375 (2010)
  21. Tsantis, S., Dimitropoulos, N., Cavouras, D., Nikiforidis, G.: A hybrid multi-scale mod- el for thyroid nodule boundary detection on ultrasound images. Computer Methods and Programs in Biomedicine, 86–98 (2006)
  22. Polat, K., Sahan, S., Gunes, S.: A novel hybrid method based on artificial immune rec- ognition system (AIRS) with fuzzy weighted pre-processing for thyroid disease diagno- sis. Expert Systems with Applications 32, 1141–1147 (2007)
  23. Seabra, J.C.R., Fred, A.L.N.: Towards the Development of a Thyroid Ultrasound Bio- metric Scheme Based on Tissue Echo-morphological Features. In: Fred, A., Filipe, J., Gamboa, H. (eds.) BIOSTEC 2009. CCIS, vol. 52, pp. 286–298. Springer, Heidelberg (2010)
  24. Selvathi, D., Sharnitha, V.S.: Thyroid Classification and Segmentation in Ultrasound Images Using Machine Learning Algorithms. In: Proc. of Int. Conf. on Signal Processing, Communication, Computing and Networking Technologies, pp. 836–841. IEEE (2011)
  25. Dogantekin, E., Dogantekin, A., Derya, A.: An expert system based on Generalized Discriminant Analysis and Wavelet Support Vector Machine for diagnosis of thyroid diseases. Expert Systems with Applications 38, 146–150 (2011)
  26. Kodaz, H., Seral, O., Arslan, A., Salih, G.: Medical application of information gain based AIRS: Diagnosis of thyroid disease. Expert Systems with Applications, 3086– 3092 (2009)
  27. Keles, A.: ESTDD: Expert system for thyroid diseases diagnosis. Expert Systems with Applications, 242–246 (2008)
  28. Polat, K., Sahan, S., Gunes, S.: A novel hybrid method based on artificial immune rec- ognition system (AIRS) with fuzzy weighted pre-processing for thyroid disease diagno- sis. Expert Systems with Applications 32, 1141–1147 (2007)
  29. Pechenizkiy, M., Tsymbal, A., Puuronen, S., Patterson, D.W.: Feature extraction for dynamic integration of classifiers. Fundamenta Informaticae 77(3), 243–275 (2007)
  30. Sierra, A.: High order Fisher’s discriminants. Pattern Recogn. 35, 1291–1302 (2002)
  31. Sierra, A., Echeverria, A.: Evolutionary Discriminant Analysis. IEEE Trans. Evolutio- nary Computation 10(1) (February 2006)
  32. Hassan, R., Nath, B., Kirley, M.: A data clustering algorithm based on single hidden markov model. In: Proceedings of the International Multiconference on Computer Science and Information Technology, pp. 57–66 (2006)
  33. Kim, H.C., Ghahramani, Z.: Bayesian Gaussian process classification with the EM-EP algorithm. IEEE Transactions on Pattern Analysis and Machine Intelligence 28(12), 1948–1959 (2006)
  34. Pasi, L.: Similarity classifier applied to medical data sets. In: Int. Conf. on Soft Compu- ting, 10 Sivua, Fuzziness in Finland 2004, Helsinki, Finland & Gulf of Finland & Tallinn, Estonia (2004)
  35. Myles, A.J., Brown, S.D.: Decision pathway modeling. Jnl. of Chemometrics, 286–293 (2004)
  36. Raymer, M.L.: Knowledge Discovery in Biological Dataset Using a Hybrid Bayes clas- sifier/Evolutionary Algorithm. IEEE Trans. on Bioinformatics and Bioengineering (2003)
  37. Ozyılmaz, L., Yıldırım, T.: Diagnosis of thyroid disease using artificial neural network methods. In Proc.of Int. Conf. on Neural Information Processing 4, 2033–2036 (2002)
  38. Duch, W., Adamczack, R., Grabczewski, K.: A new methodology of extraction, optimi- zation and application of crisp and fuzzy logical rules. IEEE Trans. Neural Net. 12, 277–306 (2001)
  39. Cheong, T.S., Yoon, C.H.: A memory based class recursive partition averaging. IEEE Tencon, 1038–1041 (1999)
  40. Abe, S., Thawonmas, R.: A fuzzy classifier with Ellipsoidal regions. IEEE Trans. Fuzzy Syst. 5(3) (August 1997)
  41. Serpen, G., Jiang, H., Allred, L.: Performance analysis of probabilistic potential func- tion neural network classifier. In: Proc. of Artificial Neural Netw. in Engg. Conf., vol. 7, pp. 471–476 (1997)
  42. Mailloux, G.C., Bertranti, M.: Texture Analysis Of Ultrasound B-Mode Images By Segmentation. Ultrasonic Imaging 6, 262–277 (1984)
  43. Morifuji, H.: Analysis of ultrasound B-mode histogram in thyroid tumors. Nippon Geka Gakkai Zasshi 90(2), 210–221 (1989)
  44. Hirning, T., Zuna, I., Schlaps, D.: Quantification and classification of echographic find- ings the thyroid gland by computerized b-mode texture analysis. Eur. J. Radiol. 9, 244– 247 (1989)
  45. Smutek, D., Šara, R., Sucharda, P., Tjahjadi, T., Švec, M.: Image texture analysis of so- nograms in chronic inflammations of thyroid gland. Ultrasound Med. Biol. 29, 1531– 1543 (2003)
  46. Keramidas, E.G., Iakovidis, D.K., Maroulis, D., Dimitropoulos, N.: Thyroid Texture Representation via Noise Resistant Image Features. In: IEEE Int. Symp. on Comp. Based Med. Sys., pp. 560–565 (2008)
  47. Keramidas, E.G., Maroulis, D., Iakovidis, D.K.: TND: A Thyroid Nodule Detection System for Analysis of Ultrasound Images and Videos. J. Med. Syst., 1–11 (2010)
  48. Chen, Y., Hou, C., Lee, M., Chen, S., Tsai, Y., Hsu, T.: The Image Feature Analysis for Microscopic Thyroid Tissue Classification. In: 30th Annual Int. IEEE EMBS Conf., 4059–4062 (2008)