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# Diffusion Process Classification in Thyroid Gland Parenchyma Based on Texture Analysis of Sonographic Images: Preliminary Results

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**Abstract** *Sonography is a widely used non-invasive diagnostic tool. Analyzing changes in sonograms provides a means of diagnosing and monitoring chronic thyroid gland diseases. Nonetheless, conventional sonography is still qualitative. To improve the diagnosis reliability, quantitative image analysis is highly desirable for the assessment of various thyroid gland conditions. In this paper, we report preliminary results of our effort in texture classification of thyroid gland sonographic imagery, more specifically, on classification of diffuse processes for distinguishing between normal tissue and chronic lymphocytic thyroiditis (Hashimoto's Thyroiditis). Other conditions will be studied in the future.*

## 1 Introduction

This effort is a part of a three-year collaborative project between the First Faculty of Medicine of the Charles University in Prague and the Center for Machine Perception at the Czech Technical University. The goal of the project is to aid the diagnosis of diffusion processes in thyroid gland parenchyma, which is currently done (a) subjectively from a sonogram and/or (b) quantitatively by a laboratory immunological, hormonal, and metabolic sample analysis. In the project, we aim (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.

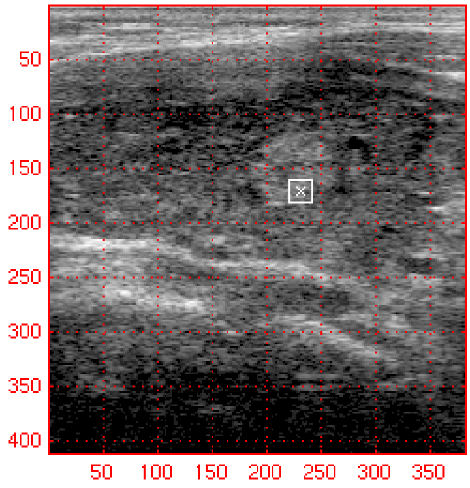
This paper reports the results of our preliminary experiments. These experiments were designed to assess the feasibility of the project goals. We focused on the stability of the visual texture in sonograms and on the choice of texture features suitable for recognition. The texture-based recognition itself was not yet attempted in a larger scale.

## 2 Methods and Experiments

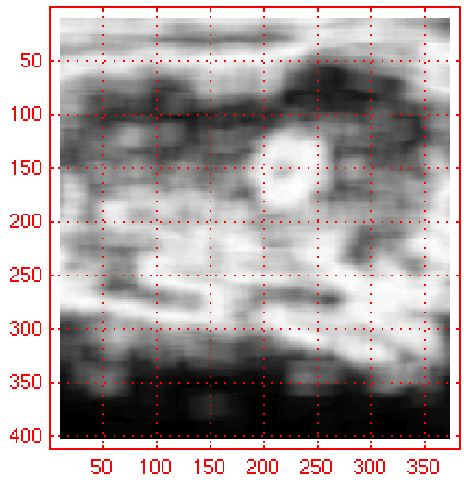
In the first experiment of our project we studied the stationarity properties of the apparent texture in sonographic images of thyroid gland, as measured by a first-order texture statistic. We found the statistic sufficient to discriminate between normal and unhealthy tissue within (the same) image. The experiment we performed is illustrated in Fig. 1. In Fig. 1(a), an image is shown of a longitudinal cross-section of the left lobe of the thyroid gland of a 63-year-old woman with hyperthyroidism due to Grave's disease. A solitary nodule is apparent in the image. The white rectangle marks the region from which a texture sample was taken. The similarity map shown in Fig. 1(b) was computed by comparing same-size neighborhood of each image pixel with the sample. The $\chi^2$ statistic on histograms [12] was used. Note that the nodule is clearly visible along with the tissue showing similar first-order statistics. This suggests that the 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. Indeed, this conclusion has been confirmed by many authors in the literature on sonographic image analysis.

Our current research focuses on the selection of a subset of texture features suitable for the discrimination among the common diffuse 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, the boundary of the gland is roughly delineated by an expert, see Fig. 2. This can be done very fast by a simple-to-use interactive tool.

Since the standard diagnostic assessment is done subjectively by a specialist, based on the sonographic images, and since the specialist is trained to perform recognition from textural properties, texture characteristics observable only by human visual system are probably sufficient. From the psychophysical evidence it is known that human visual system is capable of preattentive texture discrimination from up to second-order texture properties [7]. 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 (two-dimensional histograms) 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 sono-




(a)




(b)

**Figure 1:** The stability of texture in sonographic images.

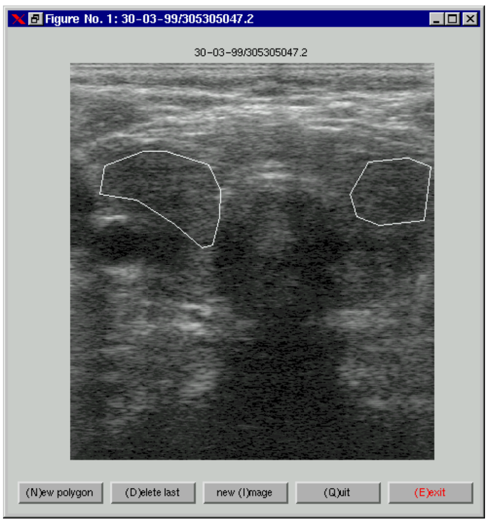



**Figure 2:** Expert-drawn boundary of the region of interest.

graphic images, see e.g. [3, 5, 11, 13].

In our second experiment, nine Haralick texture features [4] were computed from the co-occurrence matrix corresponding to a one-pixel separation in the direction of ultrasonic wave propagation. The features used are:

| | |
|---|---|
| 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. |

A small dataset of sonographic images was acquired for two healthy individuals and two patients with lymphocytic thyroiditis (LT). Ten images of transverse cross-section were scanned for each of the subjects. After manual segmentation, texture samples were defined as $21 \times 21$ rectangular windows within the segmented boundaries. Each sample was assigned a label according to the patient diagnosis (Healthy, LT) and a set of the nine features was computed for each sample. By analyzing this collection of samples for a given $n$, the number of features, the goal was to find the $n$-tuple of features of

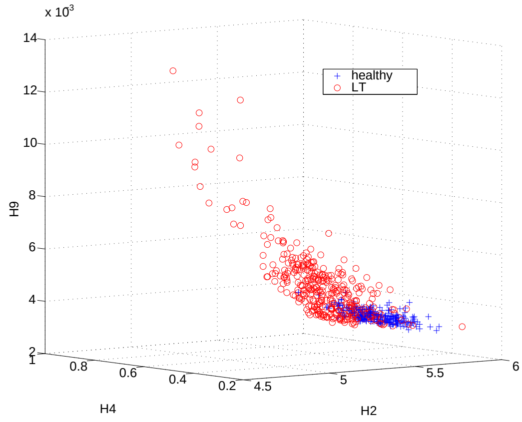
1. the most linear discriminative power $f$, and
2. the highest recognition stability $s$.

The discriminative power is measured by Fisher's linear discriminant [2] 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 and a test sets; all possible divisions are tested to evaluate the stability. The minimum Euclidean distance classifier was used.

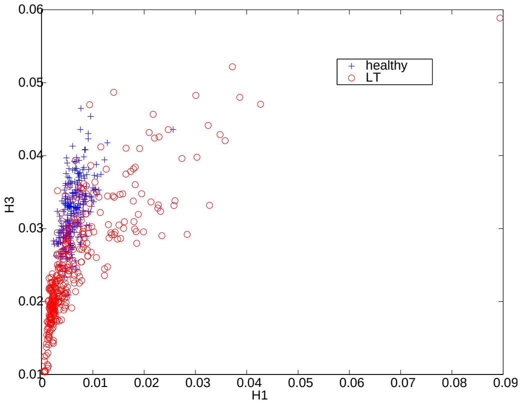
For $n = 3$, the combination of features of the best discriminative power *and* the best stability were H2–H4–H9 ($f = 1.1824$, $s = 42.7\%$) and H1–H5–H9 ($f = 1.2422$, $s = 15.3\%$). See Fig. 3(a) for distribution of points in feature space. For $n = 2$ the best discriminative pair of features is H1–H3 ($f = 1.1936$), see Fig. 3(b). For $n = 1$ the best discriminative feature is H5 ($f = 0.9659$). 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.

## 3 Conclusion

As can be seen from the results, the discriminative power $f$ is still too low for the features to be used in a setup of a guaranteed performance. We therefore plan extending the set of texture features by computing co-occurrence matrices for other separations as well or using other aproaches to parametric texture description (as suggested in [1, 6, 8, 9, 10], for instance). The aim is to find a better set of stable and discriminative features, preferably those that allow us to capture the




(a) H2–H4–H9




(b) H1–H3

**Figure 3:** Distribution of all measurements in feature space for the best triple (a) and the best pair (b) of features.

global shape of the co-occurrence histogram. To this end, we need to acquire a large data set, which is the subject of our ongoing effort.

### Acknowledgements

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