Prostate Tissue Texture Feature Extraction for Suspicious Regions Identification on TRUS Images

S.S. Mohamed, J. Li, M.M.A. Salama and G. Freeman

In this work, two different approaches are proposed for region of interest (ROI) segmentation using transrectal ultrasound (TRUS) images. The two methods aim to extract informative features that are able to characterize suspicious regions in the TRUS images. Both proposed methods are based on multi-resolution analysis that is characterized by its high localization in both the frequency and the spatial domains. Being highly localized in both domains, the proposed methods are expected to accurately identify the suspicious ROIs. On one hand, the first method depends on a Gabor filter that captures the high frequency changes in the image regions. On the other hand, the second method depends on classifying the wavelet coefficients of the image. It is shown in this paper that both methods reveal details in the ROIs which correlate with their pathological representations. It was found that there is a good match between the regions identified using the two methods, a result that supports the ability of each of the proposed methods to mimic the radiologist's decision in identifying suspicious regions. Studying two ROI segmentation methods is important since the only available dataset is the radiologist's suspicious regions, and there is a need to support the results obtained by either one of the proposed methods. This work is mainly a preliminary proof of concept study that will ultimately be expanded to a larger scale study whose aim will be introducing an assisting tool to help the radiologist identify the suspicious regions.

KEY WORDS: Biomedical image analysis, decision support, computer-aided diagnosis (CAD), image processing

INTRODUCTION

Prostate cancer is the second most common type of cancer for North American men. In 2002, it claimed the lives of 30,200 Americans and 4,300 Canadians, while 207,200 new cases have been confirmed in the two countries¹.

Prostate-specific antigen value analysis and digital rectal examination are performed to detect signs of cancer during screening, and then prostate biopsy is performed for conclusive diagnostic of the disease. However, prostate biopsy might lose some of the cancer cases. Thus, it would be beneficial to aid the biopsy operation which will lead to enhance the diagnosis accuracy. This is usually accomplished with transrectal ultrasound (TRUS) image analysis. In TRUS analysis, a trained radiologist is able to manually identify, with a moderate degree of confidence, the benign and malignant regions in the prostate on the TRUS image from intensity, local texture, and spatial knowledge regarding cancer tissue distribution. This information is then used for biopsy planning and guidance.

The goal of this research is to design a computer-aided diagnosis method to segment the suspicious regions of interest (ROIs) within the prostate on TRUS images. A successful ROI segmentation algorithm could improve both the efficiency and effectiveness of the prostate cancer diagnostic process. It could potentially lead to aiding the

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Fig 1. Suspicious regions identified by the Gabor-based algorithm. (a) TRUS images with the experts' marked regions, (b) obtained candidate regions using the ROI identification algorithm, and (c) the selected regions after incorporating the expertise information.

biopsy operations required for high fidelity diagnosis results. This is the main motivation of this work.

The local texture property is suggested in this work. In image processing, texture can be defined as: "Texture is concerned with the spatial arrangement of local (gray level) intensity attributes which are correlated within areas of the visual scene corresponding to surface region"⁴. They also look at the intensity and spatial features to take their decision. The cancer and non-cancer tissues are reported to have different parenchyma, which reflects and scatters the acoustic energy differently⁵. Part of this difference is lucid as local texture variation on TRUS images.

Regular textures are usually defined by a texture primitive of a specific size that is repeated at a certain spatial frequency. Simple statistical approaches include applying the standard deviation, uniformity, and entropy measures to the local histogram. These measures effectively describe the coarseness or smoothness of the texture⁶, thus characterize the periodicity parameter well, but not

explicitly the orientation and scale parameters. Moreover, the histogram based methods do not take into account the relationship among neighboring pixels; they only depend on the gray level value of each pixel.

Spectral approaches such as the Fourier spectrum analysis are also considered effective at characterizing the periodicity parameter. However, the results of the transform are not localized in the spatial domain, thus the method is ineffective when identifying texture regions in an image.

Different textural feature extraction techniques such as the gray level dependence matrix (GLDM) and the gray level difference vector (GLDV) were applied in^{2,3} to extract features from only to the identified ROIs from the TRUS images. The GLDM was also used successfully in⁷ for prostate texture feature extraction using TRUS images. The problem with these textural feature extraction techniques is that they might not be able to effectively distinguish between textures when the texture primitives are located at different scales. These methods were successful in^{2,3} since they

Fig 2. Suspicious regions identified by the Gabor-based algorithm. (a) TRUS images with the experts' marked regions, (b) obtained candidate regions using the ROI identification algorithm, and (c) the selected regions after incorporating the expertise information.

Fig 3. Suspicious regions identified by the Gabor-based algorithm. (a) TRUS images with the experts' marked regions, (b) obtained candidate regions using the ROI identification algorithm, and (c) the selected regions after incorporating the expertise information.

were applied to the ROIs selected by the Gabor filter method.

The Gabor multi-resolution analysis was used earlier in^{2,3} to internally segment the suspicious regions in the gland. However, the ROIs obtained in^{2,3} used the radiologist's manual segmentation as the gold standards. The method proposed in^{2,3} obtained excellent segmentation results and it did match the radiologist's segmentation. Therefore, it is considered an excellent method to mimic the radiologist's opinion. Yet, the manual segmentation is not considered accurate enough as it depends mainly on the conducting radiologist, illumination, and different variables. Therefore, another method is proposed in this work to increase the confidence in the segmentation results obtained by either of the proposed ROI identification methods. The second method proposed in this work is based on extracting local texture feature with the aid of wavelet analysis.

Both proposed methods are considered multi-resolution-based methods. The basis for the multi-

resolution analysis using either the Gabor filter or the wavelets lies in the argument that most relevant tissue textures are to be located at specific and finite resolution ranges, where the texture at other resolutions ranges are most likely noise or other scales that are not relevant to the analysis at hand. Multi-resolution analysis including both the Gabor filter and the wavelet decomposition provides the tool with which to zoom into the resolution of interest.

The wavelet analysis was used earlier for texture segmentation in⁸ where 25 natural textures were segmented with almost perfect accuracy. Intuitively, wavelet decomposition should be able to uniquely characterize textures as it takes into account all of the orientation, scale, and periodicity characteristics of a texture. In the area of diagnostic medical imaging, it was applied successfully for prostate segmentation using TRUS images in⁹. The wavelet approach has been applied to liver and breast cancer detection in ultrasound images and mammography¹⁰⁻¹².

Fig 4. Suspicious regions identified by the Gabor-based algorithm. (a) TRUS images with the experts' marked regions, (b) obtained candidate regions using the ROI identification algorithm, and (c) the selected regions after incorporating the expertise information.

Fig 5. Suspicious regions identified by the Gabor-based algorithm. (a) TRUS images with the experts' marked regions, (b) obtained candidate regions using the ROI identification algorithm, and (c) the selected regions after incorporating the expertise information.

In the next section, the proposed Gabor multi-resolution method is briefed. The non-linear texture feature extraction filter is presented in "Gabor-filter-based TRUS Image Segmentation" section. In the "Results and Discussion" section, the results of both proposed approaches are shown and compared. The "Algorithm Comparison" section compares the two proposed algorithms. The major findings of this work are summarized in the last section.

The ultrasound images used in the subsequent analysis are obtained during clinical TRUS sessions using Aloka 2000 ultrasound machine with a broadband 7 MHz linear transducer and a field of view of approximately 6 cm. An experienced radiologist manually outlined the malignant and benign regions. Manual segmentation was used as the gold standard in the performance evaluation of both methods. Before tissue segmentation, the contour of the prostate was segmented using the deformable model approach⁹. The outlined prostate was used as the input for the proposed texture

feature extraction filter to characterize and identify the malignant and benign regions.

GABOR-FILTER-BASED TRUS IMAGE SEGMENTATION

Region of interest segmentation or internal gland segmentation is a crucial phase for cancer recognition using TRUS images, and it is usually performed by the aid of an expert radiologist. With the objective of assisting the radiologist's assessment and getting accurate fast results, there is a great need for an automated ROI segmentation algorithm. As mentioned in the previous section, multi-resolution analysis is an excellent method for texture investigation. Multi-resolution analysis using Gabor filter was proposed and used for prostate ROI segmentation in^{2,3}. The used ROI segmentation algorithm is able to segment the image according to the frequency response of the pixels. The pixels that have similar

Fig 6. Ideal texture mapping to linearly separable feature space.

response are assigned to the same cluster. The Gabor function is chosen for this application for its high localization in both the spatial frequency domain and the spatial domain. Furthermore, the ROI identification algorithm used in this work relies on observing the regions selected by the expert radiologist and integrating its properties into the algorithm. The properties integrated in the algorithm are the ROI perimeter as well as its frequency level.

The details of the ROI identification algorithm are explained in detail in². Examples of some TRUS images with the experts' marked regions are shown in (a) of Figures 1, 2, 3, 4 and 5. The obtained candidate regions using the ROI identification algorithm are shown in (b) of the same figures. In (c) of each of those figures, the selected

regions after incorporating the expertise information are shown. The expertise information was utilized in this work by examining all the radiologist's identified regions and recording their circumferences and frequency levels. The candidate regions segmented by the algorithm whose circumferences and frequency levels were within the recorded values are identified as suspicious.

It is clear from the figures that the ROI identification algorithm is successful in identifying the suspicious ROIs.

The ROI identification results are excellent where the radiologist's marked regions were identified by the algorithm. However, additional regions were identified that were overlooked by the radiologist. Therefore, further analysis of the texture of the identified ROIs is important.

Fig 7. Decomposing a complex texture to reveal the regular sub-textures at different scales.

Algorithm Discussion

In the presented figures, the proposed algorithm identified the regions that the radiologist marked plus some extra regions that the radiologist did not identify. For example, in Figure 1 two out of the three identified regions did match the radiologist's identified regions. Regarding the extra regions that were identified by the proposed algorithm, these regions have the same texture properties as the regions identified by the radiologist. This means that those regions are worth looking at by the radiologist. At this point, we are trying to provide the radiologist a second opinion depending on the features embedded in the image that he cannot see with the naked eyes. The proposed algorithm has learned those features from the images marked by the radiologist and any region in the image that would have similar features is expected to be identified.

Typically identified regions are supposed to be examined by an expert radiologist who will determine whether they are really suspicious.

Our main goal in this research is to assist the radiologist in his decision making process by giving him another look at these images.

WAVELET-BASED TRUS IMAGE SEGMENTATION

In many image processing applications, it is important to distinguish between regions containing different textures. For texture characterization, the proposed filter must be able to capture the orientation, scale, and periodicity features associated with the texture. The Gabor filter was able to capture this information in the previous section, however the used gold standards were the doctor's segmented gland. Hence, another method is proposed to segment the gland and the results of the two proposed methods' segmentation should be compared. The second proposed method is based on the wavelet decomposition of the TRUS image, and it is summarized in the following subsections.

Fig 8. Overview of the proposed textural feature extraction filter.

Fig 9. Wavelet decomposition details at the four finest scales.

Defining Texture Characterization

Figure 6 illustrates the problem formulation and the ideal solution. The prostate region of the TRUS image is supposed to be used as input to the filter. Texture feature values are then obtained at the output of the wavelet-based filter, which would ideally have linearly separable malignant and benign distributions for good classification results.

Typically complex textures rarely have regular patterns. Thus, it is difficult to characterize such textures by orientation, scale, and periodicity descriptors. However, all textures could be viewed as a combination of sub-textures on several scales and this can be illustrated in Figure 7. On decomposing textures into components on different scales, regular

Fig 10. Wavelet decomposition level 1 detail difference distribution in the malignant and benign regions.

Fig 11. Enhanced wavelet decomposition level 1 detail differences.

sub-texture patterns characterizing the original texture on a particular scale might appear. In the example in Figure 7, the original texture is complex and difficult to directly characterize. However, when the original texture is decomposed into its components on four scale levels, from the finest to coarsest, regular patterns characterizing this texture at decomposition levels 2 and 3 could be noted.

The decomposition of a complex irregular texture in Figure 7 reveals some regular sub-textures on certain levels of the decomposition. However, at other levels of the decomposition, the sub-textures are irregular. Therefore, the major challenge in characterizing a complex texture using the proposed wavelet analysis consist of: (a) identifying the scales at which its sub-textures are regular and could be characterized, and (b) finding a textural feature measure which would take into account the orientation and periodicity

Fig 12. Local feature value distributions with the threshold a set to 10, 5, 3.5, and 2, respectively.

Fig 13. Local feature distributions with different degree of connectivity measure b .

characteristics of the texture. The proposed approach uses wavelet decomposition to aid in the characteristic scale identification and to capture the periodicity feature of the texture. A local texture feature will be defined to capture the orientation of the texture primitives.

Textural Feature Extraction Filter Implementation

The proposed non-linear filter consists of three levels of sub-filters that are illustrated in Figure 8.

The first level of the proposed filter consists of a wavelet decomposition sub-filter, which transforms the original image in the intensity domain to wavelet decomposition details $w_i(m, n)$ in the wavelet domain. The subscript i represents the different scale levels of the wavelet decomposition. The wavelet decomposition details are then passed through a bank of local feature sub-filters. In the proposed algorithm, *energy* is the local feature calculated. The local feature sub-filters maps the wavelet decomposition details to the local feature domain, while keeping the local feature values

localized in the spatial domain. The local feature values at different scales of the wavelet decomposition form the output of the filter and are used to characterize and identify the individual textures in the spatial domain. The following section describes the proposed method in more detail.

Fig 14. Sample classification result 1 with local feature value thresholds of 8 and 25.

Fig 15. Sample classification result 2 with local feature value thresholds of 8 and 25.

Proposed Wavelet-based Method

Wavelet Decomposition Sub-filter

The wavelet decomposition expresses the image data as a superposition of scaling functions, which present a coarse representation of the image, and wavelets, which represent the details of the image. The common expression for the discrete wavelet transform (DWT) in 2-D is as follows:

$$f(m, n) = \sum_k \sum_l c_{i_{\max}}(k, l) 2^{i_{\max}/2} \varphi(2^{i_{\max}/2} m - k, 2^{i_{\max}/2} n - l) \\ + \sum_k \sum_{i=1}^{i_{\max}} d_i(k) 2^{i/2} \psi(2^{i/2} m - k) \\ + \sum_l \sum_{i=1}^{i_{\max}} d_i(l) 2^{i/2} \psi(2^{i/2} n - l) \\ + \sum_k \sum_l \sum_{i=1}^{i_{\max}} d_i(k, l) 2^{i/2} \psi(2^{i/2} m - k, 2^{i/2} n - l)$$

where $c_{i_{\max}}(k, l)$ is the approximation coefficients, $d_i(k, l)$ is the difference coefficients, $\varphi(m, n)$ represents the scaling function and $\psi(m, n)$ represents the wavelet.

The proposed wavelet decomposition filter takes as input the original image and outputs the wavelet decomposition details at scale levels from $i=1$ (finest scale) to $i=i_{\max}$, where $i_{\max}$ is the coarsest scale level required to describe the texture. The wavelet decomposition is accomplished with the discrete filter D9 from Daubechies¹³.

The used filter is implemented with a DWT quadrature mirror filter (QMF). To maintain the resolution at each scale, the filtered results are not down-sampled as is the norm in common QMF designs.

Local Feature Filter

In order to construct a local feature filter that maximally linearly separates the malignant and benign regions, textural characteristics that distinguish the two regions should be identified. This means that on plotting the probability density functions of both classes, their peaks should be as far as possible so that they can be separated by thresholding the local feature's value.

Fig 16. Classification result 3 with local feature value thresholds of 8 and 25.

Fig 17. Classification result 4 with local feature value thresholds of 8 and 25.

The proposed approach attempts to mimic the prostate biopsy operation. In the biopsy operation, tissue samples are obtained in regions of the prostate that are deemed to have high probability of cancer. The tissue samples are then observed using the microscope to determine the grade of cancer. The prostate cancer grading system was developed by Gleason¹⁴. From¹⁴, it can be concluded that, pathologically, the more serious the tumor, the more the glands will lose shape and structure and start to fuse.

Although it is doubtful that glandular level details could be captured by a 7-MHz transducer, due to its limited resolution, it is likely that part of this textural pattern is reflected in the fine resolution speckles in the TRUS image due to the differing parenchyma of the malignant and benign tissues.

Passing the input image in Figure 6 through the wavelet decomposition filter, the detail differences on the four finest resolution scales are given, which is displayed in Figure 9.

Examining the wavelet decomposition detail difference images at the finest resolutions, $W_1(m, n)$ and $W_2(m, n)$, it could be noted that the texture in the benign regions have a more ordered appearance. However, the textures in the malignant regions are more disordered and granular. This is consistent with the pathological description of

tumor, with the benign regions consisting of uniform glands and malignant regions having destroyed uniform structures.

Figure 10 shows the histogram of the wavelet decomposition detail difference $W_1(m, n)$.

From Figure 10, it could be noted that at the finest wavelet decomposition level, the detail difference values in the malignant region are distributed in a more narrow range around zero as compared to the detail difference values in the benign region. This implies that it is possible to choose a threshold σ as a tool to separate the malignant and benign regions. Since the distribution shows that for detail difference values below σ , the associated pixel is much more likely to be benign than malignant. It is found that by shifting $W_1(m, n)$ up by the value σ , the details in malignant and benign regions can be enhanced visually. This is because in the original $W_1(m, n)$, values above 0 appear as bright image elements while those below appear as dark ones. As $W_1(m, n)$ is shifted up by the value σ , due to the more narrow distribution of the malignant region difference values, the perceived brightness is increased effectively in the malignant region compared to the benign region. This is shown in Figure 11 where σ is set to 3.5.

Fig 18. Classification result 4 with local feature value thresholds of 8 and 25.

Fig 19. Classification result 4 with local feature value thresholds of 8 and 25.

It can also be noted in Figures 10 and 11 that in the fine scale wavelet decomposition detail the benign region is characterized by almost uniform horizontal lines. In the proposed algorithm, an attempt is done to capture this characteristic by counting the amount of horizontally connected image elements with values below the threshold σ in a local neighborhood, which constitutes the local feature value for the center image element of that local neighborhood. The degree of connectivity is defined in this work by a parameter b , such that if b is set to 3 and there are three horizontally connected pixels below the threshold σ in the local neighborhood, the local feature counter would increase by 1.

To find the optimal values of σ and b to separate the malignant and benign distributions in the local feature domain, the neighborhood within which the local feature values are counted is set to be 24×24 image elements. Then, to find the optimal value for the threshold σ , b is set to be constant of 2, and the distributions of the local feature values in the malignant and benign regions were plotted with $\sigma=10$, $\sigma=5$, $\sigma=3.5$, and $\sigma=2$. The histogram of local feature value distributions is displayed in Figure 12.

From Figure 12, it can be noted that the threshold yielding the highest linear separation for the local feature values in the malignant and benign regions is $\sigma=3.5$. At this threshold, the modes of the malignant and benign distributions are separated by a feature value distance of 25, which approximately covers half of the malignant distribution range.

Likewise, we can find the optimal characterizing degree of connectivity value b , by plotting the feature value distributions when b is varied. In Figure 13, the feature value distributions are plotted with σ held constant at 3.5 and b set to 1, 2, 3, and 5, respectively.

From Figure 13, it is noticeable that $b=2$ and $b=5$ yields good linear separation of the local feature distributions. For $b=2$, the modes of the distributions are separated by feature value distance of 20, which is approximately half of the range of the malignant distribution. For $b=5$, the modes of the distributions are separated by a distance of 16, which almost covers the entire range of the malignant distribution. Therefore, a characteristic degree of connectivity value of 5 is selected for the subsequent analysis.

Identifying Regions with Proposed Texture Feature Extraction Filter

With the local feature distributions characterized by the parameters σ and b , TRUS images suspected to have malignant tumor could be evaluated with the following steps:

1. Apply the proposed filter to the TRUS image, the input image is then transformed to the wavelet domain and then the local feature domain. The local feature values are then calculated for each discrete image element.
2. Classify the image elements using the local feature values as input to a classifier.
3. The classifier used in step two could be a complex classifier such as a neural network or fuzzy inference system. However, to demonstrate the effectiveness of the textural feature extracted using the proposed algorithm, the simplest classifier, thresholding, will be used for the subsequent analysis.

Figure 14 demonstrates the classification result by setting the local feature value threshold to 8 (dark gray) and 25 (light gray) for the training image (white represents benign region).

RESULTS AND DISCUSSION

In this section, the effectiveness of the proposed wavelet-based textural feature extracted is examined by applying the proposed approach to 23 TRUS images distinct from the training image used to characterize the local textural feature distributions. Thresholding is used as the classification method. In Figures 15, 16, 17, 18, 19 and 20, the desired classification, enhanced level 1 detail difference image, and the resulting classification of eight of the evaluation images are displayed. For

the resulting classification image, feature value thresholds of 8 and 25 are used.

The proposed wavelet-based textural feature could effectively identify most of the malignant regions in the evaluation images. Most of the segmentation results are already apparent in the enhanced level 1 detail difference image. In fact, the enhanced detail image contains lots of information that could be effective as a decision support tool for radiologists for manual region segmentation. The value of the extracted textural features lies in their ability to be used as input to complex

Fig 20. Comparison between both algorithms. (a) Doctor's annotation, (b) wavelet segmentation, (c) Gabor segmentation.

classifiers for robust automated malignant and benign region identification.

ALGORITHM COMPARISON

The two proposed algorithms in this work rely on the same multi-resolution analysis base. The Gabor filter designed for this work was located at high frequency since it is expected that the difference in texture between the cancer and non-cancer textures occurs at high frequency. This algorithm did not

need any training images, and it also involved some information that was extracted from the doctor's marked regions. As shown from the figures, it is clear that the proposed method was able to identify the suspicious regions effectively.

Moreover, another multi-resolution-based method is proposed in this work that is based on the same idea but it looked at all the different detail levels. It is also clear from the figures that the wavelet-based methods did obtain very good gland segmentation.

Both methods were designed independently and were applied on the same set of images. The ROI

Fig 21. Comparison between both algorithms. (a) Doctor's annotation, (b) wavelet segmentation, (c) Gabor segmentation.

segmentation results for both of the proposed algorithms are compared and the results are shown in Figures 20, 21 and 22 in which panels (a) of each of those figures are the radiologist's outlined regions, panels (b) in each of the figures are the wavelet-based segmentation, and panels (c) in each of the figures show the Gabor-filter-based segmentation. It was found from the figures shown that both methods highly agree on the resulting segmentation results, which proves the ability of each of them to identify the suspicious regions.

From the results shown in this paper, any or both of the proposed methods can be considered a decision support for the doctor and can help in the doctor's decision making process.

It is also worth mentioning that this current study is a proof of concept and is considered a preliminary study to prove the ability of both methods to mimic the radiologist's decision. This study did achieve its goal. In our future work, a more comprehensive dataset that includes the biopsy result will be used and analyzed.

Fig 22. Comparison between both algorithms. (a) Doctor's annotation, (b) wavelet segmentation, (c) Gabor segmentation.

CONCLUSIONS

In this paper, two different methods are proposed to internally segment the prostate gland from the TRUS images for the purpose of suspicious region identification. Both methods are based on the multi-resolution analysis. The first method depends on only one Gabor filter placed at high frequency to capture the frequency changes while the other method depends on the wavelet decomposition that extracts a local texture feature which linearly separates the cancer and non-cancer regions within the prostate using TRUS images. The wavelet-based filter separates the complex texture details in the TRUS image into sub-components at different resolution scales. It is demonstrated that the decomposition details on the finest scale are a coarse representation of pathological inter-nodule arrangements that is indicative of the degree of abnormality. Moreover, a single textural pattern is extracted with the proposed textural extraction filter from the level 1 decomposition details in order to construct a local texture feature that separates the normal and suspicious feature values. The effectiveness of these two methods is verified by applying the feature to classify suspicious regions in 23 TRUS images using the simple thresholding approach. Both algorithms highlighted almost the same suspicious regions in the test images. This result indicates that the proposed methods did achieve their goal of suspicious region identification. Moreover, the results show the ability of either the Gabor-based method or the wavelet-based method to act as a decision support for doctors to choose the biopsy locations. Since the only available gold standards in this work are the radiologist's identified ROIs, that are irreproducible and hard to obtain, therefore, obtaining the same ROIs using both the proposed methods proves the importance of each of them to identify the suspicious ROIs.

This will ultimately lead to enhance the sensitivity and specificity of the cancer recognition system.

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