

SVM과 회전 불변 텍스처 특징을 이용한 TRUS 영상의 전립선 윤곽선 검출

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요약

전립선은 남자에게만 있는 장기이다. 전립선의 질병을 진단하기 위하여 일반적으로 TRUS 영상이 사용되는데, 희미한 전립선 경계나 잡음, 좁은 그레이 레벨 분포 때문에, 전립선의 경계를 검출하는 것은 상당히 어려운 작업 중의 하나이다. 본 논문에서는 SVM을 사용하여 TRUS 영상에서 자동적으로 전립선 분할을 하는 방법을 제안한다. 이 방법은 전처리, 가버 특징 추출, 훈련, 전립선 분할 과정으로 진행된다. 전처리 과정에서 잡음 제거는 스틱 필터와 top-hat 변환이 적용된다. 회전 불변 텍스처 추출을 위하여 가버 필터 뱅크가 사용된다. 훈련과정에서 SVM은 전립선과 비전립선의 각 특징을 얻기 위해 사용되며, 마지막으로 전립선 경계가 추출된다. 여러 실험 결과로 제안 방법은 충분히 유효하고, 의사의 수동 추출 방법과 비교했을 때 10%미만의 경계 차이를 보였다.

키워드: 가버 특징, 전립선 암, 전립선 윤곽, SVM

Detecting the Prostate Contour in TRUS Image using Support Vector Machine and Rotation-invariant Textures

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Abstract

Prostate is only an organ of men. To diagnose the disease of the prostate, generally transrectal ultrasound(TRUS) images are used. Detecting its boundary is a challenging and difficult task due to weak prostate boundaries, speckle noise and the short range of gray levels. In this paper a method for automatic prostate segmentation in TRUS images using Support Vector Machine(SVM) is presented. This method involves preprocessing, extracting Gabor feature, training, and prostate segmentation. The speckle reduction for preprocessing step has been achieved by using stick filter and top-hat transform has been implemented for smoothing. Gabor filter bank for extraction of rotation-invariant texture features has been implemented. SVM for training step has been used to get each feature of prostate and nonprostate. Finally, the boundary of prostate is extracted. A number of experiments are conducted to validate this method and results shows that the proposed algorithm extracted the prostate boundary with less than 10% relative to boundary provided manually by doctors.

Keywords : Gabor feature, Prostate Cancer, Prostate Contour, SVM

1. Introduction

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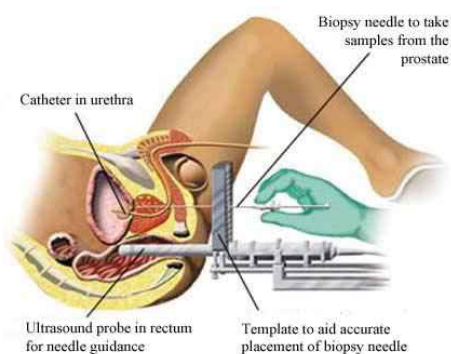
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According to the American Cancer Society, dead rate is decreasing every year caused by prostate cancer, but it is 23 per 100,000 people in 2007 [1]. Prostate cancer is the most frequently diagnosed cancer in men and the second cancer-related cause of death for them [2][3]. The rate is second highest value

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following the dead rate of lung and bronchus. Hence diagnosis of the cancer of the early stages is crucial. Ultrasound(US) imaging is a widely used technology for diagnosing and treatment this kind of cancer [4]. Especially, prostate transrectal US (TRUS) prostate images are captured easier and with lower cost. In (Figure 1) an example of TRUS image capture is shown.

US imaging is the main modality for prostate cancer diagnosis and treatment, due to many of its clinical advantages, expensive and easy to use. Accurate segmentation of prostate boundaries from US images plays an important role in many prostate-related applications such as the accurate placement of the needles and biopsy, the assignment of the appropriate therapy in cancer treatment, and the measurement of the prostate gland volume [5]. Moreover, the shape of the prostate in US images is considered as an important indicator for staging prostate cancer. But, because the boundaries between prostate and nonprostate of the image are ambiguous, an automatic extraction of the boundaries has some difficulties [6][7]. Such that, they are very weak texture structure, low contrast, fuzzy boundaries, speckle noise and shadow regions. To cope with the problems, different methods have been studied.



(Figure 1) Placements of human organs and US probe

Deformable segmentation using G-SVM was

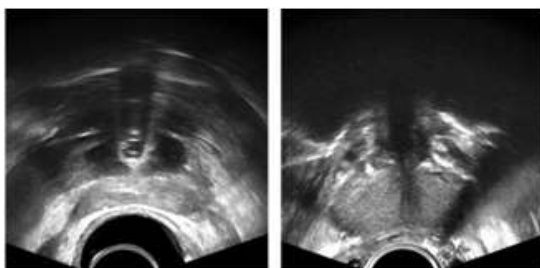
proposed based 3D prostate images [6]. New paradigm for the edge-guided delineation was proposed, providing the algorithm-detected prostate edges as a visual guidance for the user to manually edit [8]. Statistical shape model for outlining prostate boundary from 2D TRUS images was designed [9]. Level set based method was presented to detect prostate surface from 3D US images [10]. Automatic segmentation for the prostate from 2D TRUS was proposed using adaptive learning local shape statistics [11]. Automatic segmentation of the prostate in 3D TRUS images was presented by extracting texture features and by statistically matching geometrical shape of the prostate [12].

Until now most studies needed a help of human expert and didn't find any tumors. Our method has preprocessing, extracting Gabor feature, training and prostate segmentation. First step processes histogram equalization, removes background and probe, and tick filters for removing speckle noise. The reason why it removes the background and the probe is to reduce the computing space. The removed spaces absolutely are nonprostate region. Histogram equalization enhances contrast and equalizes the contrasts of different images. Extracting Gabor feature step extracts and characterizes texture features using Gabor filters at multiscales and multiorientations. Training step trains Gabor texture features according to whether the pixels belong to prostate and nonprostate using SVM. By the results of SVM, each pixel of the test image is classified to one of two. And then, since none of all pixels in the images are accurately classified, the final step applies snake-like algorithm and gets the smooth boundaries between them. The results experimented from 20 test images made difference by 10% compared to one of human expert.

2. Related Studies

2.1 US Prostate Contouring

US prostate image has a lot of noise and is hard to delineate the boundaries like (Figure 2) Especially, the base and apex parts of prostate are generally unclear or broken, since these boundaries are almost parallel to US beams of the transducer. Therefore, the images of the two parts are almost impossible to delineate the boundaries without reference of their neighbor's boundaries.



(Figure 2) Images of the base and the apex

The boundary of deformable model is subsequently driven to the boundary between the tentatively labeled prostate and nonprostate tissues, while its shape is limited by pre-constrained shape [4][6]. Tentative tissue labeling and subsequent deformation are repeated until they converge to the boundary in the prostate images. Another method is to use 3D segmentation [6][12]. Using 3D image the method get the statistical boundary model from apex to base. The boundaries of an image are adjusted within a certain limit of the pre-acquired 3D model. Disadvantages of these methods can't find abnormal protrusions like tumor.

2.2 Gabor Transform and SVM

Gabor transform is a special case of the short-time Fourier transform and used to determine the sinusoidal frequency and phase content of local sections of a signal as it changes over time. The function to be transformed is first multiplied by a Gaussian function, which can be regarded as a window,

and the resulting function is then transformed with a Fourier transform to derive the time-frequency analysis. The window function means that the signal near the time being analyzed will have higher weight. Gabor transform of a signal $x(t)$ is defined by this formula

$$G_x(t, f) = \int_{-\infty}^{\infty} e^{-\pi(\tau-t)^2} e^{-j2\pi f\tau} x(\tau) d\tau$$

Gaussian function has infinite range and it is impractical for implementation. But take a look at the distribution of Gaussian function.

$$\begin{cases} e^{-\pi a^2} \geq 0.00001; |a| \leq 1.9143 \\ e^{-\pi a^2} < 0.00001; |a| > 1.9143 \end{cases}$$

Gaussian function with can be regarded as 0 and also can be ignored. Here, is time(sec). Thus Gabor transform can be simplified as

$$G_x(t, f) = \int_{-1.9143}^{1.9143} e^{-\pi(\tau-t)^2} e^{-j2\pi f\tau} x(\tau) d\tau$$

Here, τ is window time at the center of window. This simplification makes Gabor transform practical and realizable. Gabor transform is invertible. The original signal can be recovered by the following equation.

$$x(t) = \int_{-\infty}^{\infty} G_x(t, f) e^{j2\pi t f} df$$

The standard SVM takes a set of input data and predicts, for each given input, which of two possible classes comprises the input, making the SVM a non-probabilistic binary linear classifier. Given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other. The original optimal hyperplane algorithm by Vapnik in 1963 was a linear classifier. Linear SVM gives some training data D , a set of n points of the form.

$$D = \{(x_i, y_i) | x_i \in R^p, y_i \in \{-1, 1\}\}_{i=1}^n$$

where the y_i is either 1 or -1 , indicating the class to which the point x_i belongs. Each x_i is a p -dimensional real vector. We want to find the maximum-margin hyperplane that

divides the point shaving $y_i = 1$ from those having $y_i = -1$.

[13] suggested a way to create nonlinear classifiers by applying the kernel trick to maximum-margin hyperplanes in 1992. The resulting algorithm is formally similar, except that every dot product is replaced by a nonlinear kernel function. This allows the algorithm to fit the maximum-margin hyperplane in a transformed feature space. The transformation may be nonlinear and the transformed space high dimensional; thus though the classifier is a hyperplane in the high-dimensional feature space, it may be nonlinear in the original input space.

3. Gabor Texture Extraction and Training

In the algorithm, the first three steps are repeated several times as the training images.

3.1 Preprocessing

Preprocessing step processes histogram equalization to enhance the contrast of images by transforming the values in an intensity image, so that the histogram of the output approximately matches a specified histogram. Stick filtering filters to reduce the speckle noise. Morphological filtering is used to smooth filtered image and enhanced contrast near edges. Final step gets background and probe which will be used to be excluded for training. Histogram equalization considers a discrete gray scale image, x , and lets n_i be the number of occurrences of gray level, i . The probability of an occurrence of a pixel level, i in the image is

$$P_x(i) = p(x=i) = \frac{n_i}{n}, 0 \leq i < L$$

Here, $P_x(i)$ is in fact the image's histogram for pixel value I , L is the total number of gray levels in the image and, n is the total number of pixels in the image. The stick

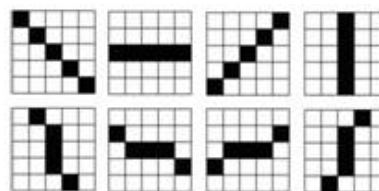
filtering algorithm challenges the problem of filtering speckle in US images without losing edge detail. The stick filter determines the mean of neighboring pixels in the direction of the stick - the most likely direction of the linear feature passing through (x, y) . If n is the stick's length, there are $2 \cdot n - 2$ possible orientations. We use 5 length pixels as shown (Figure 3) Morphological filtering applies the top-hat and bottom transformation on output of stick filter (F_s) with using a ordinary neighborhood window. We use a disk with radius 3 in top-hat, bottom-hat transformation.

$$H_t = top - hat(F_s)$$

$$H_b = bot - hat(F_s)$$

$$F_p = F_s + H_t - H_b$$

H_t is the top-hat and H_b is the bottom-hat transformation and F_p is the preprocessed image. We get background and probe, and then exclude them in step of training. Generally the background is black and is apparently unusable region. The probe which is generally an exploring needle in (Figure 1) but is a half circle shaped black region in (Figure 2). This is useless region as well.



(Figure 3) Filtering masks of five length pixels

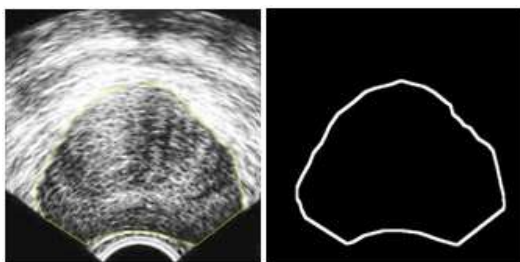
3.2 Extracting and Training Gabor Textures using SVM

The dilation and rotation of the mother function obtains Gabor filter bank. Here, we use that total numbers of the orientations are $K=4$, the scale numbers of the scales are $S=2$. So the basic rotation and scale factors are $\psi = \pi/K$ and $a = (U_h/U_l)^{1/S-1}$, respectively. U_h and U_l are parameters that determine the frequency range of Gabor filter bank. We use $U_h=0.1$ and $U_l=0.025$. Using the scale variables

and the rotation variables, the (s,k)th Gabor filter is

$$g_{s,k}(x,y) = asg(as(xcos(k\psi) + ysin(k\psi)) as(-xsin(k\psi) + ycos(k\psi)))$$

Gabor filter bank has two important properties, the frequency spectrum of the filter bank has a multiscale and multiorientation structure and each filter can be separated into two parts, i.e., the real part and the imaginary part. The real part is regarded as a smooth filter and the imaginary part is done as an edge detection filter. Using Gabor filter bank offers three advantages. First, it can smooth the image and remove speckle noises. Second, the multiscale structure enables hierarchical implementation. Third, the multiorientation structure enables the extraction of edge direction, edge strength and rotation-invariant features. We use the imaginary parts, but the real part Gabor features can be used. So the proper negotiation is needed. In this paper, we use 8 Gabor texture features per pixel which consist of K=4, S=2 and the imaginary part Gabor features. Each pixel should be classified to prostate or nonprostate to train the features using SVM.



(Figure 4) Prostate area from human expert

Originally, no one knows whether each pixel belongs to which region. To classify the region, the human expert is needed. The inner part of the contours drawn by the expert is prostate and the outside of the contours is nonprostate. The pixels around the contour acquired from the expert and the useless region are excluded in the training process. Why the pixels around the contour are

excluded is that they don't have classifiable features comparing to other regions.

Next, each pixel has 8 Gabor texture features which will be trained and have the following input format.

```
-1 1:33.248316 2:34.518724 3:19.255745 4:4.296715
5:33.996764 6:35.103513 7:19.049476 8:3.813344
1 1:-5.961116 2:-1.852036 3:2.131680 4:4.366701
5:-6.335777 6:-1.963415 7:1.260157 8:3.865562
```

-1 and 1 of first columns mean nonprostate and prostate, respectively. The numbers from 1 to 8 mean each pixel's Gabor feature orders that the first 4 features (1-4) are S=1 and K=1, 2, 3, and 4, and the next 4 ones (5-8) are S=2 and K=1, 2, 3, and 4, in the order named. The real numbers are the values of Gabor texture feature. After training the features, a number of support vectors and their coefficients are acquired. <Table 1> is support vectors. All the first values, 1s, are just indices that the values are from 1 to the number of support vectors, the second values, 1-8, are the same as the input indices. Their coefficients consist of -1 or 1 as the number of support vectors.

Indices	Gabor texture features
(1,1)	10.3537
(1,2)	11.3592
(1,3)	15.5525
(1,4)	16.1532
(1,5)	16.2178
(1,6)	15.9830
(1,7)	12.4169
(1,8)	11.4315

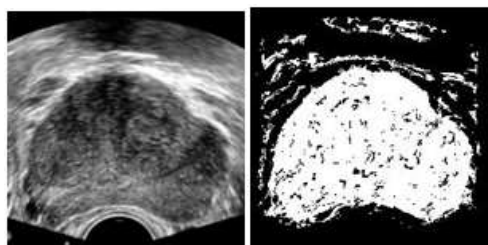
<Table 1> SVs from trainings

3.3 Grouping the Pixels

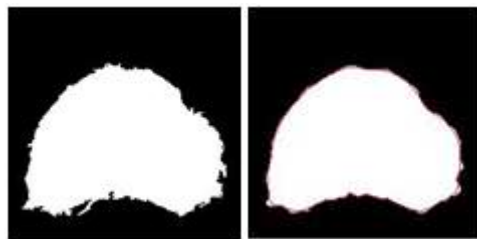
The input format for predicting whether each pixel belongs to prostate or nonprostate is same as one of training step. But here all the pixels are tested without excluding any pixel. The results from prediction have -1 or 1, nonprostate or prostate, respectively. (Figure 5) shows a test image and its labels which the black ones are nonprostate, -1, and the

white ones are prostate, 1.

Algorithm to exclude the wrong classified pixels is needed from the labels. The pixels not included in one big white label and the pixels not included in one big black label may be only excluded as shown in (a) of (Figure 6). After removing noises, the contour has rough line around meeting the prostate and non prostate. Real prostate boundary doesn't have protrusion, so protrusions need to be removed. We use 7x7 mask. This mask is used to find a block that one side is opened and the other three sides are closed in different sides.



(Figure 5) Test image and its predicted labels



(Figure 6) Labels after excluding wrong classified pixels, and labels after removing protrusions and smoothing with radius=30

3.4 Smoothing the Contours

A contour of a 2D region is defined by an ordered set of points where the neighboring elements contain the neighboring points. Such representation can be obtained with many techniques such as boundary tracing and chain codes. In a simple 2D point set or a curve the points do not have to line in a specific order. The contour smoothing is done by projecting all the contour points onto the local regression line. For each point, N neighboring points

which lie on the contour are sampled on each side and a local regression line is computed. Then the current point is projected on this line. Applying this algorithm to all the points smoothes the contour and in a way brings the points closer. $2N+1$ is the number of total points contributing to the computation of the local regression line. The higher the number of point is, the smoother the curve is. Because of the linear nature of fitting, when too much smoothing is desired, some important features such as protrusions may be loosed. This in a way is a wrong over-smoothing. A way to be less prone to such errors is to use Gaussian weighted least squares fit. To do this, the algorithm is the following and the labels after smoothing with radius = 30 shows on the right in (Figure 6).

```

chain_code[1..2][] = Convert2DContours(x_pos,
    y_pos) ; // x_pos and y_pos are bin image
maxX = max(chain_code[1][]);
maxY = max(chain_code[2][]);
minX = min(chain_code[1][]);
minY = min(chain_code[2][]);
For all j of chain_code[1..2][j]with radius=(30 or 20)
    [xm,ym]=middle_point(chain_code[1][j],radius*2+1);
    [a, b, c] = weighted_ortho_least_square(xm, ym,
        chain_code[1..2][j]);
    [x2, y2] = project_point_on_line(a, b, c,
        chain_code[1..2][j]);
    if (x2>=minX && y2>minY && x2<=maxX
        && y2<=maxY)
        Xs[j]=x2;    Ys[j]=y2;
    else
        Xs[j]=chain_code[1][j]; Ys[j]=chain_code[2][j];
    end
end // Final Xs and Ys are the smoothed contour

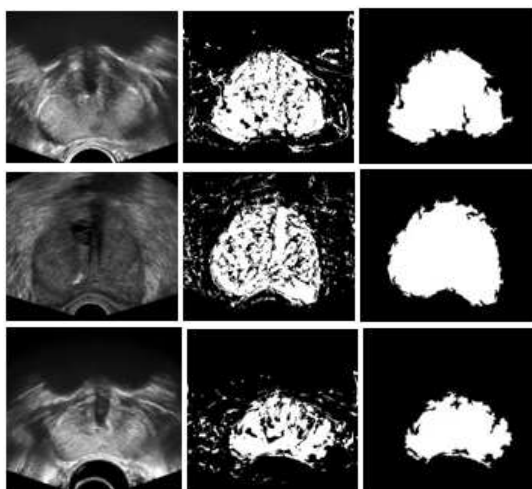
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4. Experiments and Evaluations

4.1 Grouping the Pixels from SVM

In (Figure 7), there are test images, their predicting labels, and labels after removing the island labels, which the white labels are predicted as prostate and the black labels as

nonprostate. We use SVM to predict whether each pixel is prostate or nonprostate using the training model. The reason the white labels are distributed in the black labels is why the texture features of them are similar, so removing the island labels is needed. Parameter used in Gabor filter bank that frequency is [0.025, 0.05, 0.1], orientation is [$\pi/4$, $\pi/2$, $\pi*3/4$, π], scale is [1, 2] and matrix size is 26, so center point of the matrix is [13, 13]. To remove protrusions we use 7x7 mask and to smooth the contour we use radius, 20 and 30.



(Figure 7) Testing images, their predicting labels and labels after removing islands



(Figure 8) Delineating boundaries by human expert (dotted line) and the proposed method(solid red line)

4.2 Objective and Subjective Evaluations

Actually, even human experts have differences of their drawn boundaries, but they are very similar, not same. In the (Figure 8), the solid line is the delineating boundaries by the proposed method and the dashed line is

one by human expert. For quantitative comparison, we used difference between two boundaries. In this paper, we can use radius = 20 or 30, however, the figure shows radius = 30. The difference (D) comes from the following equation. Here, E means expert, P means the proposed method.

$$D = \text{count}(\text{for all pixels } E(x, y) \text{ and } P(x, y) \text{ labels}(E(x, y) \neq P(x, y))) / \text{count}(\text{prostate of } E)$$

Although the difference between the boundaries of human expert and the proposed method is bigger than other test images, D is not too big because the size of the prostate is occupying the big region. <Table 2> shows D for 3 images of 20 testing images. The value, 0.109, means that 10.9% labels are wrong classified. The wrong classified labels are distributed on the boundary of prostate and nonprostate. It took 5.2 seconds on average for 20 experimental images.

Image and resolution	radius = 20	radius = 30
Image 1(304x248)	0.109	0.107
Image 2(250x222)	0.111	0.116
Image 3(260x226)	0.084	0.087
Image 4(208x208)	0.098	0.102
Image 5(588x560)	0.117	0.112

<Table 2> Differences(D) between the boundaries of the expert and the our method

5. Conclusion

This paper proposed a TRUS prostate segmentation using Gabor texture features, SVM, and snake-like contour smoothing algorithm. As the boundary between prostate and nonprostate is not clear and even the textures of them are hard to classify, especially for US prostate image. First, after processing the training images, the pixels (1 or -1) that human expert classifies all the pixels as prostate and nonprostate region are transformed by Gabor filter bank. Gabor texture features acquired by the transform are trained by SVM whose outputs are support

vectors. These support vectors are used for classifying the pixels with prostate and nonprostate. Finally the test image is classified with two regions which are not clear. Using noise reduction and protrusion removal, a rough contour is determined and is smoothed by snake-like algorithm. The proposed method through these processing has difference about 10% comparing to human expert's contours. Our future studies is to improve the computation time, to apply human expert's knowledge, and finally to implement 3D segmentation.

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