

Extraction of Liver Capsule from High-Frequency Ultrasound Images via Drift Iterative Search Algorithm

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Abstract

Aiming at the prior medical knowledge that hepatic ascites only occurs in the severe period of liver cirrhosis, and the severe rupture of the liver capsule curve, when ascites occurs visually, can easily lead to the wrong location of the liver capsule, a transposed grayscale statistical threshold method is proposed to solve the problem. Realize the identification of liver ascites. By analyzing the visual characteristics of the liver image, the gray value of the upper half of the ultrasound image is counted column by column from a mathematical point of view, the gray distribution curve is drawn, and the relevant threshold is set for corresponding judgment. At the same time, the gray value above the ascites detection boundary is set to zero. The ablation experiment proved that the ascites detection method and post-processing operation proposed in this paper provide effective support for the precise positioning of the liver capsule curve, quantitative analysis and diagnosis of liver cirrhosis in the later stage. The Hessian matrix is sensitive to linear structure to achieve image enhancement. In view of the low accuracy of the existing liver envelope curve detection method and the incomplete quantitative evaluation of liver cirrhosis, it is proposed to use drift iteration under the synergistic effect of multiple filters. A search algorithm extracts the liver capsule.

Keywords

Liver Cirrhosis, Liver Capsule, Detection of Hepatic Ascites, Extraction of Liver Capsule, Computer-Aided Diagnosis

1. Introduction

In clinical practice, a low-frequency ultrasound probe of 3.5 - 5.0 MHZ is commonly used for liver disease inspection. This low-frequency ultrasound imaging has a wide range but cannot clearly display superficial liver lesions. In view of the superficial diffusion characteristics of liver cirrhosis, high-frequency ultrasound of 4 - 10 MHZ is used in this paper. The probe is used to obtain high-frequency ul-trasound images of the superficial liver layer. [Figure 1](#page-1-0) respectively lists two cases of normal liver and cirrhosis liver high-frequency ultrasound images. As can be seen from the figure, liver high-frequency ultrasound images are generally composed of fat layer, liver capsule and liver parenchyma. Under normal conditions, the liver capsule is smooth and slender, and the echo of the liver parenchyma is uniform; with the development of liver cirrhosis, the liver capsule will thicken and break, showing a wavy or jagged shape, and the echo of the liver parenchyma will increase, and the number of nodules will increase. When entering liver cirrhosis and developing into severe, hepatic ascites may even occur. The comparison of features of liver high-frequency ultrasound images is shown in [Table](#page-1-1) [1.](#page-1-1)

Due to the acoustic properties of the examined tissue, the texture of the ultrasound image of the liver appears grainy. However, ultrasound images are noisy, which makes the texture features of liver parenchyma too abstract and difficult to distinguish. In contrast, the liver capsule, as a curvilinear structure, is more intuitive visually and is conducive to identification and description. Its geometric features have been widely used in the diagnosis of liver cirrhosis and the evaluation of the course of the disease. At present, there are mainly: artificial

	Normal	Cirrhosis
Ascites	N ₀	Hepatic ascites may occur in severe cases
Liver capsule	Smooth and slender	Thickened, fractured, jagged or wavy
Liver parenchyma	Even echo	Echoes thicken and nodules increase
fat layer liver capsule liver parenchyma		ascites
Normal		liver cirrhosis
(a)		(b)

Table 1. Comparison of characteristics of high frequency ultrasound images of the liver.

Figure 1. High frequency ultrasound images of the liver.

supervision and gradient optimization methods, dynamic programming algorithms, multi-scale multi-objective optimization methods, multi-scale methods constrained by spatial context, and traversal search methods based on morphological processing, etc.

2. Liver Capsule Extraction from Liver Images

Liu et al. [\[1\]](#page-11-0) used the Canny operator for edge detection to generate a potential edge set, and then used dynamic programming to find the most qualified liver envelope line segment in the rectangular frame image, and obtained the complete envelope line through interpolation connection. At the same time, the continuous The morphological changes of the liver capsule were described by the two indexes of sex and smoothness, so as to classify the course of liver cirrhosis. The classification accuracy rates were 92.08%, 80.23%, 75.12% and 93.58%, respectively.

Wang *et al.* [\[2\]](#page-11-1) used multi-scale filtering, skeleton extraction and multi-objective optimization to realize liver cirrhosis extraction, used Gaussian modeling and defect detection to locate liver parenchymal lesions, and proposed 4 geometric features and 3 texture features to classify liver cirrhosis, the four classification accuracy rates were 92.46%, 80.49%, 83.93% and 91.98%.

Zhao et al. [\[3\]](#page-11-2) proposed three spatial context constraints to extract the liver envelope curve, and used two new geometric feature descriptors for morphological estimation and classification. The final classification accuracy rates of normal and cirrhotic stages were 92.50% and 74.71%, 70.08% and 86.17%. Nowadays, more scholars are working on the assessment of liver cirrhosis by integrating the geometric features of the liver capsule and the texture features of the liver parenchyma. Compared with a single feature, the combined feature presents better performance.

Liu *et al.* [\[4\]](#page-11-3) extracted the features of liver capsule and liver parenchyma from liver images, based on deep learning and two-level network ideas, used the improved Cifar network to carry out severe staging of liver capsule features, and used Resnet network to perform other liver parenchyma features. The stages were staged, and the voting method was finally used to classify the course of liver cirrhosis, and the accuracy rates of the four classifications were 95.00%, 88.9%, 94.10% and 92.30%.

2.1. Recognition of Hepatic Ascites Based on Transposed Grayscale Statistical Threshold Method

Hepatic ascites is a complication caused by liver function damage and portal hypertension in the late stage of cirrhosis. In the ultrasound image, the gray value of the ascites area is low, mostly concentrated in the upper half of the image, and located between the muscle fat layer and the liver capsule, as shown in [Fig](#page-1-0)[ure 1\(b\).](#page-1-0) In order to locate the liver capsule more accurately, it is necessary to judge whether there is ascites in the ultrasound image of the liver. In the past two years, scholars have noticed the role of ascites features in assisting the precise positioning of the liver capsule. For example, Fu et al. obtained the edge image through canny calculation, and substituted the upper and lower coordinates of the maximum distance between the curves into the ascites energy equation to judge Presence or absence of ascites. Liu *et al.* used the sliding window method to scan the upper half of the liver image step by step, and judged whether there was ascites by calculating the proportion of ascites area. In this paper, the liver ascites was first identified, and then the scale difference and Hessian matrix [\[4\]](#page-11-3) were used to enhance the liver ultrasound image, highlight the linear structure of the liver capsule, and extract the liver capsule curve under the synergistic effect of multiple filters, so as to quantitatively evaluate the course and staging diagnosis of cirrhosis. The flow chart of hepatic capsular extraction is shown in [Figure 2.](#page-3-0)

In this paper, based on the characteristics of ascites in liver ultrasound images, a transposed grayscale statistical threshold method is proposed. As shown in [Figure 3\(a\),](#page-4-0) first rotate the image with a width of and a height of 90 degrees counterclockwise, and limit the scanning range of the coordinate axes to the left half, which is the upper half of the original image. As shown in **Figure 3(b)**, the average gray value is calculated column by column, and then the gray curve is drawn, as shown in Figure $3(c)$, all continuous widths below the threshold are calculated. According to the image characteristics of a given data set, the ascites region occupies the lowest part of the upper half of the image. If the maximum continuous width is greater than that, it is judged that there is ascites in the image. At the same time, in order to reduce the interference of subsequent extraction, the midpoint is taken as the boundary of ascites detection, and the pixel value of the upper part is zero. In this way, the influence of similar structures such as fat layers on the optimal extraction of the liver capsule can be effectively avoided, and the detection accuracy can be improved.

2.2. Multi-Filter Synergy

Since there are a large number of structures in the liver ultrasound image that are similar to the gray value of the liver capsule, this poses a great obstacle to the precise extraction of the capsule line. Therefore, this paper proposes a method

Figure 3. Transposed grayscale statistical threshold method process.

that combines transverse filtering and local filtering to process the image. Firstly, starting from the overall situation, the set rectangular window traverses the whole image. If the average gray value of the rectangular window is lower than the threshold, all the noise in this area is filtered out. Secondly, the set sliding window further scans the image, and if the average gray value of the sliding window is lower than the threshold, the noise of this window is filtered out. The schematic diagram of horizontal filtering combined with local filtering is shown in [Figure 1,](#page-1-0) and Labels (1) and (2) correspond to horizontal filtering and local filtering, respectively.

As shown in [Figure 4,](#page-5-0) most of the noise in the liver parenchyma area is filtered out by transverse filtering, but there are still a small number of noise points under the liver capsule (the part marked with a red box), which may affect the positioning of the liver capsule in the later stage. Interference, so local filtering is used to filter such noise. In this way, under the action of double filtering, most of the noise in the liver image can be eliminated, laying a good foundation for the later location of the liver capsule.

2.3. Drift Iterative Search Algorithm

As shown in [Figure 5,](#page-5-1) considering that the structure of the liver fat layer is similar to the liver capsule and there are many curves, searching from top to bottom

Figure 4. Schematic diagram of transverse filtering combined with local filtering.

Figure 5. The effect of transverse filtering combined with local filtering.

is easy to locate errors. Therefore, this study starts with the liver parenchyma and extracts the curves of the liver capsule from bottom to top. However, the synergistic effect of the above double filters has basically eliminated the noise of the liver parenchyma, which greatly promotes the automatic extraction of the liver capsule. In this section, the accurate positioning of the liver capsule is realized by the drift iterative search method within the potential range [\[5\],](#page-11-4) and an error correction mechanism is added at the same time, and the horizontal filter

is used to filter the noise, so that the capsule extraction is more accurate.

Finally, the specific idea is as shown in [Figure 6:](#page-6-0) start from the lower left corner of the image, and perform a reverse search from bottom to top. If the absolute value of the difference between adjacent pixels is greater than the threshold $t₄$, it is considered that there is a jump state, and the difference between the two jumps The linear structure is identified as the liver capsule area, and when the second jump state occurs, the search of the column is stopped, and this point is identified as the boundary point of the liver capsule. Immediately starting from this point, limit the upper and lower search boundaries, and iterate to the right step by step to dynamically limit the potential line segment of the search envelope line, and the boundary threshold is t_5 .

Experiments have found that when ascites exists, this method may wrongly detect the upper fat layer and muscle layer, so it is necessary to constrain the upper medium layer, which is also the reason for setting the gray value above the ascites boundary to zero in the process of judging the characteristics of ascites reason.

In addition, when the liver capsule is broken, there may be a curved segment similar to the liver capsule line above the break, which can easily be mistaken as a part of the liver capsule. In response to this situation, an error correction mechanism is added, and horizontal filtering is used again to filter out the above-mentioned parts one by one. In this way, a complete and accurate liver envelope curve can be obtained.

Figure 6. Drift iterative search schematic.

3. Dataset and Experiment

3.1. Dataset

Used dataset is provided by the Biomedical Research Ethics Committee of Shanghai Changzheng Hospital (Ethics Permission Number: 2017SL013). Itcan be accessed by clicking DATASETI and find DATASET I.

According to the Child Pugh criteria [\[5\],](#page-11-4) the degree of liver cirrhosis is divided into: Level A (mild), Level B (moderate), and Level C (severe). This article collected 47 patients with liver cirrhosis who were treated in Changzheng Hospital Affiliated to Second Military Medical University, including 18 mild cases, 16 moderate cases, and 13 severe cases [\[6\].](#page-11-5) The diagnosis of liver cirrhosis was confirmed by laboratory, ultrasound or CT examination, and patients with fatty liver, schistosomiasis liver disease and other organic liver diseases were excluded. In addition, 20 people without liver disease through physical examination, ultrasound, and laboratory examination were randomly selected as the normal control group, and there were no statistically significant differences in age, gender, and physical fitness among the groups.

Among them, the instruments and methods used in the hospital are: GE Voluson E8 ultrasonic diagnostic instrument, 11 L linear array probe, frequency 4 - 10 MHz. Ask the subject to lie on his back, place the probe under the xiphoid process and the right intercostal space, scan the liver tissue, adjust the image depth and gain to ensure that the liver capsule and the superficial layer of the liver parenchyma are clearly displayed, and the two sides of the liver. The two-dimensional sonograms of the lobe liver capsule were stored separately for later quantitative feature analysis [\[7\].](#page-11-6)

In addition, based on the data set in this paper and repeated experiments based on image features, the parameter settings in this section are shown in [Ta](#page-7-0)[ble 2.](#page-7-0)

3.2. Experiment Analysis

1) Ablation experiment

In order to verify the necessity of judging the characteristics of ascites and post-processing described in Section 2, this section conducts ablation experiments

[\[8\]](#page-12-0) on whether to judge the characteristics of ascites. We performed liver capsule location extraction for the judgment of no ascites and the judgment of ascites respectively, and the results are shown in [Table 3.](#page-8-0) The results showed that there were still a large number of line segments above the liver capsule detected under the conditions of no ascites judgment and zero-setting processing, which could not be eliminated even by multi-filtering in the later stage, because the upper fat muscle layer was extremely similar to the capsule line [\[9\]](#page-12-1) [\[10\].](#page-12-2) When there is severe hepatic ascites, the capsule is severely broken and the boundary is not clear, so the upper medium layer can be easily detected, which can be mistaken for a part of the liver capsule, resulting in detection errors [\[8\].](#page-12-0) Therefore, pre-judging ascites and zeroing the upper area are very effective for accurate positioning of the liver capsule [\[11\].](#page-12-3)

2) Experimental results

[Table 4](#page-9-0) shows the extraction effects of the liver capsule in each step. It can be seen that the linear structure enhancement step greatly highlights the linear part of the liver image, and the transverse filtering and local filtering eliminate the noise points similar to the liver parenchyma. Especially for the image in the last row of the table, the angle between the capsule and the horizontal direction is too large, which makes the horizontal filter unable to filter out the area under the liver capsule, which will undoubtedly increase the burden of later extraction, so adding local filtering can effectively avoid this deficiency place. In this way, the area under the liver capsule is basically free of noise points, so the iterative drift search can accurately and directly locate the liver capsule, and at the same time, it can maintain fidelity to the break of the capsul[e \[12\].](#page-12-4)

In addition, in order to quantitatively evaluate the effect of this algorithm on liver capsule extraction, this paper makes summary statistics on the accuracy of

Table 3. Experimental demonstration of ablation effect of ascites judgment.

Table 4. Demonstration of the effect of liver capsule extraction.

liver capsule extraction, which are 100%, 100%, 93.75% and 92.31%, respectively, as shown in [Table 5.](#page-10-0) Experiments show that the algorithm in this paper has good detection performance for the given data set of the hospital, and can efficiently and accurately locate and extract the liver envelope curve. At the same time, this paper is compared with the previous methods. As shown in Table 6, the extraction accuracy of each stage exceeds the existing research methods. It can be seen that under the preprocessing scheme in this paper, the liver capsule extraction algorithm with multi-filter synergy proposed in this study has high value for automatic extraction of liver capsule, and can be used for the extraction and quantification of liver capsule morphological features in the later stage. Evaluating the course of liver cirrhosis provides strong technical suppor[t \[8\].](#page-12-0)

4. Discussion

The experimental results show that the algorithm can accurately extract most of the liver capsule, but also true the characteristics of the rupture of the capsule. In

Table 5. Accuracy of liver capsule extraction.

Table 6. Comparison of the accuracy of liver capsule extraction.

addition, the ablative experiment on the process of ascites judgment confirmed the necessity of this step. The localization of liver envelope line provides effective support for the calculation of quantitative characteristics of liver envelope, and is also a necessary prerequisite for the later diagnosis of cirrhosis. Therefore, how to use the extracted liver capsule for quantitative evaluation to determine the degree of cirrhosis is the focus and purpose of our next work.

5. Conclusion

In this paper, a multi-filter collaborative drift iterative search method for liver capsule extraction is proposed, which greatly reduces the obstruction of the fatty muscle layer for liver capsule localization by searching from bottom to top. Based on the characteristics of ascites in liver images, the transposed gray statistical threshold method was first proposed to judge whether there was ascites or not. The upper half of the liver image was scanned column by column for gray statistics, so as to identify hepatic ascites. The characteristics of ascites can effectively support the classification of later severe cirrhosis. The scale difference of liver ultrasound images in the time domain can highlight the linear structure on the one hand, filter the fine noise on the other hand, and use the Hessian matrix sensitive to the linear structure to achieve image enhancement, especially the linear enhancement of the liver capsule. Then combined with lateral filtering and local filtering to remove liver parenchyma and similar noise, different Windows were set respectively, and the noise was filtered to the maximum extent through the gray threshold. Finally, a drift iterative search algorithm was proposed under the synergistic action of double filtering to limit the search boundary and locate the liver capsule curve from the liver parenchyma within the potential range. At

the same time, an error correction mechanism is added and transverse filtering is adopted to filter the noise, which makes the envelope extraction more accurate.

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Authors' Contributions

Jingwen Zhao and Furong Jiang propose the method and are responsible for writing the thesis. Jialin Song and Xiang Liu focus on data collection, analyzing images and experiments based on high-frequency ultrasound datasets. Li'na Wei and Guyue Zhang specialize in algorithm implementation. Jingwen Zhao supervises the research work.

Conflicts of Interest

The authors declare no conflict of interest.

References

- [1] Liu, X., Zhan, Z.Q., Yan, M., et al. (2017) Computer-Aided Cirrhosis Diagnosis via Automatic Liver Capsule Extraction and Combined Geometry-Texture Features. 2017 IEEE International Conference on Multimedia and Expo (ICME), Hong Kong, 10-14 July 2017, 865-870.
- [2] Wang, S.H., Xiang, L., Zhao, J.W., et al. (2016) Learning to Diagnose Cirrhosis via Combined Liver Capsule and Parenchyma Ultrasound Image Features. 2016 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), Shenzhen, 15-18 December 2016, 799-804.
- [3] Zhao, J.W., Wang, S.H., Liu, X., Liu, Y. and Chen, Y.Q. (2018) Early Diagnosis of Cirrhosis via Automatic Location and Geometric Description of Liver Capsule. The Visual Computer, 34, 1677-1689. <https://doi.org/10.1007/s00371-017-1441-2>
- [4] Liu, X., Ma, R.L., Zhao, J.W., et al. (2021) A Clinical Decision Support System for Predicting Cirrhosis Stages via High Frequency Ultrasound Images. Expert Systems with Applications, 175, Article ID: 114680. <https://doi.org/10.1016/j.eswa.2021.114680>
- [5] Wang, W.B., Li, C.B. and Zheng, C.J. (2020) Hessian-Based Directional Adaptive Gabor Wavelet for Retinal Vessel Segmentation. Advances in Lasers and Optoelectronics, 57, 208-215.
- [6] Pugh, R. (2010) Transection of the Oesophagus for Bleeding Oesophageal Varices. British Journal of Surgery, 60, 646-649. <https://doi.org/10.1002/bjs.1800600817>
- [7] Frangi, R.F., Niessen, W.J., Vincken, K.L. and Viergever, M.A. (1998) Multiscale Vessel Enhancement Filtering. In: Wells, W.M., Colchester, A. and Delp, S., Eds, International Conference on Medical Image Computing and Computer-Assisted Intervention, Vol. 1496, Springer, Berlin, 130-137.

<https://doi.org/10.1007/BFb0056195>

- [8] Virmani, J., Kumar, V., Kalra, N. and Khandelwal, N. (2013) Prediction of Liver Cirrhosis Based on Multiresolution Texture Descriptors from B-Mode Ultrasound. International Journal of Convergence Computing, 1, 19-37. <https://doi.org/10.1504/IJCONVC.2013.054658>
- [9] Meyes, R., Lu, M., de Puiseau, C.W., et al. (2019) Ablation Studies in Artificial Neural Networks. ArXiv: 1901.08644.
- [10] Shortliffe, E.H. and Buchanan, B.G. (1975) A Model of Inexact Reasoning in Medicine. Mathematical Biosciences, 23, 351-379. [https://doi.org/10.1016/0025-5564\(75\)90047-4](https://doi.org/10.1016/0025-5564(75)90047-4)
- [11] Wang, S.H., Liu, X., Zhao, J., Song, J.L., Zhang, J.Q. and Chen, Y.Q. (2016) Learning to Diagnose Cirrhosis via Combined Liver Capsule and Parenchyma Ultrasound Image Features. 2016 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), Shenzhen, 15-18 December 2016, 799-804. <https://doi.org/10.1109/BIBM.2016.7822627>
- [12] Wardeh, R., Lee, J.G. and Gu, M. (2011) Endoscopic Ultrasound-Guided Paracentesis of Ascitic Fluid: A Morphologic Study with Ultrasonographic Correlation. Cancer Cytopathology, 119, 27-36. <https://doi.org/10.1002/cncy.20123>