Efficient Image Texture Analysis and Classification for Prostate Ultrasound Diagnosis

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Abstract

An efficient, integrated image textural analysis and classification of transrectal prostate ultrasound images into clusters potentially representing cancerous or normal tissue areas is presented. Preliminary image texture analysis has shown the potential for doubled diagnosis accuracy from 38-42% for prostate cancer with current clinical methods, to 88-92%. In addition, image texture analysis makes prostate cancer locating possible for more precise, less invasive biopsy/treatment, instead of 6-way random biopsy. However, the initial image texture analysis on a miniVAX could take 8 days CPU time per image, i.e., more than 5 months for 20 cross-sections per patient. Over the last 10 years, we have improved the processing from 8 days to less than 10 seconds per image on a PC. The approach is based on Haralick's textural features [1] and the Minimum Squared Error (MSE) clustering algorithm. The Java Textural Analysis/Classification (JTAC) application developed as part of this project offers significant reduction in run time, potentially allowing more accurate, objective diagnoses to be performed within clinical settings, and allows the investigation of parameters associated with textural and clustering processes. Using this integrated approach, specific results for several cases are tested and general conclusions are drawn.

Keyword: *Image Texture Analysis, Prostate Ultrasound Diagnosis, Mean Square Error Clustering*
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1. Prostate Ultrasound Diagnosis

Prostate cancer is the most common cancer in US men, beside skin cancer. Several testing protocols currently are available to detect prostate cancer with combined accuracy of 38-42%: 1) Digital Rectal Examination (DRE), 2) Prostate Specific Antigen (PSA), 3) Transrectal Ultrasound (TRUS): most cancerous tissue is hypoechoic (dark areas), but not all [2]. TRUS is too expensive/invasive as a screening tool, thus is typically used as a biopsy aid. 4) Biopsy.

2. High-Performance Texture Analysis

Image texture is characterized by a given pixel and the pattern in a local area around the pixel. Texture depends on: 1) the size of the area; 2) the relative sizes of the discrete tonal features; and 3) the spatial distribution of discrete tonal features.

A means of analyzing texture within an image involves the creation of Gray Level Co-occurrence Matrix (GLCM), which is an indication of how different combinations of gray levels exist in a portion of the image. GLCM is generated for a small square window of the image. Within the window, unordered pairs of pixels are examined that are separated by a given distance and are oriented to each other by a given angle. In general, the window is small, between 3x3 and 21x21 pixels, and angles of 0º, 45º, 90º, or 135º are used. An entire image can be analyzed by moving the window across the image in an overlapping manner, advancing one pixel column to the right, then one pixel row downward at a time.

Five of the fourteen features proposed by Haralick are chosen including Angular Second Moment, Contrast, Inverse Difference Moment, Entropy, and Sum Entropy from similar texture diagnosis on live/kidney. In addition, correlation may be an important parameter as well.

Significant reduction in textural analysis processing time was achieved by implementing techniques based several observations: 1) GLCM is symmetrical. 2) GLCM is extremely sparse. 3) As the window scanned horizontally across the region of interest (ROI), only the data associated with the far left and the far right of the window actually changed. 4) The maximum number of nodes that would be needed could be created at the beginning of the analysis and placed in a "spare" linked list. 5) Several other time saving techniques were developed including the use of a look-

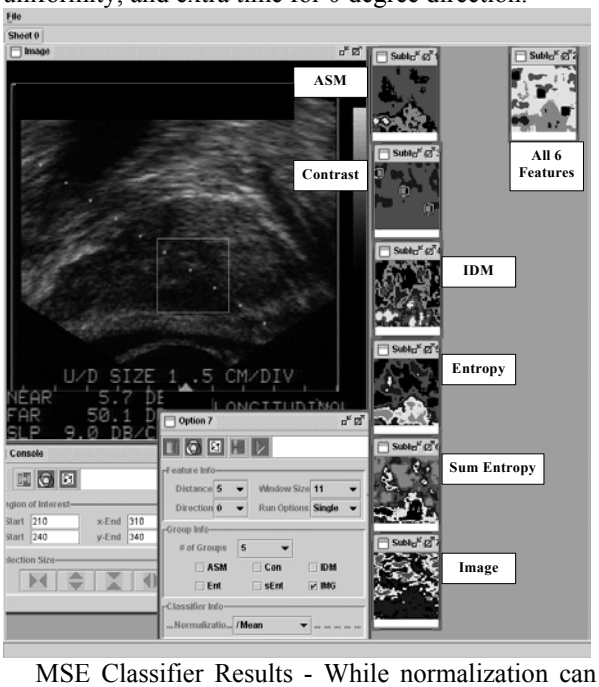
up table for logarithmic calculations, the use of pre-calculated values whenever possible, and was implemented in C for performance.

3. MSE Clustering

An *unsupervised* clustering method was chosen, since training data for the target tissue was not readily available, and it can possibly overcome several of the difficulties associated with the ultrasound images, including artifacts that are present in the image that indicate measurement and biopsy tracks and ultrasound sector boundaries. An MSE classifier was developed in C and chosen over the Agglomerative Neural Network for providing similar results, but ran significantly faster. Enhancement was made so that the user could select several levels of data normalization so that spurious data will not bias the outcome. The MSE classifier was verified by using the Fisher Iris data [3].

4. Texture Analysis/Clustering Performance

Textural Analysis - Presently, the maximum image size is 1024x1024 and can be extended. Results of the time tests show that the speed is dependent on ROI size, scanning window Size, pixel pair distance, image uniformity, and extra time for 0 degree direction.



MSE Classifier Results - While normalization can reduce any error that may result from an excessively large parameter biasing the results, normalization can also cause problems by reducing the separation among dispersed clusters. In addition, the mean used is highly dependent on the ROI chosen by the investigator and could skew the data set leading to misleading or inaccurate results. Instead of the current user-specified number of clusters, an algorithm can be designed to automatically detect a suitable number of clusters

5. Clinical Image Texture Diagnosis

A basic Image Texture Clustering framework has been developed to support further research with a significant reduction in run time. Normalization of data appears to be required to correctly classify the data within the textural clustering. However, the most suitable normalization may be data dependent.

With the JTAC application, typical run times for a Small to medium (about 100x100) ROI with five clusters are approximately 5 seconds (down from previous 8 days of CPU time), which is reasonable for a potential clinical setting. Further performance improvement of the tool to achieve faster run times is still possible.

Research should progress into using multiple directions simultaneously. Associated with this, the Correlation feature should be considered as one of the features included in the classification process. Entropy and Sum Entropy were closely correlated to each other and one could be eliminated from the classification process.

For future study, the color-coded cluster tissue sample images can potentially represent various degrees of seriousness of the abnormality in sample images similar to Gleason score for prostate cancer.

The approaches presented within this project provide a beginning framework for biomedical experiments and many micro/macro image textural analysis/clustering applications from pathological image analysis to remote sensing. Additional improvements can be made to the various segments within JTAC to better facilitate additional research.

6. References

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