Local Threshold Adaptive Endoscope Intestinal Center Localization Method Based on Morphological Reconstruction

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Abstract. In order to solve the problem of inaccurate localization of intestinal center in the process of endoscopic navigation, a local threshold adaptive localization method based on morphological reconstruction is proposed in this paper. On the basis of image reconstruction and combined with local threshold, it is necessary to find the intestinal center point of the endoscope image and guide the movement of the endoscope in the intestinal tract through the guidance of the intestinal center point, which is an important basis for the navigation path planning of the endoscope by combining the endoscope with visual navigation. In this paper, 355 continuous real endoscope intestinal images were taken to locate the center point, and accurate intestinal center points were obtained. The center points were used to guide the front end of the endoscope, which played a navigation role in the endoscope and visual navigation.

Keywords: Morphological reconstruction, Endoscopic navigation, Dark center method of endoscope, Local threshold adaptive

1 Introduction

In traditional endoscopy, the doctor sends the endoscope into the body by observing the real-time image transmitted by the endoscope lens, and controls the forward and backward movement and angular rotation of the endoscope inside the intestine with clinical experience. This method requires doctors with rich clinical experience to independently judge the central area of the intestine in the image. However, due to the special structure of the intestine, there are many bends. The smooth endoscopy based on experience is prone to inaccurate judgment of the center point. In order to overcome the problem of inaccurate positioning of the center of the intestine during endoscopic surgery, many scholars are committed to combining endoscopy and visual navigation. As a result, research on endoscopic navigation methods has continuously emerged. Common methods include dark area extraction and search Radial method [1], optical flow method [2, 8], magnetic
navigation tracking method [3], distance conversion method [4] and so on. The dark area extraction path finding method adopts the traditional maximum between-class variance method to set the threshold for image segmentation, but the dark area of the endoscopic image often has large differences. Improper selection of the threshold is easy to cause inaccurate positioning. The optical flow method is In the process of use, it is necessary to meet the three premises of constant brightness, consistent space, and small motion range. However, during endoscopy, the brightness and space change greatly, which is prone to misjudgment; magnetic navigation tracking method is mostly used in capsule endoscopes. In use, staying in the human body for a long time is prone to missed diagnosis; the distance change method needs to establish a boundary field and a source distance field, specify the source point, and in the case of bowel bends with extremely irregular shapes, the search for the center point will appear deviation.

In order to solve the above problems, this paper proposes to combine image morphological reconstruction [5] with local threshold self-adaptation. Without modifying the endoscope, only through image processing methods, the endoscopy surgery and visual navigation combining technologies, analyzing and processing endoscopic images, planning the central path of the intestine, and providing doctors with the direction of endoscopic advancement, thereby reducing the technical dependence on operating physicians and reducing the occurrence of medical accidents. As an important part of image processing, image morphology reconstruction is applied in different fields, such as image restoration, face recognition, remote sensing images, and medical imaging. Image reconstruction usually divides the image into a target area and a background area. According to the needs of image reconstruction, by operating the image texture, grayscale, morphology and other information, the interest information of the reconstructed image is often more prominent and more convenient for The path planning of the intestine can provide doctors with more effective information on the direction of the endoscope.

In this paper, the local threshold adaptive algorithm based on morphological reconstruction of the colonic endoscope is improved based on the dark center method. On the premise of satisfying real-time performance, the dark area extraction path finding method is caused by improper threshold selection. The problem of inaccurate positioning of the intestinal center point will be discussed in detail in the follow-up part of this article based on the local threshold adaptive endoscopic path navigation method based on morphological reconstruction.

2 Endoscopic image processing

2.1 Morphological reconstruction

Morphological reconstruction is widely used in image processing, mainly including two images, a marker image (Maker) and a mask image (Mask), and a structural element. Use structural elements to define continuity, place structural elements in the marked image to see if they can fill the marked image well, mark the position of the structural elements that can be completely placed in the marked image, and use the mask image as a constraint. When the pixel value of the mask image has been changing, the image continues to be processed until the pixel value of the mask image no longer changes, and the conversion is stopped. This method can be used to obtain information such as the texture and grayscale of the image. Through further operations on the information of interest, the ultimate goal is achieved. In this paper, the grayscale information of the image is mainly processed on the basis of open operation reconstruction.
Morphological reconstruction mainly includes two processes, select the marker image and the mask image, and then reconstruct. When selecting a marked image, it is necessary to select the connected parts of the image based on the principle of keeping the interest information in the original image to generate a marked image. The selection of structural elements is mainly based on the shape and size of the reserved part. The effective information of the final marked image generated by different structural elements is different. After determining the marked image and the mask image, the image morphology reconstruction is started.

The flow chart of morphological reconstruction is shown in Figure 1:

![Figure 1. Flow chart of morphological reconstruction.](image)

In the process of reconstruction, according to mark image to the mask image rebuilding adopt the method of "quick mixing reconstruction", in order to avoid when scanning the image, the emergence of two or two areas of the maximum area caused by repeated scanning of extremely similar, using inverse raster scanning and raster scanning, this paper for the tag in the image, mask image to remember, the method is as follows:

1. First, reverse raster scanning $F$ was used to scan the mask image:
   \[ J(p) \leftarrow \max_{q \in N_c(P) \cup \{P\}} J(q) \cap I(P) \]  
   where, $N_c(P)$ represents the non-null value of adjacent pixels of $p$ when raster scanning is used. If $q \in N_c(P)$, $J(q) < J(p)$ is simultaneously $J(q) < F(p)$, pixel $p$ is transferred to the end of the queue.

2. Scan $F$ with raster method:
   \[ J(p) \leftarrow \max_{q \in N_c'(P) \cup \{P\}} J(q) \cap I(P) \]  
   where, $N_c'(P)$ represents raster scanning, scanning the adjacent pixel set of $p$ before, and obtaining the minimum value $\Lambda$.

3. For any pixel $q \in N_c(p)$, take out the first pixel in the queue, and store $q$ in the last value of the queue when $J(q) < J(p)$ and $J(q) \neq F(p)$ occur. At this time, the value of $q$ is $J(q) \leftarrow \min \{J(q), I(q)\}$. Repeat this process until the queue is empty.

**2.2 Local threshold adaptive image segmentation**

After morphological reconstruction, the need to set threshold for image segmentation, further endoscope image processing in this paper, the purpose is to find the center of the intestinal tract, and in the endoscope image, intestinal areas are usually dark areas in the images of the area, and the deeper the color, dark area in the image area shows that the depth of the gut.

In this paper, the traditional maximum between-classes variance method and the local threshold adaptive algorithm are compared.
Traditional image segmentation, the between-cluster variance method is more commonly used threshold segmentation method, used to automatically set the threshold, the image of the target area and background area separately, when the target region and background region of the maximum variance between, can get the best threshold value, usually in the histogram, the peak valley between two peaks of a grey value is the optimal threshold, for general target and the background of the difference is obvious, or is the dark areas in the image area is larger when the effect is best, but when the target region and background region difference is small, and dark area is relatively small, usually not ideal segmentation results.

In this paper, the endoscope image threshold segmentation processing mainly according to the grey value of image, the image of the area is made up of multiple identical or similar grey value, and a single grey value to form a large area, and the lower the grey value said the color of light and shade area, the adaptive setting threshold, adaptive search for the minimum gray value of dark area, and set it as the best threshold, the image segmentation and binarization, the image grey value is greater than the threshold value in the region is set to the background region, the grey value less than or equal to the threshold of the locale for the target area, the reconstruction image for $P$, threshold for $T$:

$$
P = \begin{cases} 
255, & P \leq T, \text{The target area} \\
0, & P > T, \text{Background region}
\end{cases}
$$

(3)

3 Experimental results and analysis

3.1 Experimental results and analysis

The data used in this experiment comes from the real video image of colonoscopy endoscopy surgery in Tsinghua Changgeng Hospital. The captured video image contains the straightening and turning operations of the endoscope in the intestine, and the area of the dark area in the endoscope image is different. When the position is different, with a frame of 25 frames per second, a total of 355 images. The image size is 576 768, which is output in RGB format. Each pixel is composed of three color components R, G, and B. The endoscopic image is converted into a grayscale image and the image is reconstructed.

Figure 2 shows the original grayscale image of the endoscope. The image is compared with the dark area extraction method based on the maximum between-class variance method most commonly used in traditional algorithms and the local threshold navigation method based on morphological reconstruction in this paper.

![Figure 2. Gray image of the original image.](image)

Figure 3 shows the comparison of the three-dimensional distribution before and after gray-scale morphological reconstruction. Figure 3(a) is the gray-scale distribution of the image before reconstruction, and Figure 3(b) is the gray-scale distribution of the
reconstructed image. By comparing and analyzing the two images, it can be seen that the gray distribution of the image before reconstruction is more scattered, which is not conducive to image segmentation by setting a threshold, and after the image is reconstructed, the gray value of the darker area on the image is darker. Further reduction, darkens the color of the image, and the gray value of the brighter area increases, the color of the area is brighter, and the contrast between the target area and the background area is enhanced, as can also be seen from the figure on the right. The gray distribution after reconstruction is more concentrated, which is more conducive to image segmentation by setting a threshold.

Figure 3. Comparision of three-dimensional distribution images before and after grayscale morphology reconstruction.

Figure 4 shows the comparison of the histograms of the two methods. Figure 4(a) is the maximum between-class variance method, and Figure 4(b) is the algorithm of this paper. According to the gray characteristics of the image, different gray values appear in the statistical image Times.

Among them, Figure 4(a) is the maximum inter-class variance method. By dividing the image into the background area and the target area according to the grayscale characteristics of the image, when the variance is the largest, the image segmentation effect is the best, and the two The value between the peaks is adaptively set as the segmentation threshold of the image, at this time; Figure 4(b) in this paper is based on the local threshold setting method of image morphology reconstruction. After the image is reconstructed, the minimum grayscale in the image is counted Value and set the lowest grayscale value as the threshold at this time.
Figure 4. Histogram comparison of two algorithms.

Figure 5 shows a comparison of the intestinal center positioning of the two algorithms. Figure 5(a) represents the target area after threshold image segmentation obtained by the maximum between-class variance method. Figure 5(b) represents the reconstruction of this paper based on image morphology. The target area after threshold image segmentation is obtained by a method combined with local threshold adaptation. From the comparison of the two algorithms, we can see that for the same image, the area of the target area obtained is also different due to the different thresholds. Figures 5(c) and 5(d) correspond to the final results of the intestinal center positioning points of Figures 5(a) and 5(b), respectively. The positioning center point in Figure 5(d) is significantly better than that of Figure 5(d). c) Closer to the center of the intestine.

Figure 5. Comparison of intestinal center positioning between two algorithms.
3.2 Advantages of this method

This paper uses image morphology reconstruction technology to strengthen the contrast difference between the target area and the background area, highlighting the dark area of the intestine. Compared with the image before reconstruction, the gray value difference between the highlighted area and the dark area after reconstruction is obvious. Moreover, the gray distribution is concentrated, and the lowest gray value is used as a threshold to divide the image, which further reduces the target area, makes the center point positioning more accurate, and provides an important basis for the path planning of endoscopes and visual navigation.

4 Conclusion

This paper aims at the problem of inaccurate positioning of the path center point during endoscopic navigation, and proposes a local threshold adaptive endoscopic image navigation method based on morphological reconstruction. The morphological reconstruction method is used to highlight the intestinal dark area. The display on the image, combined with the local threshold adaptive method, quickly divides the endoscopic image into the dark area and the background area of the intestine, which can provide accurate path planning for the navigation center of the endoscope without modifying the endoscope. The center point positioning meets the navigation requirements of endoscopic surgery, and can play an important role in the future application of intelligent medical robot endoscope and visual navigation.

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