Chronic Inflammatory Processes in Thyroid Gland – Texture Analysis of Sonographic Images

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Abstract *One of the basic diagnostic and monitoring tools for the diseases of the thyroid gland is sonography. Nonetheless, conventional sonography is still qualitative. To improve the diagnosis reliability, quantitative image analysis is highly desirable. In this paper, we report preliminary results on computer distinguishing between an ultrasound image of chronic inflammation – Hashimoto's lymphocytic thyreoiditis and healthy tissue. The combination of texture entropy, correlation and uniformity of energy and combination of cluster tendency, texture homogeneity and uniformity of energy proved to be most efficient parameters for discriminative power and recognition stability. There is possibility to use this quantitative tissue characterisation in clinical diagnostic process. Other conditions will be studied in the future.*

1. Introduction

One of the basic diagnostic and monitoring tools for the diseases of the thyroid gland is sonography and one of the most frequent thyreopathies is the chronic inflammation – Hashimoto's lymphocytic thyreoiditis. But the assessment of the findings such diffuse processes is difficult, because individual diagnosis does not have enough specific ultrasound images and the conclusion of the examination is made qualitatively from the size of the gland, perfusion, structure and echogenicity of its parenchyma. To improve the diagnosis reliability, quantitative image analysis is highly desirable.

The final diagnosis of diffuse process in thyroid gland is usually assembled from clinical findings, ultrasound findings, laboratory results (immunological, hormonal and metabolic blood sample analysis) and cytology findings (fine needle aspiration biopsy).

The goal of our project is to aid the diagnosis of diffusion processes in thyroid gland parenchyma. We want (1) to find if there is a correlation between the standard laboratory measurements and quantitative properties of the visual texture of the sonograms, and (2) to help diagnose the various parenchyma conditions based solely on the sonogram texture analysis.

This paper reports the results of our preliminary experiments of texture classification – distinguishing between normal tissue and the chronic inflammation process in the thyroid gland. In the future other diffuse processes will be studied.

2. Methods and Experiments

In the first stage of our project we studied the stationarity properties of the apparent texture in sonographic images of thyroid glands, as measured by a first-order texture statistic. We found the statistic sufficient to discriminate between normal and unhealthy tissue within (the same) image. This suggests that the apparent texture of sonographic B-mode images is stationary over a Cartesian-reconstructed image and may be stable enough to be used for classification based on texture properties.

In the next stage 240 ultrasound B-mode images (10 transversal and 20 longitudinal scans from different places of the gland) of two patients with clinical diagnosis Hashimoto's lymphocytic thyreoiditis and two healthy individuals was acquired. Ultrasound device Toshiba ECCO-CEE, model SSA-340A was used for the examination. The frame-grabber (the input signal for the grabber was identical with the output for monitor of the sonograph machine) was used for digitalisation with a spectral resolution of 8 bits (256 grey levels).

Our current research focuses on the selection of a subset of texture features suitable for the discrimination between the chronic inflammation changes and a healthy parenchyma. Since we are dealing with a diffuse character of the process, the idea is that the images, after segmentation, are suitable for recognition without any interest point detection. To avoid the automatic segmentation problem, an expert roughly delineates the boundary of the gland.

After this manual segmentation, texture samples were defined as 21x21 rectangular windows within the segmented boundaries. Each sample was assigned a label according to the patient diagnosis (HLT, Healthy).

Since the first-order features are prone to heavy distortion caused by image contrast and brightness settings on the sonograph, we selected second-order statistical texture properties based on co-occurrence matrices as features useful for recognition. This is in agreement with the literature where the second-order statistics are reported as the most successful for texture-based classification of sonographic images, see e.g. [2, 4, 7, 9].

Nine Haralick texture features [3] were computed from the co-occurrence matrix corresponding to a one-pixel separation in the direction of ultrasonic wave propagation for each sample. The features used are listed in the following table (Tab.1):

Tab 1. – Haralick texture features

H1 cluster tendency
H2 texture entropy
H3 texture contrast
H4 texture correlation
H5 texture homogeneity
H6 inverse difference moment
H7 maximum probability
H8 probability of run length of 2
H9 uniformity of energy

By analysing this collection of samples for a given n, the number of features, the goal was to find the group of n of features of

1. the most linear discriminative power f, and
2. the highest recognition stability s.

The discriminative power is measured by Fisher's linear discriminant [1] computed over the test set. The stability is computed as the percentage of cases for which a particular combination of features gives the best recognition rate under a random division of the input data into a training set and a test set; all possible divisions are tested to evaluate the stability. The minimum Euclidean distance classifier was used.

3. Results

For n = 3, the combination of features of the best discriminative power and the best stability were texture entropy (H2), correlation (H4) and uniformity of energy (H9) (f = 1.1824, s = 42.7%) and cluster tendency (H1), texture homogeneity (H5) and also the uniformity of energy (H9) (f = 1.2422, s = 15.3).

For n = 2 the best discriminative pair of features is cluster tendency (H1) and texture contrast (H3) (f = 1.1936).

For n = 1 the best discriminative feature is texture homogeneity (H5) (f = 0.9659).

4. Conclusion

There is possibility to calculate, by means of computer texture analysis of ultrasound images, quantitative tissue characterisation of the chronic inflammatory processes in thyroid gland, which the human visual system is not capable to achieve [5] and to use this characterisation in clinical diagnostic process.

It seems that texture homogeneity, cluster tendency, and uniformity of energy are more important for classification than other features. These three features are strongly related to the shape of the co-occurrence histogram.

As can be seen from the results, the discriminative power, f, is still too low for the features to be used in a daily clinical work as the only tool for distinguishing between normal healthy thyroid tissue and chronic inflammatory parenchyma.

Therefore we plan extending the set of texture features, computing texture features for co-occurrence matrices for other separations or using other approaches to parametric texture description. The aim is to find a better set of stable and discriminative features, preferably those that allow us to capture the global shape of the co-occurrence histogram.

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