

# Textural Analysis Of Prostate Cancer In Transrectal Ultrasound Images.

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*Abstract. In this paper, a method for analysis of transrectal ultrasonography images for computer-aided diagnosis of prostate cancer is presented. Several feature extraction methods are tested in a typical Statistical Pattern Recognition supervised setting, with an approximate k-nearest neighbors classifier. Very promising results are obtained in a difficult task where even trained urologists cannot discriminate benign from malignant tissue in the images.*

## 1 Introduction

Prostate cancer is one of the main causes of death from cancer in men, and current methods, like Digital Rectal Examination (DRE), Prostate Specific Antigen (PSA) test and Transrectal Ultrasonography (TRUS) are not reliable for an early detection [5]. Several biopsies are routinely performed to patients suspicious of the disease. This can be painful and a source of bleeding and infection risks.

Although other imaging techniques, such as Axial Tomography or Magnetic Resonance, can be useful, TRUS is the basic diagnostic tool, since it is innocuous, inexpensive and widely used to guide biopsies. Unfortunately, it is now accepted that ultrasound images do not provide reliable diagnostics of prostate cancer, so the final diagnostic is always based on the histologic results. A tool that could highlight the areas most likely to contain cancer would be very valuable. The main goal is to decrease the risk of a cancer remaining undetected in a biopsy session. De la Rosette *et. al.* [2] proposed the use of textural features and decision trees, and obtained partially significant results on a selected set of cancer patients.

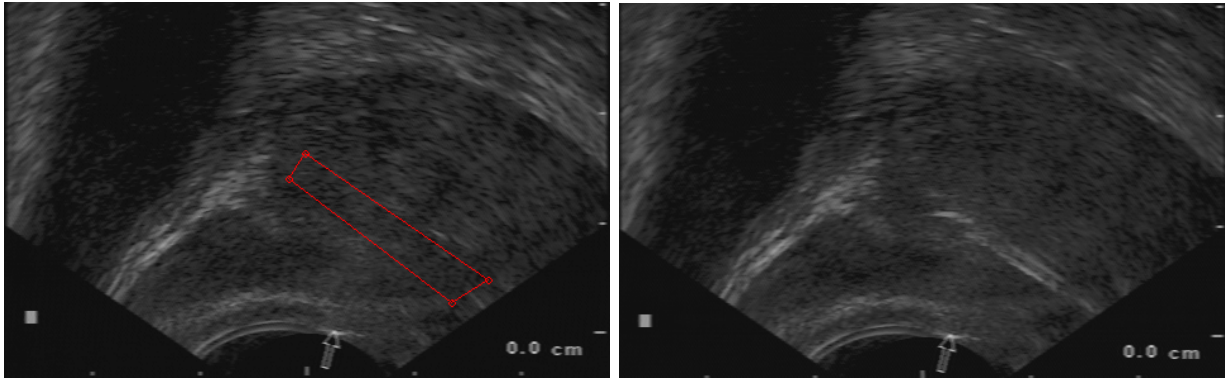
## 2 Patients and data

The data used in this work have been acquired in collaboration with the Urology Department of the Hospital "La Fe" in Valencia, Spain. 143 TRUS-guided biopsy sessions involving 5 to 6 biopsies, were acquired from 143 different patients between February 2000 and February 2001. No selection of the patients was performed so as the data set be representative of a real population of patients susceptible to a prostate biopsy.

The images were acquired at a resolution of  $768 \times 576$  pixels and a depth of 8 bits per pixel by means of a conventional frame grabber connected to the video output of the ultrasonograph. A de-interlacing process was used to obtain images of  $384 \times 288$  pixels. Fifty images, during ten seconds, were recorded for each biopsy, keeping 3 of them from the period of 2

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**Figure 1. Two images of the same TRUS-guided biopsy. The first image was taken 400 ms before the puncture. The instant of the shot is shown in the second image.**

seconds previous to the puncture. The number of biopsies recorded in the 143 sessions was 757. The total number of images was thus  $757 \cdot 3 = 2,271$ .

A polygon corresponding to the cylinder from where tissue was extracted was labeled in each image, as shown in Figure 1. From the 143 patients, 98 at random formed the training set, and the other 45 the test set. Similar *a priori* probabilities for both sets were enforced. The number of pixels in the training and test sets were  $2,7 \times 10^6$  and  $10^6$  approximately.

### 3 Approach

A typical non-parametric supervised setting was used, feature extraction followed by a classification phase. A  $k$ -nearest neighbors classifier implemented with a fast  $kd$ -tree approximate search algorithm and the following confidence criterion function have been used:

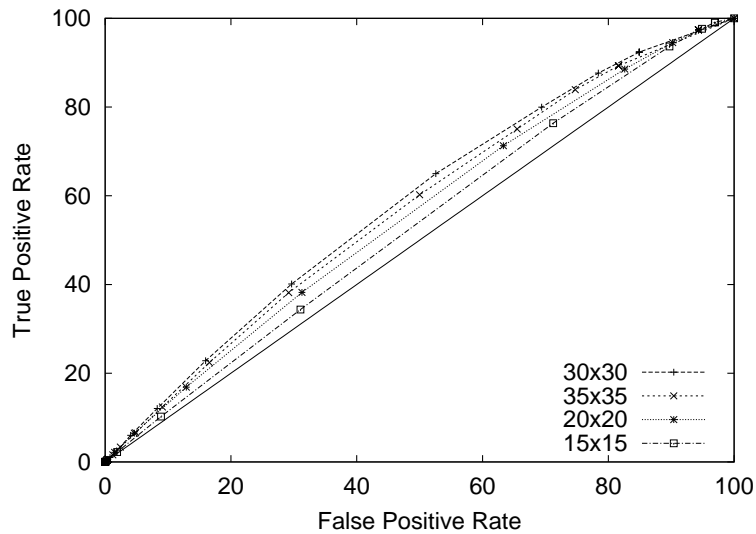
$$f_c = \frac{\sum_{i \in s_c} \frac{1}{d(p, n_i)}}{\sum_{i=1}^k \frac{1}{d(p, n_i)}}$$

where  $f_c$  is the confidence of class  $c$ , and  $s_c$  is the set of sub-indices of the prototypes belonging to class  $c$  among the  $k$  nearest neighbors found:  $n_1 \dots n_k$ . Only the confidence of the “positive test” class, *cancer*, is computed. A threshold  $T$  is used so that a pixel is considered cancer if its confidence is larger than  $T$ .

Most approaches to tissue segmentation in medical images use texture descriptors as Spatial Gray Level Dependence Matrices (SGLDM, or Cooccurrence Matrices) [3], Fractal features [1], and other kinds of textural features [4]. So far, we have tested SGLDM descriptors, specifically: Angular Second Moment, Contrast, Correlation, Variance, Inverse Difference Moment, Sum Average, Sum Variance, Sum Entropy, Entropy, Difference Variance and Difference Entropy, but work is planned on other kind of features.

### 4 Experiments

A number of experiments are being carried out to determine if the feature extraction and the classification schemes proposed can predict the malignancy in a TRUS image of a previously unknown patient, a task that even trained urologists cannot perform reliably using only the information in the image.



**Figure 2. R.O.C. of some tests with SGLDM features and different window sizes.**

In figure 2, the results with SGLDM textural descriptors in windows of  $15 \times 15$  to  $30 \times 30$  pixels centered in each pixel of the images are shown. Previously, each image was subject to a standard vector quantization pre-process so as its number of gray-levels was reduced from 256 to exactly 20. Twelve matrices corresponding to four angles ( $0$ ,  $\frac{\pi}{4}$ ,  $\frac{\pi}{2}$  and  $\frac{3\pi}{4}$ ) and 3 distances (1 to 3 pixels) were used. Each resulting vector (of 132 dimensions) was then projected into a 20-dimensional space using Principal Component Analysis.

## 5 Conclusions

The first pixel-level results are encouraging since they show a correlation between the textures present in the image and the presence of cancer cells in the tissue (the error intervals at 95% confidence are so small for the test-set used, with more than one million observations, that they cannot be seen in the graph), but to assess the clinical value of the model, tests on complete images comparing the decisions of the urologists with and without the aid of the system have to be performed. We think that the low-level texture-oriented information provided by this system can be a good complement to the high-level geometrical skills of the human visual system and the expertise of a trained urologist.

## References

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