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Prostate Ultrasound Image Processing

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Introduction

Prostate cancer is the second most common cancer found in men in the United States and a leading factor in cancer-related deaths. It is a major health issue causing a dramatic impact on the lifestyle of elderly men. Treatment is, however, available, but most successful when the cancer is in an early stage; treatment of an advanced cancer, especially if the spread is beyond the prostate, can be very complex and in many cases incurable. To find the cancer still in an early stage it important for men over the age of 50 to get an annual screening. Presently, several different screening techniques are used to diagnose the presence of the prostate carcinoma, the most common of which are digital rectal examination (DRE), prostate specific antigen (PSA) test and transrectal ultrasound (TRUS). In cases where the presence of cancer is highly suspected, a biopsy usually follows the screening to fully confirm the diagnosis.

The DRE is a procedure in which the doctor checks the size, shape, and texture of the prostate by inserting a finger into the rectum of the patient. This procedure is not accurate because only the back wall of the prostate is examined (the middle and front of the prostate remain undiagnosed) and only if the cancer is in an already advanced stage, will a noticeable difference in the texture be recognized.

The PSA test, which commonly accompanies the DRE, measures the amount of prostate specific antigen in the blood. A high PSA level usually indicates the presence of cancer, however, because common diseases and infections of the prostate, such as benign prostatic hypertrophy (BPH) and prostatitis, cause an elevation in the PSA level the accuracy of the diagnosis cannot be determined. Furthermore, many patients with normal PSA levels were later diagnosed with cancer.

TRUS is the most common medical imaging modality used in the screenings, followed by X-ray computer axial tomography (CAT) which is used to diagnose the spread of the cancer beyond the prostate. TRUS is inexpensive, provides the radiologist with enough detail to recognize any abnormalities within the prostate, and can also be used in guiding a biopsy in real-time. TRUS usually accompanies the DRE and PSA test, because it does not provide enough detail to be used as the only screening technique in the diagnosis.

In a typical TRUS screening, the prostate is manually delineated in the ultrasound image to calculate its size and volume, which are additional details used to support the diagnosis. Because manual segmentation of the prostate is very tedious and usually prolongs the diagnosis, automated delineation of the prostate is necessary. Computer aided segmentation leads to faster, and more accurate and precise results, without much interference from the doctor, [7]. Segmentation of the prostate within the ultrasound image can be further used for real-time biopsy guidance, automatic volume determination, and computer automated analysis of the prostate for cancer and abnormal regions.

Different methods of delineating the prostate, such as those presented in [3,5,7,8], have shown to be successful in segmenting the prostate, however still requiring the input of the doctor to identify the prostate. The present study presents an algorithm of automatically identifying the prostate within the TRUS image. Successful automatic identification of the prostate is crucial to the success of an automatic segmentation algorithm. A method of delineating the prostate is also presented.

Algorithm Design

Introduction

Detection of the prostate body in a TRUS image can be understood as detection of edges, because region boundaries in medical ultrasound images are linear features created by different tissue properties. The detection of edges in ultrasound images is a challenging task because of the high level of speckle noise corrupting the image. High contrast regions can, however, be successfully detected by low-pass filtering the image and applying edge-detection operators (eg. Sobel, Prewitt, Laplacian of Gaussian [11]) to highlight the linear features.

TRUS prostate images present the additional difficulty of low contrast boundaries which are difficult to identify after low-pass filtering because low-pass filters, although reduce speckle noise, also rid of much detail. A different filtering method, presented by Czerwinski in [1], is used for speckle filtering.

Speckle Reduction

Traditional Filtering

Low-pass filters are successful in filtering the speckle from the TRUS prostate images, because speckle has similar characteristics to random multiplicative noise and low-pass filters filter out such noise by attenuating high frequency detail in the image based on global or regional details. The most simple and most commonly used low-pass filter is the arithmetic mean filter, or simply averaging filter. The averaging filter is mathematically defined as:

Filter 1 (Arithmetic Mean Filter) Given original image f and a small neighborhood of n pixels, S_{xy}, surrounding pixel (x,y) such that $S_{xy} \in f$ and $(x,y) \in S_{xy}$, the gray level of pixel (x,y) in filtered image g is $g(x,y) = 1/n \sum$ figure $S_{xy}(i)$, where $S_{xy}(i)$ is the ith of n pixels in S_{xy}.

From the above definition, one can see that if a pixel is part of the noise, its gray level is attenuated by taking the average gray level of the pixels surrounding it; the averaging filter smooths areas of high frequency and changes already constant areas only by little. A more complicated filter is the median filter, which is defined as:

Filter 2 (Median Filter) Given the details of Filter 1, the gray level of pixel (x,y) in g is $g(x,y) = \mathbf{median}\{S_{xy}(i)\}$, for $i = 1 \ldots n$.

The above non-linear filter is more robust than the averaging filter. Gray levels that are likely to be noise will not be averaged into the interpolated result, because the filter chooses the gray level that is closest to the majority of the pixels - the median gray level. Similar to the above filters, taking into account the values of neighboring pixels to interpolate the new pixel value, although with better performance than the arithmetic mean filter in keeping edge detail is the geometric mean filter defined below:

Filter 3 (Geometric Mean Filter) Given the details of Filter 1, the gray level of pixel *(x, y)* in *g* is $g(x,y) = \left[\prod \text{figure } S_{xy}(i) \right]^{\mu}$, where $\mu = 1/n$.

Filters 1 through 3 replace the gray level $f(x,y)$ by taking into account the surrounding detail and attenuating the noise by lowering the variance, σ^2. These filters are known as smoothing spatial filters, with the median and geometric mean filters outperforming the arithmetic mean filter in reducing noise while still preserving edge details. Increasing neighborhood size, *n*, results in higher noise attenuation, but also loss of edge detail. For further details on spatial filters and in-depth explanations see [4].

Sticks Filtering

Further study of the performance of low-pass filters and adaptive low-pass filters has shown that these filters, although successfully filter much of the speckle, cause a loss of detail in low-contrast border regions. An alternative method of filtering speckle, using *sticks* as proposed in [1] and used in [7] as a smoothening filter, was implemented with success.

The sticks filtering algorithm challenges the problem of filtering speckle in ultrasound images, without losing edge detail, by determining weather a linear feature passes through pixel *(x,y)* and then calculating the filtered pixel intensity $g(x,y)$, which is the arithmetic mean of neighboring pixels in the direction of the *stick* - the most likely direction of the linear feature passing through *(x,y)*. Below is a formal definition.

Filter 4 (Sticks Filter) Given original image *f*, stick length, *n*, and stick thickness *k*, the set of all sticks is $S = \{s_{\theta i} \mid i = 1 \ldots 2n-2\}$, where $s_{\theta i}$ is a stick of length *n*, thickness *k* and orientation θ_i. Assuming *n* is the length in pixels, there are $2n-2$ possible orientations the stick can be uniquely arranged in. Mathematically, a stick can be described as a spatial filtering mask:

$$s_{\theta i}(s,t) = \{ 1/n, \text{ if } (s,t) \text{ is along angle } \theta_i;\ 0, \text{ otherwise.} \},\ \text{for all } (s,t) \in D[\, s_{\theta i} \,]. \qquad \mathbf{(1)}$$

From the above definition of a stick, it is important to see that convolving *f* with $s_{\theta i}$ smooths the speckle while highlighting the linear features in direction θ_i. However, pixels with lines passing through them in direction θ_j, where $j \neq i$, will be assigned an undesired gray level. To correctly filter f, it is important to define the set of all images, each highlighting a different direction θ_i :

$$H=\{h_i \mid i=1...\ 2n-2\}, \text{ where } h_i=f * s_{\theta i} . \qquad \textbf{(2)}$$

Each pixel (x,y) will then be have a gray level $g(x,y)$, such that,

$$g(x,y)=\mathbf{max}\{h_i(x,y)\}, \text{ for } i...\ 2n-2. \qquad \textbf{(3)}$$

By implementing the concept of a *stick* passing through each pixel (x,y) and using that stick as a basis for the interpolated intensity $g(x,y)$, the final filtered image g, will be smooth and contain contrast enhanced region borders. An example of a set of sticks S, of length five pixels and one pixel thickness is shown in Fig. **1**, where the white and black pixels have a value of 0 and $1/5$, respectively.

Figure 1. Set of sticks with $n=5$ and $k=1$.

Various stick lengths and thicknesses have different filtering effects. Increasing stick length leads to a more smoothly filtered image, at the expense of weakly highlighting tightly bound curves - a result of the stick being longer than some of the boundary edges. Similarly, thicker sticks suppress more noise at the expense of making thin boundaries less visible. A thick stick can be used to smooth noise similar to an arithmetic mean filter, with the addition of highlighting broad region differences.

Generally, it is important to implement a stick length that is longer than the noise correlation length and shorter than the length over which boundary edges are straight. Fig. **2** shows an image filtered with different stick lengths and thicknesses. All three filtered images clearly show an increase of contrast near the prostate borders, and reduced speckle noise with increasing stick length. An in-depth study of the effects of stick length and thickness on ultrasound image filtering is presented in [**2**].

Figure 2. a.) Original image. b.) Filtered: *n=5 k=1*. c.) Filtered: *n=7 k=3* d.) Filtered: *n=15 k=1*.

Region Identification

The algorithm used in the present study to identify the prostate body region is based on the prostate center seeking algorithm presented in [8].

Algorithm 1 (Region Identification) Given original image f, the speckle noise is low-pass filtered using the sticks filter with a stick length of 5 pixels and thickness of 3 pixels to get f_l, which is again filtered using the sticks filter, however, now with a stick length of 15 pixels and thickness of 1 pixel to get the smooth image f_s. Similar to the algorithm presented in [8], the top-hat transformation h_s, and bottom-hat transformation b_s, of f_s are used to increase the contrast near edges according to the following equation:

$$f_c = f + h_s - b_s. \qquad \textbf{(4)}$$

Small regions in f_c are then filled, resulting in f_f, which is further transformed by a global thresholding function, to get f_t, where:

$$f_t(x,y) = \left[\, 1 + \left(m \,/\, f_f(x,y)\right)^E \,\right]^{-1}, \text{ where } m = \mathbf{max}\{f_f\} - \mathbf{mean}\{f_f\} \text{ and } E = 7. \qquad \textbf{(5)}$$

The thresholded image is then binary thresholded and a dilation with a small disk is performed to close any small gaps, with f_b as the result. The binary image f_b is then eroded $k-1$ times with a similar small disk used for the dilation, assuming that the kth erosion will result in an empty image. The result is a small number of pixels within the prostate body. Please see [4] for a description of thresholding functions, including (5), and further information on morphological operators (e.g erosion, dilation, top-hat, bottom-hat, etc.).

The performance of the algorithm proposed in [8] and the algorithm proposed in the present study was tested on 144 random images. Fig. 3 shows a successful and unsuccessful mapping of the prostate. The algorithm proposed in the present study had a 88.9% success rate in mapping a point in the prostate body, while the algorithm proposed in [8] had a 84.0% success rate, the present algorithm showing an improvement of 4.9%.

Figure 3. a.) Successful mapping. b.) Unsuccessful mapping.

Region Delineation

Given the mapped point within the prostate body, the second goal of the present study is to detect the edges of the prostate, moving radially out from the found point. To highlight the edges, the image is filtered to reduce speckle noise and different traditional operators, including Sobel, Canny, Prewitt, and Laplacian of Gaussian are used to create an edge map. The edge map is then used to create an external force for active contours, called the *gradient vector flow* (GVF) [10].

An active contour, or snake, is a curve, $\boldsymbol{x}(s)$, with internal (tension and rigidity) and external (linear features and boundaries) forces, that moves through the spatial domain of an image, minimizing an energy function, E, where

$$E= \text{Snake energy function.}\ 1/2\left[\alpha|\boldsymbol{x}'(s)|^2+\beta|\boldsymbol{x}''(s)|^2+E_{ext}\boldsymbol{x}(s)\right]\ ds, \qquad \textbf{(6)}$$

and α is the adjustable weight of the snake's tension, β is the adjustable weight of the snake's rigidity and $\boldsymbol{x}'$ and $\boldsymbol{x}''$ are the first and second derivatives of $\boldsymbol{x}$ with respect to s. A normalized GVF field is used as the external force to minimize E and iteratively solve the GVF snake according to:

$$\boldsymbol{x}_t(s,t)=\alpha\boldsymbol{x}''_t(s,t) - \beta\boldsymbol{x}''''_t(s,t)+\boldsymbol{v}, \text{ where } t \text{ is time and } \boldsymbol{v} \text{ is the GVF field.} \qquad \textbf{(7)}$$

The above equations and further details regarding the solution to the GVF snake are explained in detail in [9] and [10].

The GVF snake is successful in delineating objects in images with low speckle, including MRI images, however Fig. 4 shows the result of a GVF snake (red) in an ultrasound image, initialized on the point detected within the prostate (yellow). To solve the GVF, the original image was filtered using the sticks filter and the Canny method was used to create the edge map to which the GVF algorithm, with 500 iterations, was then applied. As shown in Fig. 4 the convergence of the GVF snake towards the prostate boundary (green) clearly failed because of the presence of false boundaries within the prostate after filtering, indicating the need to improve speckle filters and edge detection methods.

Figure 4. Initial snake (yellow) converged (red) towards prostate boundary (green).

Conclusion

The present study presents a different method of filtering speckle noise without the loss of much edge detail in the filtering process. Under the assumption that the prostate body has a lower average gray lower than its boundary, an algorithm based on sticks filtering to detect the body of the prostate is developed, with a success rate of 88.9%. The second goal of the study, to delineate the prostate body, was unsuccessful - the GVF snake failed to even closely converge towards the prostate boundaries. Studies of incorporating different prostate segmentation methods are presented in [3,5,7,8], and considered as alternatives in future studies.

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Biography

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