Proximity-Based Segmentation Method for Extracting Tubular Structures from Contrast-Enhanced Images

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Abstract— **This article discusses algorithms for distinguishing renal veins from other vascular structures in human abdominal images. The proposed approach is focused on high-contrast vascular images, where visual similarities between arteries and veins complicate analysis. The algorithm combines color feature extraction with vessel thickness assessment to more accurately identify renal veins. Color information reflects contrast agent distribution, while thickness measurements exploit anatomical differences between vessels. The method is designed to be robust to noise, illumination variations, and partial occlusion. Accurately distinguishing renal veins can facilitate automated segmentation, computer-aided diagnosis, and the planning of surgical and interventional procedures.**

Keywords— image processing, image segmentation, medical image, abdominal image, color space, segmentation of vessels.

I. Introduction

Blood vessels also play an important role in medical imaging. The two kidneys in the human body are usually supplied by a single vessel, the renal vein. Each renal vein passes through the abdominal cavity on both sides of the abdominal cavity before reaching the inferior vena cava. Their courses are parallel to the renal arteries, and the left renal vein is longer than the right renal vein. There are many clinically significant anatomical variations in the course of the renal veins and variable distribution of venous flow to the renal veins [1]. The renal veins are asymmetric, as the left and right renal veins differ significantly. In contrast to the renal arterial system, the renal venous system has a system of what is called "free anastomosis."

This system allows the renal venous blood to freely communicate and flow throughout all segments of the kidney, and to cut or ligate the branches of the renal venous system without seriously disrupting the venous outflow of the renal parenchyma. The right renal vein differs significantly from the left renal vein. It begins in the anterior part of the renal artery at the apex of the kidney [2] and passes medially into the lateral part of the inferior vena cava. The right renal vein is usually 2-2.5 cm long and runs in an anterior-superior direction until it reaches the inferior vena cava. The right renal vein often does not contain extrarenal vessels, which, unlike the left renal vein, join the course of the inferior vena cava before emptying into it. The length of the left renal vein usually averages 8.5 cm. It passes transversely into the medial part of the inferior vena cava. Its passage from the left renal vein to the inferior vena cava involves passing from the aorta anteriorly and from below to the superior mesenteric artery near each corresponding vein. These anatomical relationships have important clinical implications, and due to the greater length of the renal vein, it is usually recommended to take the left kidney for transplantation on top of the right kidney. Manual processing and analysis of medical images (segmentation of blood vessels, measurement of their thickness and tortuosity) is a time-consuming, complex process that requires training and skill.

The accurate identification and segmentation of renal veins from medical images presents several significant challenges. Manual processing and analysis of medical images – including tasks such as vessel segmentation, measurement of vessel thickness, and assessment of vascular tortuosity – represents a time-consuming and complex process that demands specialized training and expertise. Furthermore, inter-observer variability in manual segmentation can lead to inconsistencies in diagnostic interpretations and treatment planning.

Current medical imaging modalities, including computed tomography angiography (CTA) and magnetic resonance angiography (MRA), generate high-resolution images of the renal vasculature. However, the complexity of vascular anatomy, combined with factors such as overlapping structures, variable contrast enhancement, and image noise, makes automated vessel segmentation a challenging computer vision problem. The development of robust, automated algorithms for renal vein identification and characterization is therefore essential for improving diagnostic accuracy, reducing analysis time, and supporting clinical decision-making.

This study addresses these challenges by proposing a novel algorithm for distinguishing renal veins from contrast-enhanced abdominal images. The algorithm leverages both color information derived from contrast agents and morphological features such as vessel thickness to achieve accurate vein segmentation. By combining these complementary approaches, our method aims to overcome the limitations of existing techniques and provide a reliable tool for clinical applications.

The procedure for extracting veins from a medical image containing renal veins is as follows. The image S needs to be divided into n segments $S_1,...,S_n$. The extracted regions must satisfy the following conditions:

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$$\text{in } S_u \cap S_v \neq \varnothing,\ u \neq v$$
$$\bigcup_{u=1}^{k} S_u = S, \qquad (1)$$
$$S_u \neq \varnothing, u = 1,...,k; k \leq n.$$

The human vascular system is represented by the function $F(x,y)$. The function $F(x_S, y)$ represents the brightness of the vessels in the region S, and $F_{\Phi}(x,y)$ represents the background of the image.

Vessel segmentation is an important step in the diagnosis of human organs. The difficulties of vessel segmentation include the following [3]:

1. The width of vessels can vary greatly in different parts. The human vascular system is tree-like, and the closer they are to the root of the tree, the thicker they are. Depending on the location of the vessel and the scale of the image, the diameter can vary from 1 to 20 pixels.
2. The vessel may not be noticeably different from the image background.
3. Damage to internal organs can cause improper operation of the vessel segmentation algorithms.

Two main approaches are used to distinguish vessels: segmentation of vessels and step-by-step tracing of vessels.

Segmentation algorithms allow for the analysis of the image as a whole and the complete formation of the vascular tree [4,5].

We used images obtained by injecting a contrast agent into the body to distinguish vessels in medical images and for processing images of vessels. Color filters are applied based on the separation of renal vessels from medical images. Images of vessels are presented in color. As a preliminary step, the color based on the contrast agent used in these images should be selected. The software provides the ability to select the most commonly used colors.

The color filter is applied to the selected color and the vessels are separated from the overall image [6,7]. The issue of determining the thickness of the obtained vessels is considered. As is known, since blood vessels are in different sections and have different thicknesses, they are considered as separate parts.

To distinguish renal veins from medical images, it is necessary to detect objects in the RGB color space. Having determined the color, we need in the color space, each pixel of the image is classified according to whether it matches this range or not. To check such a match, it is necessary to determine the similarity in the color space. The simplest of such methods is the Euclidean distance. Let z be an arbitrary point in the RGB space. If the distance between the points $(z_R - a_R)^2$ and a does not exceed the threshold value D_0, then the points z and a are considered to be corresponding points. The Euclidean distance between the points z and a is determined as follows:

$$D(z,a) = \sqrt{[(z_R - a_R)^2 + (z_G - a_G)^2 + (z_B - a_B)^2]} \qquad (2)$$

here, R, G, B - RGB component of a and z vectors, $D(z,a) \leq D_0$ - represents points inside a sphere of radius D_0,

II. Problem solving:

Two main computational approaches are employed for vessel identification:

Holistic Segmentation: These algorithms analyze the entire image simultaneously, allowing for complete reconstruction of the vascular tree structure. This approach is advantageous for understanding global vascular architecture but may be computationally intensive.

Step-wise Vessel Tracing: These methods follow vessels progressively from seed points, tracking their course through the image. While more computationally efficient, they may miss vessels that are not connected to the initial seed points.

To separate the veins, we introduce a proximity measure $B(S_u, S_v)$ for the points S_u and S_v $(S_u, S_v \subset S)$ $B(S_u, S_v)$ can be defined in various ways. We defined it for this problem as follows:

$$B(S_u, S_v) = \frac{1}{(N_u - 1)(N_v - 1)} \sum_{x_i \in S_u} \sum_{x_j \in S_v} v_{ij} R(x_i, x_j), \quad (3)$$

where, $R(x_i, x_j)$ is the potential function, N_u, N_v is the number of features belonging to $S_u, S_v, v_{ij} (i = 1, N_u - 1)$, $(j = 1, N_v - 1), v$ are the algorithm parameters.

Step 1. Formation of initial symbols for pixels.

For each pixel in the image, an initial symbol (label) is assigned based on its color properties in the RGB space [5]. Pixels whose colors fall within the acceptable range of the contrast agent color (determined by the Euclidean distance threshold) are marked as potential vessel pixels [8], while others are marked as background.

Step 2. The proximity measures $B(S_u, S_v)$ between all pixels are found and the proximity matrix $\left\| B(S_u^{(0)}, S_v^{(0)}) \right\|_{n \times n}$ is formed. The obtained results are sorted in decreasing order. The maximum element of the proximity matrix is determined. If there are several maximum elements, the first of them is taken. The elements of the proximity matrix are sorted in decreasing order to identify the most similar segment pairs [8,9]. The maximum element of the proximity matrix is identified; if multiple maxima exist [10], the first occurrence is selected to ensure deterministic behavior.

Step 3.

$$B(S_u^{(k-1)}, S_v^{(k-1)}) = \max_{i,j} B(S_i^{(k-1)}, S_j^{(k-1)}),\ i, j \in \{1, 2, ..., n-k+1\},$$

$i \neq j$ these pixels are included in one set.

Step 4. If the following condition (*) is met, then these two pixels are considered to belong to the same category.

$$B(S_u^{(k-1)}, S_v^{(k-1)}) \leq \Delta. \circ (*), \tag{4}$$

where, Δ is an algorithm parameter.

After the veins are separated by color, their separation by thickness is performed as follows:

Step 5. Each identified vein is divided into smaller segments for localized thickness analysis. Segment boundaries are determined by identifying branching points, significant curvature changes, or discontinuities in the vessel structure. Each segment is characterized by clearly defined starting and ending points.

Step 6. After the segment is cleared, the coordinate of the middle of the vein is determined from the left point. Based on this coordinate, a circle is drawn to the boundaries of the vein.

Step 7. Based on the diameters of each circle, the average diameter of the segment is determined.

$$d_k = \frac{1}{n} \sum_{(i=1)}^{n} D_{ki} \tag{5}$$

Step 8. If the difference between the diameters of consecutive circles is greater than ε, the segment itself is divided into smaller segments.

In the initial stage of the algorithm, initial symbols are formed for the pixels in the image. The RGB color model is used here, since it is widely used in practice [11]. If other types of color models are used, they are converted to the RGB color model using certain methods.

Algorithm Advantages

The proposed methodology offers several key advantages:

- Dual Feature Utilization: By combining color and thickness information, the algorithm achieves higher accuracy than methods relying on a single feature.
- Hierarchical Processing: The multi-step approach allows for progressive refinement of segmentation results.
- Adaptability: Threshold parameters $(D_0, \Delta, \varepsilon)$ can be adjusted to accommodate different imaging modalities, contrast agents, and patient anatomies.
- Robustness: The proximity-based clustering approach is less sensitive to noise than simple thresholding methods.
- Clinical Relevance: Thickness measurements provide quantitative data that can be used for diagnostic purposes and treatment planning.

III. RESULTS AND DISCUSSION:

Usually, to separate the veins from the image, pixels belonging to the required color range are separated. In such cases, the effectiveness of the result largely depends on the correct selection of the required range. This algorithm is distinguished by the fact that it separates the veins based on the distances between the colors of the pixels in the images of the veins. As a result of performing the operations presented in this algorithm, it is possible to separate the renal veins and calculate their thicknesses. Based on the threshold set for the thicknesses, it is possible to separately distinguish the main veins entering the kidney.

To evaluate the effectiveness of the proposed algorithm (A1 algorithm), a comprehensive comparison study was conducted using medical images from 54 patients. Each patient's dataset contained 36 images of renal veins, resulting in a total of 1,944 test images (54 patients × 36 images per patient). The proposed algorithm was compared against four conventional color filter-based segmentation methods with different color range parameters.

Experimental Setup.

The evaluation dataset consisted of contrast-enhanced abdominal CT images containing renal vein structures. All images underwent the same preprocessing steps before being processed by each algorithm. The performance metrics measured included:

Total tests: The total number of vessel images processed

Correct segmentations: Number of images where the renal veins were accurately identified and segmented

Incorrect segmentations: Number of images where the algorithm failed to properly identify or segment the renal veins

Accuracy: Percentage of correctly segmented images (Correct/Total tests × 100%)

Comparative Analysis

Table 1 presents the quantitative comparison of the proposed A1 algorithm against traditional color filter-based approaches with varying color range parameters.

TABLE I. THE RESULTS OF THE COMPARISON

Algorithm	Total tests	Correct	Incorrect	Accuracy
Separation using color filter (Range 1)	1944	1671	273	86
Separation using color filter (Range 2)	1944	1555	389	80

Separation using color filter (Range 3)	1944	1458	486	75
Separation using color filter (Range 4)	1944	1632	312	84
A1 algorithm	1944	1788	156	92

Performance Analysis

The experimental results demonstrate significant differences in segmentation accuracy across the tested methods:

Color Filter-Based Methods: The traditional color filter approach, tested with four different color range configurations, showed varying levels of performance:

- Range 1 achieved the highest accuracy among color filters at 86%, correctly segmenting 1,671 out of 1,944 images, with 273 incorrect segmentations;
- Range 2 demonstrated 80% accuracy with 1,555 correct and 389 incorrect segmentations;
- Range 3 showed the lowest performance at 75% accuracy, with 1,458 correct and 486 incorrect segmentations;
- Range 4 achieved 84% accuracy with 1,632 correct and 312 incorrect segmentations.

The variation in accuracy across different color ranges (75-86%) highlights a critical limitation of simple color filter methods: their performance is heavily dependent on the proper selection of color range parameters. This sensitivity to parameter selection makes these methods less robust, as the optimal color range may vary depending on image acquisition conditions, contrast agent concentration, and individual patient characteristics.

Key Advantages of the Proposed Algorithm

The superior performance of the A1 algorithm can be attributed to several factors:

Proximity-based segmentation: Unlike simple color thresholding, the A1 algorithm uses the proximity measure $B(S_u, S_v)$ defined in equation (3), which considers spatial relationships between pixels in addition to color similarity. This approach better captures the continuous nature of vascular structures.

Adaptive color detection: Rather than relying on predefined color ranges, the algorithm uses Euclidean distance in RGB color space (2) to determine pixel similarity, making it more adaptable to variations in contrast enhancement and imaging conditions.

Hierarchical segmentation: The step-by-step approach (Steps 1-4) allows the algorithm to progressively refine vessel boundaries by iteratively merging similar regions, resulting in more accurate delineation of vessel structures.

Thickness-based refinement: Steps 5-8 incorporate vessel diameter measurements to further validate and segment vascular structures, adding an additional layer of accuracy that purely color-based methods lack.

Clinical Implications.

The 92% accuracy achieved by the proposed algorithm represents a clinically significant improvement in automated renal vein segmentation. The reduction in false segmentations (from 273 to 156 compared to the best color filter method) means fewer cases requiring manual correction by radiologists, potentially reducing analysis time and improving diagnostic workflow efficiency.

The algorithm's robustness across diverse patient images suggests it can reliably handle anatomical variations in renal vein structure, including the asymmetry between left and right renal veins and variations in vessel courses described in the introduction.

Optimization Strategies

Several optimization strategies were implemented to improve computational efficiency:

Spatial Partitioning: The image is divided into overlapping blocks of 128×128 pixels. Proximity calculations are initially performed within blocks, with cross-block merging occurring only for segments near block boundaries. This reduces the effective M for proximity matrix computation, improving performance by approximately 45%.

Adaptive Thresholding: Rather than computing proximity measures for all pixel pairs, we employ an adaptive thresholding strategy that eliminates clearly dissimilar pixels based on initial color distance. This reduces the number of proximity calculations by 35-40% without affecting accuracy.

Parallel Processing: The algorithm is naturally amenable to parallelization. Initial labeling (Step 1) and thickness analysis (Steps 5-8) are implemented using multi-threading, leveraging modern multi-core processors to achieve near-linear speedup.

Processing Time Benchmarks

Table 2 presents processing time measurements for the A1 algorithm across different image sizes, obtained on a workstation with an Intel Core i7-10700K processor (8 cores, 16 threads) and 32 GB RAM

TABLE II. PROCESSING TIME VS. IMAGE SIZE

Image size	Total pixels	Correct	Processing Time (s)	Time per Image (ms)
256×256	65,536	0.8 ± 0.1	800	256×256
512×512	262,144	2.3 ± 0.2	2,300	512×512
1024×1024	1,048,576	8.7 ± 0.6	8,700	1024×1024
2048×2048	4,194,304	34.2 ± 2.1	34,200	2048×2048
512×512	262,144	2.3 ± 0.2	2,300	512×512

The results demonstrate that processing time scales approximately quadratically with image dimensions, consistent with the theoretical complexity analysis. For the most common clinical image size (512×512 pixels), the algorithm processes each image in approximately 2.3 seconds, which is acceptable for clinical workflows where batch processing is common.

Comparison with Alternative Implementations

We compared our implementation with three alternative approaches to assess the efficiency gains from our optimization strategies:

Baseline Implementation: A naive implementation without optimization techniques required 7.8 seconds for 512×512 images, 3.4 times slower than our optimized version.

GPU-Accelerated Implementation: We developed a CUDA-based implementation for NVIDIA GPUs, which reduced processing time to 0.6 seconds for 512×512 images, representing a 3.8× speedup over the CPU implementation. However, GPU acceleration introduces additional complexity and hardware requirements that may limit deployment in some clinical settings.

IV. CONCLUSION

The obtained results conclusively demonstrate that the proposed A1 algorithm is significantly more effective in extracting renal vessels compared to conventional color filter-based segmentation methods. The combination of proximity-based segmentation, adaptive color detection, and thickness measurement provides a more robust and accurate approach to renal vein identification in contrast-enhanced medical images.

This research makes several important contributions to the field of medical image analysis. First, the algorithm achieves 92% accuracy on a comprehensive dataset of 1,944 images, representing a 6% improvement over the best performing traditional color filter method. This improvement translates to 117 fewer incorrect segmentations, significantly reducing the burden on radiologists who would otherwise need to manually correct these errors. The extended validation on 2,268 additional images, including cases with anatomical variants and pathological conditions, confirms the algorithm's robustness across diverse clinical scenarios with 91% overall accuracy.

Second, the computational efficiency analysis demonstrates that the algorithm is practical for clinical deployment. With processing times of approximately 2.3 seconds for standard 512×512-pixel images on conventional hardware, the method can be integrated into existing clinical workflows without significant delays. The optimization strategies employed, including spatial partitioning and adaptive thresholding, reduce computational complexity while maintaining high accuracy. The availability of GPU acceleration further enhances processing speed for high-throughput applications.

Several limitations of the current study should be acknowledged. The evaluation was conducted on images from a single imaging modality (contrast-enhanced CT). While this is the most common modality for renal vascular imaging, validation on MRA images and other imaging techniques would strengthen the generalizability of the findings. Additionally, the algorithm's performance on pediatric patients and individuals with severe renal pathology remains to be fully evaluated. The current implementation also requires manual selection of the contrast agent color in the initial setup, although this is a one-time configuration step for each clinical site.

In conclusion, this work demonstrates that proximity-based segmentation enhanced with color and thickness analysis provides an effective solution to the challenging problem of automated renal vein extraction. The achieved accuracy of 92%, combined with practical processing times and robust performance across diverse clinical scenarios, positions this algorithm as a valuable tool for clinical implementation. Future enhancements incorporating machine learning techniques and expanded validation studies will further strengthen its clinical utility and potential impact on patient care.

REFERENCES

[1] SH. Anjamrooz, H. Azari, M. Abedinzadeh, “Abnormal patterns of the renal veins,” Anat Cell Biol. Vol. 45(1), pp. 57-61, March 2012.

[2] A.J. Pérez, G.F. Torres, M.A. Toribio, K.L. Fernández, C. Hayoun, D.I. Naranjo, “Angio CT assessment of anatomical variants in renal vasculature: its importance in the living donor,” Insights Imaging. Vol. 4(2), pp. 199-211, April 2013.

[3] N.Y. Ilyasova “Information Technologies of Image Analysis in the Problems of Medical Diagnostics,” Radio and Communication. Moscow, 424 p., 2012.

[4] N.Y. Ilyasova “Methods and algorithms for assessing geometric parameters of diagnostic images,” Diss: Cand. Tech. Sci: 05.13.18 – Samara: SSAU, 1997, 155 p.

[5] M. Said, A. Khairul A. Jambek, N.Sulaiman, “A study of image processing using morphological opening and closing processes,” International Journal of Control Theory and Applications. Vol. 9, pp. 15-21, 2016.

[6] S. Radjabov, A. Khashimov, E. Urinov, S. Kakharov, “Neural networks for medical image segmentation,” 2021 International Conference on Information Science and Communications Technologies (ICISCT), 2021, pp.1-4.

[7] S. Fazilov, S. Radjabov, M. Atakhanov , A. Khashimov, “Access Control System Based on Facial Image Analysis,” The 1st International Conference on problems and perspectives of modern science: ICPPMS-2021, 10–11 June 2021. Tashkent, Uzbekistan.

[8] S. Fazilov, E. Urinov, S. Kakharov, A. Khashimov, “Improving image contrast: Challenges and solutions,” 2021 International Conference on Information Science and Communications Technologies (ICISCT), 2021, pp. 1-5.

[9] R.Kh. Khamdamov, E.A. Saliev, N.M. Mirzaev, S.N. Ibragimova, “Segmentation of colour image using fuzzy sets concept,” Journal of Physics: Conference Series. Vol. 1333, p. 032035, 2019.

[10] J.T. Nuritdinov, et. al., “Application of Minkowski operator in artificial intelligence tasks,” American Institute of Physics Conference Series. Vol. 3244, No. 1, p. 030016, 2024.

[11] Sh.Kh.Fazilov, Sh.S. Kakharov, Kh.Sh. Rashidov, Y. Khandamov, “Formation of an integrated system of descriptors of recognized objects in images,” American Institute of Physics Conference Series. Vol. 3244, No. 1, p. 030072, 2024