Methods and Systems for Processing and Analysis of Medical Images

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Abstract. This thesis introduces novel image analysis methods, focusing on texture representation, as well as on computer-aided diagnosis. The first part of this thesis deals with the area of texture representation. Binary pattern (BP)-based approaches have been utilized in a wide range of pattern recognition applications. However, noise sensitivity is still a major concern to their applicability on the analysis of real world images. To cope with this problem we propose a generic, uncertainty-aware methodology for the derivation of Fuzzy BP (FBP) texture models, which assumes that a local neighborhood can be partially characterized by more than one binary patterns. The texture discrimination capability of four representative FBP-based approaches has been evaluated on the basis of comprehensive classification and on unsupervised segmentation experiments. The results reveal that the FBP-based approaches lead to consistent improvement in texture classification and segmentation as compared with the original BP-based approaches for various types and levels of additive noise on different reference datasets. In the second part of this thesis a novel approach for thyroid ultrasound pattern representation is presented. Considering that texture and echogenicity are correlated with thyroid malignancy, the proposed fusion approach encodes ultrasound texture by fuzzy local binary patterns and echogenicity by fuzzy intensity histograms. This approach has been experimentally investigated on real ultrasound images for the discrimination of nodules from normal thyroid parenchyma. The results show that the proposed fusion scheme outperforms previous approaches proposed in the literature. Finally an original scheme for the detection of nodular thyroid tissue in longitudinal ultrasound images has been presented and implemented as a prototype software system, named TND (Thyroid Nodule Detector). This system involves a novel algorithm, for automatic detection of the boundaries of the thyroid gland, and the extraction of noise resilient textural and echogenicity image features.

1 Introduction

Texture analysis concerns a considerable range of applications such as remote sensing, biomedical image processing, visual inspection, object discrimination, terrain

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delimitation and image classification. Since the early seventies, a variety of textural feature extraction approaches has been proposed. Such an approach is the Local Binary Patterns (LBP) [9], which is based on the model of Binary Patterns (BP), to describe the local texture of an image. Several other approaches based on the BP model have been investigated by the research community, resulting in plenty of variations. Such an approach, the LBP/C, is based on the joint distribution of the LBP codes and a local contrast measure [9]. Another variation, the Local Edge Patterns (LEP) [10] describes the spatial structure of the local texture according to the spatial arrangement of edge pixels. In the same spirit, the approach of the Median Binary Patterns (MBP) [17] has been proposed, where texture primitives are determined by localized thresholding against the local median.

The applications of BP-based approaches in pattern recognition are numerous including studies on visual inspection, automatic defect detection, remote sensing, image retrieval, face recognition, and biomedical image analysis [11]. However, a major drawback of the current BP-based approaches is that the binary patterns are extracted via pixelwise comparisons. This makes them sensitive to noise and to small variations in the pixel values, thus limiting their real world applicability.

In the first part of this thesis a generic, uncertainty-aware methodology for the derivation of Fuzzy BP (FBP) texture models is proposed [2]. This novel methodology aims to provide improved BP texture representations that exhibit robustness to the presence of noise. Its application is investigated for the fuzzification of a variety of BP approaches, including the LBP, LBP/C, LEP and the MBP. The improved texture representations obtained are validated with a comprehensive and systematic experimental study on standard collections of textures and natural scenes.

The second part of this thesis deals with image processing and analysis of ultrasound medical images. Ultrasound imaging presents a valuable modality that has come to play an increasingly important role in the diagnostic evaluation of soft tissues. Recent advances in ultrasound technology lead to high frequency transducers which provide both deep ultrasound penetration and high definition images. Ultrasound technology has become the most widely employed imaging method for the diagnosis and folow-up of thyroid disorders. Many thyroid diseases can present clinically with one or more thyroid nodules. Two of the most useful sonographic features recognised by the radiologic community for detection and malignancy risk assessment of thyroid nodules are echogenicity and texture [12].

However, an inherent characteristic of ultrasound imaging is the presence of speckle noise. Several endeavours have been undertaken to improve interpretation of thyroid ultrasound images through quantitative criteria [21][22][23], but none of them take any special consideration of the noise-originated uncertainty. In order to obtain an uncertainty-aware representation of thyroid ultrasound patterns we propose a noise-resistant coding of both texture and echogenicity, based on fusion of a fuzzy distribution of local binary patterns, referred to as fuzzy LBP (FLBP) features, and ultrasound echogenicity represented by the fuzzy grey-level histograms (FGLH) [1]. In this thesis the performance of the proposed fusion scheme has been thoroughly investigated for the classification of nodular and normal thyroid ultrasound patterns. The experimental evaluation involves comparisons with several thyroid ultrasound pattern representation approaches proposed in the literature.

Then, an original, efficient, and robust scheme has been proposed for the detection of nodular tissue in longitudinal ultrasound images and videos of the thyroid gland. The proposed scheme involves a novel algorithm, for automatic definition of the boundaries of the thyroid gland, and the extraction of noise resilient image features. This methodology has been seamlessly implemented as a software system, named TND (Thyroid Nodule Detector) [3]. Extensive experimental analysis on real thyroid ultrasound data attest to the feasibility of the clinical application of the TND system.

The rest of this paper comprises three sections. Section 2 refers to the area of texture representation and presents the novel generic, uncertainty-aware methodology called Fuzzy Binary Patterns. In Section 3 image processing and analysis methods suitable for medical ultrasound images are presented. Finally the conclusions derived from this thesis are summarized in Section 4.

2 Binary Patterns Texture Representation

The concept of Binary Patterns (BP) for the representation of texture has been widely adopted as a simple, yet effective model for describing the local spatial structure of an image. This section presents the BP-based texture representation approach using a generic formulation based on crisp sets, and then the proposed methodology for the derivation of the fuzzy BP texture model, followed by an experimental evaluation of this model.

2.1 Crisp Binary Patterns

The BP texture model is based on the crisp pairwise comparison of pixel grey-levels. Each pixel p_x in a square local neighborhood is characterized by a comparison of its grey-level g_x with a reference grey-level $g_{referenc}$ that is common for all pixels in that neighborhood. Thus, two crisp sets of pixels are defined. Let B be the set of all pixels p_x of the neighborhood with grey-level g_x greater than or equal to $g_{referenc}$, and S be the set of all pixels p_x with grey-level smaller than $g_{referenc}$. Then the set B can be expressed by the following equation:

$$B \equiv \{ p_x \mid L_B(x) \} \tag{1}$$

where $L_B(x)$ is a predicate defined as $g_x \geq g_{referenc}$. Hence the set S is the complement of B ($S \equiv B^C$) relative to the universal set H of all pixels of the current local neighborhood.

A characteristic function $m_B(\mathrm{x})$ can be utilized to mathematically describe the crisp set B as follows:

$$m_B(x) = \begin{cases} 1 & \text{if } p_x \in B \\ 0 & \text{if } p_x \notin B \end{cases} \tag{2}$$

Based on these binary values, for each *n*-pixels neighborhood, a unique BP code can be computed:

$$BP_{CODE} = \sum_{x=0}^{k-1} d_x \cdot w_x \tag{3}$$

where $k \in (0, n]$ is the number of neighborhood pixels participating in the BP_{code} computation, $d_x = m_B(x)$ and $w_x = 2^x$.

Thus, each local neighborhood is characterized by a single BP code, out of 2^k possible codes. For a given image region, a histogram counts the occurrences of the BP codes for all the local neighborhoods within the region. This histogram forms a feature vector, representing the texture of that region.

2.2 Fuzzy Binary Patterns

The crisp BP approach described in the previous section is based on a hard thresholding scheme defined by the predicate $L_B(x)$. This makes the BP texture representation scheme vulnerable to the grey-level uncertainty that is inherently present in digital images. By incorporating fuzzy logic to the computation of the binary patterns, an uncertainty-aware representation of local texture can be obtained, providing improved discrimination of textures in the presence of uncertainty.

Fuzzy logic was introduced as a multivalued logic that allows intermediate values to be defined between conventional evaluations like true/false. In the context of texture representation, the crisp sets B and S defined in the previous section, can be re-defined as two fuzzy sets $\tilde{B}$ and $\tilde{S}$, of pixels p_x with grey-levels falling roughly in $[g_{reference}, g_{\max}]$ and $[0, g_{reference})$, respectively. The value of $g_{\max}$ is the maximum grey-level that can be given to a pixel.

Formally, the fuzzy set $\tilde{B}$ can be expressed as a set of ordered pairs

$$\tilde{B} \equiv \{ \langle p_x, \mu_{\tilde{B}}(x) \rangle | x \in H \} \tag{4}$$

where $\mu_{\tilde{B}}(x)$ is a membership function for the fuzzy set $\tilde{B}$ and H={0,1,2,…,n-1} for a *n*-pixel neighborhood. The membership function $\mu_{\tilde{B}}(x)$ relates a real membership grade from the closed interval [0, 1], to each p_x, representing the degree to which p_x belongs to fuzzy set $\tilde{B}$. Accordingly, the fuzzy set $\tilde{S}$ can be expressed as a set of ordered pairs

$$\tilde{S} \equiv \{ \langle p_x, \mu_{\tilde{S}}(x) \rangle | x \in H \} \tag{5}$$

where $\mu_{\tilde{S}}(x)$ is a membership function for fuzzy set $\tilde{S}$.

The membership function $\mu_{\tilde{B}}(x)$, for the fuzzy set $\tilde{B}$, can be defined as the following increasing function:

$$\mu_{\tilde{B}}(x)=\begin{cases}1 & \text{if } g_x-g_{reference}\geq T\\ \dfrac{T+g_x-g_{reference}}{2\cdot T} & \text{if } \left|g_x-g_{reference}\right|< T,\ T\neq 0\\ 0 & \text{if } g_x-g_{reference}\leq -T,\ T\neq 0\\ 0 & \text{if } g_x-g_{reference}< T,\ \ T=0\end{cases} \qquad (6)$$

Similarly, the membership function $\mu_{\tilde{S}}(\mathrm{x})$ can be defined as:

$$\mu_{\tilde{S}}(\mathrm{x})=1-\mu_{\tilde{B}}(\mathrm{x}) \qquad (7)$$

For both $\mu_{\tilde{B}}(x)$ and $\mu_{\tilde{S}}(\mathrm{x})$, $T\in[0,g_{\max}]$ represents a parameter that controls the degree of fuzziness.

According to the proposed FBP approach [7], a neighborhood of *n* pixels can be characterized by more than one ordered pairs of BP codes and C_{BP} values. A C_{BP} value expresses the contribution of a BP code to the BP histogram or in other words the degree to which a BP code characterizes a neighborhood. This degree is estimated from the membership functions $\mu_{\tilde{B}}(x)$ and $\mu_{\tilde{S}}(\mathrm{x})$ as follows:

$$C_{BP}=\prod_{\substack{\mathrm{x}=0\\ Z\in\{\tilde{B},\tilde{S}\}}}^{k-1}\mu_Z\ (x) \qquad (8)$$

where $k\in(0,n]$ is again the number of neighborhood pixels participating in the fuzzy binary patterns computation scheme. Thus each neighborhood contributes to more than one bin in the FBP histogram.

A BP code can be computed through Eq. 3 where the values of d_x should be defined as follows:

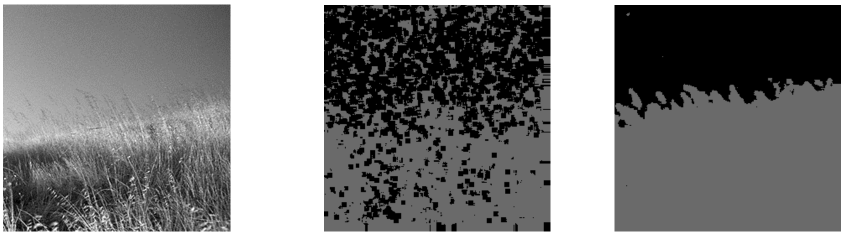
$$d_x=\begin{cases}1 & if\ Z\equiv\tilde{B}\\ 0 & if\ Z\equiv\tilde{S}\end{cases} \qquad (9)$$

It can be noticed that the proposed FBP representation reduces to the crisp BP representation for membership values restricted to $\{0,1\}$.

In the following, we applied the proposed FBP model for the fuzzyfication of four representative BP-based methodologies: Local Binary Patterns (LBP), Local Binary Patterns with Contrast (LBP/C), Local Edge Patterns (LEP), and Median Binary Patterns (MBP).

2.3 Experimental Evaluation

The four FBP-based approaches mentioned above, were evaluated in comparison with the conventional BP-based approaches in supervised classification experiments and in unsupervised segmentation experiments.



(a) (b) (c)

Fig. 1. Vistex natural scene (a) GrassLand2/context2 segmented using EM with (b) LBP/C features and (c) FLBP/FC features.

2.3.1 Evaluation Through Supervised Classification

More than 2,800 experiments were conducted using three reference datasets of natural textures. These include textures from the Brodatz [14], the Vistex [15] and the Outex13 [16] image collections. In order to assess the performance improvement of the FBP-based approaches in the presence of uncertainty, three of the most common additive noise models were applied on each one of the three image datasets. These noise additive models included the uniform, the white Gaussian, and the exponential distributions. The level of noise added was measured in terms of signal-to-noise ratio (SNR) ranging between 2 and 16 dB mean SNR in all three image databases.

The *k*-Nearest Neighbor (*k*-NN) classifier has been utilized for the classification task, and the intersection of the distributions that form the feature vectors has been considered as an effective distance measure.

The classification experiments showed that accuracies obtained for the original datasets were generally higher in the case of the FBP-based approaches. As regards the noise-degraded datasets, the classification accuracies obtained by the FBP-based approaches showed a consistent improvement over the ones obtained by the respective BP-based approaches. In many cases this improvement exceeded 15%. Characteristic examples include FLBP-LBP and LBP/C-FLBP/FC approaches for images with Gaussian noise, where the advantage exceeded 28% in some SNR levels. The FBP-based approaches resulted in a noticeable improvement in the case of exponential and uniform noise, whereas the smallest improvement was noticed in the case of exponential noise. The highest overall classification accuracy was obtained with the FLBP/FC features for all three image datasets and noise types.

2.3.2 Evaluation Through Unsupervised Segmentation

In order to validate the advantageous performance of the FBP-based texture representation approaches visually, a number of clustering-based segmentation experiments were conducted with a set of natural scenes from the Vistex image collection [15]. The segmentation task was assigned to the Expectation-Maximization (EM) clustering algorithm [13]. The FLBP/FC texture representation approach, which generally resulted in the highest classification results in the previous paragraph, was considered for these segmentation experiments. Indicative segmentation results on a Vistex image are illustrated in Fig. 1. Segmentation results showed that the clustering algorithm using the LBP/C features hardly managed to separate the two texture classes of each image, resulting in a visually unsatisfactory segmentation. On the contrary, the quality of the segmentation obtained with the FLBP/FC features is significantly better, as it includes less misclassified regions in all cases.

3 Analysis of Thyroid Ultrasound Images

Among all radiological modalities, ultrasound (US) possesses a rare combination of advantages including portability, harmlessness, real-time data acquisition and affordability. As a result ultrasonography has become the most widely employed imaging method for the diagnosis and follow-up of thyroid disorders including cancer. There are different types of thyroid cancer, but the most common are highly curable if detected early. The challenge is to utilize US imaging in order to detect thyroid nodules that are clinically occult due to their texture, size or shape. Computerized analysis improves medical image interpretation, providing a reliable second opinion in detecting lesions, assessing disease severity, and leading to more accurate diagnostic decisions.

3.1 Texture and Echogenicity Representation

There have been various attempts towards less subjective techniques for the evaluation of thyroid ultrasound images. Some of the earliest approaches were based on the use of grey-level histograms (GLH), which shows that GLH carries substantial information for the characterization of thyroid tissue. However, two ultrasound image regions may have the same histogram but still different textures, since the GLH does not encode any information related to the spatial distribution of image pixels. On those grounds latter studies [22][23] have incorporated second or higher order statistical features for texture analysis of ultrasound thyroid images including Haralick's co-occurrence features (CM) [18], Muzzolini's spatial features [19] run-length matrices (RL) [20] and Radon Transform features [21].

Although previous approaches used GLH and/or various textural descriptors for the representation of thyroid ultrasound patterns, none of them takes any special consideration of the noise-originated uncertainty in the ultrasound images. In order to obtain an uncertainty-aware representation of thyroid ultrasound patterns we proposed a noise-resistant coding of both texture and echogenicity, based on fusion of fuzzy statistical distributions. The proposed approach that is presented in this thesis suggests the use of fuzzy distributions of local binary patterns (FLBP) for the representation of ultrasound texture, and fuzzy grey-level histograms (FGLH) for the representation of ultrasound echogenicity.

3.1.1 Texture Features

A fuzzy LBP (FLBP) representation in the 3×3 local neighborhood can be obtained, for a reference value $g_{reference}$ equal to the grey-level of the central pixel p_8, from Eqs.

(3) and (9). The corresponding contributions C_{LBP} of the LBP codes in the fuzzy LBP histogram can defined through Eq. (8), for k=8 [5].

3.1.2 Echogenicity Features

Fuzzy histograms are noise resistant representations of thyroid ultrasound image echogenicity. The definition of a fuzzy grey-level histogram (FGLH) requires a membership function $\mu_g(p_i)$, specified for each grey-level $g \in [0, G)$:

$$\mu_g(p_i) = \begin{cases} \dfrac{T - |g_i - g|}{T^2} & |g_i - g| < T \\ 0 & otherwise \end{cases} \quad (10)$$

where g_i is the grey-level value of pixel p_i, G is the maximum number of grey-levels, and $T \in [0, G)$ is the fuzzification parameter. Then, the normalized fuzzy histogram of an image region can be defined as:

$$\mathrm{H}(g) = \frac{1}{N} \sum_{i=1}^{N} \mu_g(p_i) \quad (11)$$

3.1.3 Experimental Evaluation

The material used in this study is a set of B-mode thyroid ultrasound images accompanied with ground truth information provided by the Euromedica Medical Center of Athens in Greece. In total 250 square block samples from normal and nodular tissue of the thyroid gland was selected, constituting a solid dataset for experimentation.

Comprehensive classification experiments were conducted for the evaluation of proposed thyroid pattern representation approach using linear, 3rd-degree polynomial and Gaussian SVMs. The classification performance was investigated using ROC analysis. Additionally the area under ROC curve (AUC) offers a reliable single figure measure of the classification performance.

3.1.3.1 Evaluation of textural features

In the first experimental set we evaluated the FLBP features along with various textural features previously proposed for thyroid ultrasound patterns representation. Three thyroid texture representation approaches proposed in the literature were implemented and included in the experimental evaluation presented in this study. These approaches are: (a) The co-occurrence matrix features [18]; (b) The Radon domain features [21]; (c) Muzzolini's spatial features [19]. From this experimental evaluation the FLBP features (for T=13) provided the best discrimination between the nodular and the normal thyroid ultrasound patterns with the Gaussian SVMs, where maximum AUC reached 91.4%.

3.1.3.2 Evaluation of feature fusion approaches

By introducing fuzzy luminance information into the fuzzy texture representation obtained by the FLBP approach we aim to enhance the discrimination of the nodular from the normal thyroid patterns, since both ultrasound texture and echogenicity provide substantial cues to the clinical assessment of thyroid nodules [12]. To validate this theoretical argumentation we proceeded to extensive experiments, investigating the classification performance of the proposed approach in comparison with the following fusion approaches: (a) Fusion of crisp LBP and GLH; (b) The mean value of the local grey-level histogram and the sum variance estimated from the co-occurrence matrix (CM-MGL), as proposed in [22]; (c) The fusion of Muzzolini's spatial features and grey-level co-occurrence matrix features (CM-M) proposed in [23].

The results of the experimental evaluation showed that the proposed approach outperformed all the other approaches by achieving an AUC of 97.5% with the 128-bin FGLH, with T=13 and the polynomial SVM. The best classification performance achieved with the fusion of the crisp LBP and GLH is significantly lower, reaching only 89.0%. The large difference in these two representation approaches indicates the significance of fuzzy modeling in the representation of ultrasound patterns.

The fusion methodology CM-M provided the second best AUC (93.1%) with the polynomial SVM. However, this is still much lower than the maximum AUC obtained by the proposed approach. The fusion of the simple features CM-MGL provided the lowest overall classification performance (85.9%).

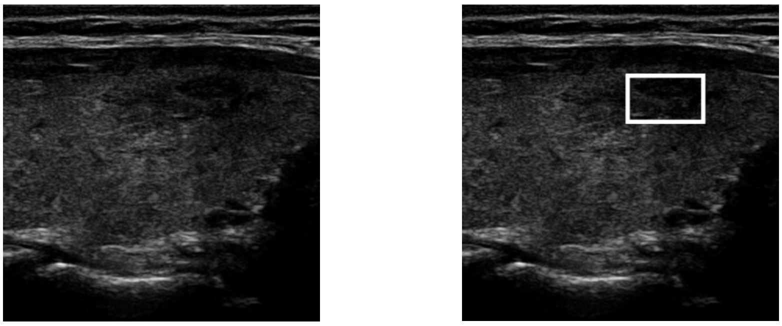
3.2 Thyroid Boundaries Detection (TBD-2) algorithm

The thyroid gland consists of two lobes located along either side of the trachea. Each lobe is surrounded by a thin fibrous capsule. That capsule can be recognized in longitudinal thyroid ultrasound images as thin hyperechoic lines. Considering that thyroid nodules reside only within the thyroid parenchyma, the image analysis operations should be performed only within the thyroid boundaries. To this end we proposed a novel algorithm referred to as TBD-2 [3][8], capable of tracking the inner and outer boundaries of each lobe of the thyroid gland. This algorithm utilizes local statistical properties of the ultrasound images inherently affected by speckle noise.

Exhaustive experiments have been performed with the TBD-2 algorithm to determine the optimal set of parameters that minimizes the error in detecting the boundaries of the thyroid lobes. For the optimal parameters values the mean accuracy in boundaries detection reached a maximum of 90.6±3.2%.

3.3 Thyroid Nodule Detection System (TND)

Finally a complete scheme for the detection of nodular tissue in longitudinal US thyroid images and videos has been proposed. This scheme involves the novel algorithm TBD-2, and the combination of noise resilient texture and echogenicity features for thyroid tissue representation, presented in paragraph 3.1. The proposed scheme has been implemented as a prototype exploratory analysis system, named TND (Thyroid Nodule Detector) [3]. TND offers a simple, practical, and user friendly



(a) (b)

Fig. 2. Indicative result images (a) Input US images with thyroid nodule. (b) output images with the nodule framed by a rectangular box.

interface providing a means to tune all the parameters that are relevant to the methods involved.

The TND system consists of five components, namely the pre-processing, ROI definition, feature extraction, feature classification and post-processing component. The functionality of the proposed system is considered in two phases, a training phase and an application phase. In the first training phase, the TND can be trained with a dataset annotated by experts, identifying different types of tissue. At the end of this phase, the produced parameters of the classification model are stored in a file. The training phase needs to be performed only once, when a new dataset is available deriving from a different type of US equipment. In the second phase, given a US image or video sequence, the TND uses the prior knowledge acquired during training phase, to detect regions of nodular thyroid tissue.

In the evaluation process of the TND system 118 longitudinal thyroid ultrasound images with nodules were acquired accompanied with ground truth information. A leave-one-out cross validation scheme has been applied on this image dataset. Multiple training and testing sessions were carried out, where different values for system parameters were applied. An exhaustive search of combinations of parameters values have been based on the minimum classification error criterion. The system has been evaluated in terms of nodule detection accuracy which accounts to the percentage of all existing nodules that have been correctly. The best overall detection performance has been accomplished with the SVM classifier where 95.2% of the existing nodules have been detected. Indicative output images are illustrated in Fig. 2.

4 Conclusions

The proposed methodology presented in the first section of this thesis, Fuzzy Binary Patterns is generic and can be applied on any BP-based texture representation approach to improve its robustness against noise. Experimental evaluation on reference datasets led to the following conclusions:

- the FBP-based approaches provide more discriminative representation of natural textures than the crisp BP-based approaches;
- the FBP texture representation is tolerant to white Gaussian, Exponential and Uniform additive noise;
- the advantage of the FBP over the crisp BP approaches becomes more evident for moderate noise levels;
- the improved texture discrimination capability of the FLBP/FC approach was qualitatively validated with unsupervised segmentation of natural scenes.

The conclusions derived from the second part of this thesis concerning methods for image processing and analysis of ultrasound medical images can be summarized as follows:

- Thyroid nodules of high malignancy risk can be discriminated from normal thyroid parenchyma using textural ultrasound image features.
- The FLBP feature extraction method provides better descriptors of thyroid ultrasound texture than previous methods.
- The classification performance obtained with the FLBP descriptors is significantly enhanced by the proposed fusion of FGLH into the FLBP feature vector. This approach leads to the best discrimination of the high malignancy risk nodules from the normal thyroid parenchyma, as compared to state of the art methods.
- Thyroid Boundaries Detection (TBD) algorithm can detect thyroid boundaries on longitudinal US images with high accuracy.
- Thyroid Nodules Detection (TND) system can provide physicians with an accurate second opinion on the problem of nodule detection.

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