Texture Characterization in Ultasonograms of the Thyroid Gland

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***Abstract*–This study tries a quantitative characterization of the thyroid tissue as far as homogeneity and echogenicity are concerned, to quantitatively evaluate thyroid texture. Digital image processing techniques offer the opportunity for texture description. Although there is no formal definition of texture, this particular method of description can quantify properties such as smoothness, coarseness and regularity. First-order and co-occurrence features are quantified and multi factor analysis is used to evaluate the optimal subset of parameters for thyroid texture.**

I. Introduction

Ultrasonography is the most well accepted imaging modality for the diagnosis and follow-up of thyroid disorders. The advantages of using ultrasonic imaging include its mobility and low cost as well as the ability to measure the dimensions of the gland, check for the presence of masses or cysts and evaluate the structure and echogenicity of the parenchyma. However, in making an overall evaluation of a sonogram a physician uses his/her clinical experience without giving any quantifiable indices [1],[2].

The most usual way to evaluate thyroid echogenicity is the comparison with the under-scattering neck muscles. Through this comparison the thyroid is characterized as normal, hypo- or hyper-echogenic. Apparently, this method is qualitative and highly subjective [3], [4]. On the contrary, thyroid texture characterization based on statistical parameters could provide an objective diagnostic tool and contribute to the use of computer assisted applications in thyroid disorders [5].

Attempts for a quantitative evaluation of the echogenicity of the thyroid included the extraction of parameters based on gray – level histograms such as mean gray-scale level, standard deviation and highest frequency gray-level. Ying et al [6] compared mean thyroid density with the corresponding of the sternomastoid muscle. Mailloux et al. used gray level histograms corresponding to different echogenicities, while Hirning et al.[7] and Lee et al [8] attempted a quantitative approach for localized lesions (masses or cysts). Recently, an interest in the characterization of diffuse changes in the thyroid gland using second-order statistical parameters has been indicated. Smutek et al.[9] analysed inflamed thyroid ultrasonograms using second – order texture descriptors and tested them through different classifiers. Their results reached a classification success up to a 100%.

The purpose of this study is a quantitative characterization of the thyroid tissue as far as homogeneity and echogenicity are concerned, in other words an attempt to quantitatively evaluate thyroid texture.

Digital image processing techniques offer the opportunity for texture description [10]. Although there is no formal definition of texture, this particular method of description can quantify properties such as smoothness, coarseness and regularity.

Published works have been based on the comparison of image features based on different extraction techniques such as Fourier power spectrum, second-order gray-level statistics, co-occurrence statistics, and gray-level run-length statistics[11]-[13]. They concluded that co-occurrence features were more representative for texture classification. Grey-Level Co-occurrence Matrix (GLCM) texture measurements have been used a lot in image texture since they were proposed they were proposed by Haralick in the 1970s, [14]-[16]. 14 different measurements were proposed. In another work a first-order statistical quantity, the mean value of gray levels of the image, was proven representative of the texture of the thyroid [17]. The GLCM is a tabulation of how often different combinations of pixel brightness values (grey levels) occur in an image [18]. Texture in images quantifies grey level differences (contrast), the defined size of area where change occurs as well as the directionality of the texture properties (Fig. 1). First order texture measurements are statistics calculated from the original image values, like variance, and do not consider close pixels relationships.

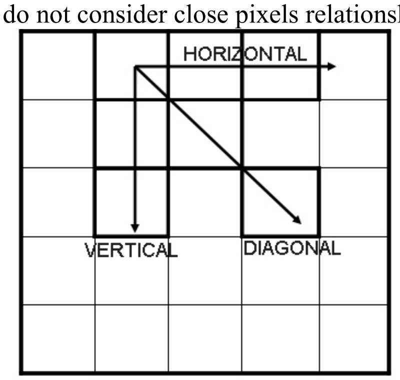

Fig.1. A different co-occurrence matrix exists for each spatial relationship (vertical, horizontal, diagonal)

Therefore, in this study first-order and co-occurrence features are quantified and multi factor analysis is used to evaluate the optimal subset of parameters for thyroid texture.

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II. Patients and Method

A. *Technique*

Thyroid ultrasonograms of 40 patients were acquired for further image processing. The selection of the patients was random. The diagnosis in each case was based on clinical examination and on the levels of thyroid hormones and antibodies. Two experienced radiologists visually assessed each ultrasonogram in order to evaluate thyroid texture. Twelve normal patients (as confirmed by their blood tests and clinical examination) had ultrasonograms with normal echogenicity, while the remaining 28 ultrasonograms were characterized as hypoechogenic.

The parameters on the sonograph were the same used for routine examination at a frequency of 6MHz and a linear transducer. The longitudinal thyroid B-mode images were converted to DICOM format by the SIEMENS sonographic imaging system with an amplitude resolution of 8bits (256 gray levels) and a matrix of 800×600 pixels. MATLAB software was used for the analysis of the images.

Due to the fact that the aim is to detect and characterize the texture of the whole gland, processing concerns the whole thyroid lobe area. The automatic segmentation of such an area is complex; therefore manual delineation of a rectangular ROI enclosing the thyroid was used (Fig.2, Fig.3).

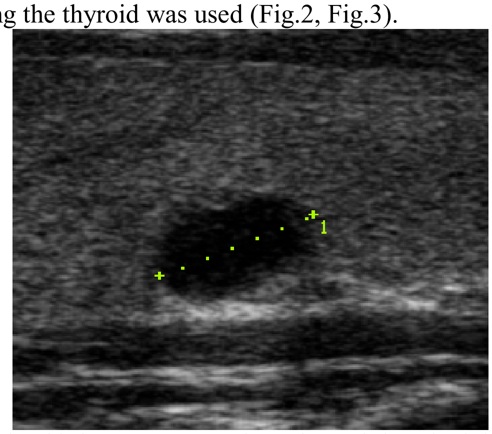


Fig.2. Thyroid ultrasonogram sample. An hypoechoic region is included.

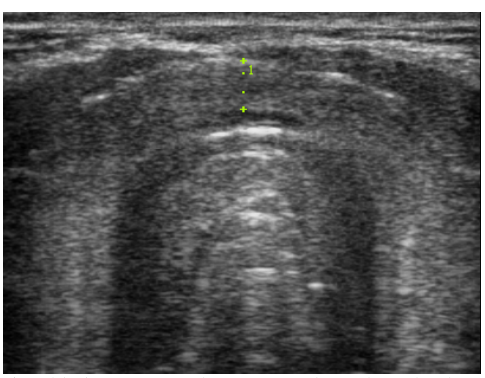


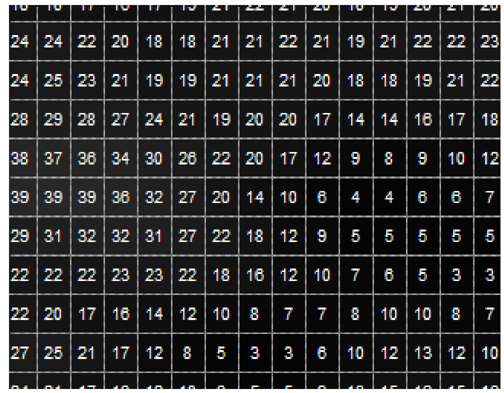
Fig.3. Thyroid ultrasonogram image. An echogenic region is selected.

B. *Image analysis*

Gray-level co-occurrence matrix (GLCM) is the two dimensional matrix of joint probabilities between pairs of pixels, separated by a distance, d, in a given direction. It is popular in texture description and base on the repeated occurrence of some gray level configuration in the texture. This configuration varies fast with distance in fine texture but tardily in coarse textures.

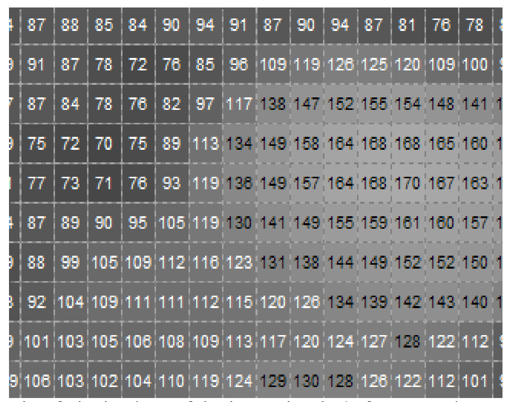
The first order statistics computed are the mean and standard deviation of the gray levels of the image.

The co-occurrence parameters were computed from the corresponding gray-level co-occurrence matrices (Fig.4, Fig.5).



24	24	22	20	18	18	21	21	22	21	19	21	22	22	23
24	25	23	21	19	19	21	21	21	20	18	18	19	21	22
28	29	28	27	24	21	19	20	20	17	14	14	16	17	18
38	37	36	34	30	26	22	20	17	12	9	8	9	10	12
39	39	39	36	32	27	20	14	10	6	4	4	6	6	7
29	31	32	32	31	27	22	18	12	9	5	5	5	5	5
22	22	22	23	23	22	18	16	12	10	7	6	5	3	3
22	20	17	16	14	12	10	8	7	7	8	10	10	8	7
27	25	21	17	12	8	5	3	3	6	10	12	13	12	10

Fig.4. Matrix of pixel values of the image in Fig.2, from the hypoechoic region.



87	88	85	84	90	94	91	87	90	94	87	81	76	78
91	87	78	72	76	85	96	109	119	126	125	120	109	100
87	84	78	76	82	97	117	138	147	152	155	154	148	141
75	72	70	75	89	113	134	149	158	164	168	168	165	160
77	73	71	76	93	119	136	149	157	164	168	170	167	163
87	89	90	95	105	119	130	141	149	155	159	161	160	157
88	99	105	109	112	116	123	131	138	144	149	152	152	150
92	104	109	111	111	112	115	120	126	134	139	142	143	140
101	103	105	106	108	109	113	117	120	124	127	128	122	112
106	103	102	104	110	119	124	129	130	128	126	122	112	101

Fig.5. Matrix of pixel values of the image in Fig.3, from an echogenic region.

This matrix results from an image through statistical, paired comparisons of the pixels' gray levels. Each element (i,j) in the matrix describes the probability that two pixels in the image with a given separation, have gray levels i and j. The separation is defined by the linear distance d and the angle θ.

$$GLCM, \quad \Phi(d,\theta) = \left[\hat{f}(i,j|d,\theta)\right]$$

This is a square matrix with dimension equal to the number of gray levels that form the image (in this case 256×256). GLCM texture considers the relation between two pixels at a time, called the reference and the neighbor pixel. The reference pixels have the same range of values as the neighbor pixels. GLCM is square and has the same number of rows and columns as the quantization level of the image. Textures are calculated within a window that is a small region of the image. The relative size of the window and the objects (echoic – anechoic regions of the ultrasonogram) determines the usefulness of the texture measurement for classification.

The elements of the GLCM are not separately used for texture characterization. This is accomplished by parameters extracted from the matrix. Many parameters have been extracted and proposed as texture descriptors, initially by Haralick et.al., but not all were proven representative. Four widely used parameters that are calculated in this study are: Energy (Angular Second Moment), Homogeneity, Correlation and Contrast (Fig.6)

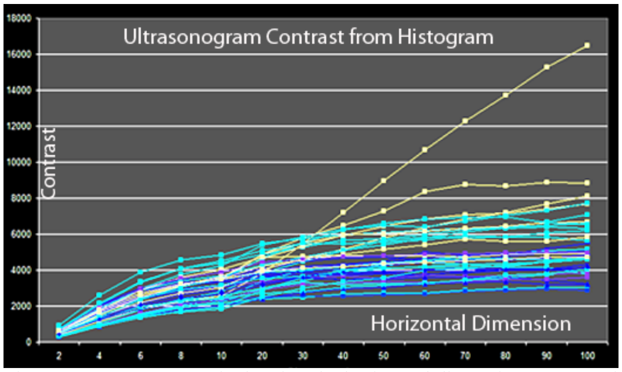


Fig.6.Images Contrast calculated to the horizontal dimension. Contrast is highly correlated

Each GLCM is calculated for a defined pixel distance. In ultrasonographic images distances are usually selected in the horizontal and vertical dimensions. In this study GLCMs are calculated for diagonal separations in order to assess their potential in texture description.

The statistical analysis aims at the automatic classification of the ultrasonograms according to their texture. Initially Principal Component Analysis (PCA) is applied in order to reduce the number of features. PCA seeks a linear combination of variables (components) so that the maximum variance is extracted from the variables. It then removes this variance and seeks a second linear combination, which explains the maximum proportion of the remaining variance and so on. This is called the Principal Axis Method and results in orthogonal (uncorrelated) factors.

In order to test the extracted components for their ability to characterize texture, a classification model is constructed using binary logistic regression. In order to build the model a random 70% of the ultrasonograms are used for model construction and the rest 30% for model testing.

III. RESULTS

It was expected that different regions of the thyroid ultrasonograms (echogenic –hypoechogenic) would have different characteristic texture measurements. So, the window selected to be smaller but big enough to include the characteristic variability of the region of interest.

Initially the patients that were proven to be healthy by their blood tests were classified as normal by clinical examination and visual assessment of the ultrasonic image (12 cases) by two experienced radiologists. The rest 28 patients were classified as pathologic, and their ultrasonograms are hypoechogenic. For each patient two images are used: the longitudinal scans of the two lobes of the thyroid. The GLCMs were calculated for 14 distances (2 to 100 pixels), horizontally, vertically and diagonally (0^0, 90^0, 45^0). In the end there is a total of 80 images and for each image 168 co-occurrence parameters.

Principal component analysis was performed in order to reduce the number of the statistical parameters and to calculate a linear combination of the most characteristic texture features that adequately describe the sample. The analysis resulted in the extraction of ten components. The texture parameters that are highly correlated to the extracted components are homogeneity for small pixel separations, correlation for large separations, and contrast for large pixel separations and energy for medium pixel separations. It has to be mentioned that the parameters calculated from GLCMs corresponding to the diagonal direction are highly correlated to the extracted components.

The ten components resulting from the PCA were used in order to construct a classification model by applying binary logistic regression. A random sample of 70% of the ultrasonograms was used to build the model and the remaining ultrasonograms tested the model's ability to classify the images correctly according to their texture. Hosmer – Lemeshow statistic certified the model's validity (sig >0.05). The classification of the ultrasonograms into normal and hypoechogenic was 100% correct from the 3^{rd} step for the images used to construct the model as well as for the ones used to test it.

IV. CONCLUSION

Until recently the attempts of a quantitative evaluation of thyroid sonograms were based on first order statistical parameters [19]. In this study second order statistical features were calculated as potential texture descriptors. From a total of 80 transverse thyroid sonograms (40 patients), 24 were characterized as of normal echogenicity (blood test, clinical examination and visual assessment) and 56 were characterized as hypoechogenic. For each sonogram 168 co-occurrence parameters were derived from GLCMs calculated for the three different main directions and 14 distances of pixel separation. PCA was applied in order to calculate an optimal number of components as a combination of these parameters. The ability of the components to characterize thyroid texture was tested through binary logistic regression. The constructed model was 100% successful in classifying correctly normal and hypoechogenic thyroid parenchyma. The next step involves the ability of this model to differentiate between more than two different texture categories

The results clearly show the potential of this method to be used in computer assisted applications [20] concerning thyroid disorders.

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