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Wireless Energy Transmission System for Capsule Endoscopy Based on Image Processing Technology

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Abstract: *The current capsule endoscopy power supply generally uses a battery, which has security risks and will affect the efficiency of capsule endoscopy to a large extent. Therefore, this paper constructs a wireless energy transmission system for capsule endoscopy based on high power and low loss transmission of image processing technology. By improving the merging mode of image processing, image processing is combined with wireless transmission to achieve efficient image processing in wireless transmission. Given the two-dimensional structure of the image, this paper also configures the block in the kernel as a two-dimensional structure. To obtain the best energy transfer performance, this paper tests all the possible combinations of the two dimensions. Then point-to-point high-frequency mode is used for inductive transmission of energy. Research shows that the wireless energy transmission system based on image processing technology can transmit energy in the frequency of 50 Hz-60 Hz, the loss rate is between 11% - 19%, and the overall efficiency has small fluctuations in different modes. Compared with wired power transmission, this system has only a small loss increase, but its efficiency is more than 30% higher than that of battery. And after 100 groups of image testing, this system takes a short time and can meet the wireless power transmission effect of capsule endoscopy.*

Keywords: *Image Processing Technology; Capsule Endoscopy; Wireless Power Transmission; Data Filling and Merging*

1. Introduction

To meet the changing needs of the medical industry for media data processing, it is necessary to improve the data processing architecture, improve the real-time performance of data processing, and relieve the pressure of energy transmission. In addition, to maximize the benefits of data, it is necessary to obtain high-value data information accurately and efficiently from a large number of low-value density data. As a computing mode, image processing can make full use of the computing and energy resources of the edge network, which can greatly reduce the demand of data transmission for network energy resources and meet the real-time demand of media data processing.

In the aspect of image processing, Liu Q studies the image restoration method based on chain code. The basic idea is to use the relative position between adjacent pixels to classify pixels, to determine which line segments between pixels need to be filled [1]. Hou J proposed a filling algorithm based on chain code and combining the advantages of boundary point parity check and region growing method [2]. Volume graphics has been widely used in modeling, industrial design, and medical imaging. Seed filling algorithm can be transplanted to three-dimensional space to solve the problem of closed space-filling. Dai l proposed an efficient 3D seed filling algorithm to solve this problem. Xue binding improved the stack structure and the stack seed method to eliminate the redundant stack and backtracking operations and improved the efficiency of the algorithm [3]. Kune r designed a 3D seed filling algorithm based on scanning slice. Because of the importance of filling algorithm in geographic information system, remote sensing data analysis, computer animation, target recognition, image reconstruction, regional coverage, industrial design, medical image, and other aspects, it is of great significance to improve the efficiency of the algorithm [4]. Zhang J proposed a target detection architecture for monitoring applications based on image processing of capsule endoscopy. Firstly, the data is preprocessed in the terminal device, and the deep learning algorithm fast r-CNN is trained in the cloud, and then it is recognized in the edge server, realizing distributed and efficient target detection in monitoring application [5].

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The object of image wireless energy transmission is a general object without category, and the object is required to have a complete and closed boundary. Its research fields are mainly divided into local region detection, salient object detection, and object recommendation status. Among them, Bing (binarized normalized gradients) proposed by Zou x is a data-driven object boundary generation algorithm, which can detect the boundary box of potential objects at the speed of 300 frames per second on the resource lightweight terminal, and can easily distinguish the object and background in the image by using this algorithm [6]. However, in practical application, there will be positioning deviation. Based on this, this paper adds the correction process of the positioning box to improve the accuracy of positioning.

In this paper, a wireless energy transmission system for capsule endoscopy is constructed based on high power and low loss transmission of image processing technology. The image processing technology is studied. By improving the merging mode of image processing, image processing is combined with wireless transmission to achieve efficient image processing in wireless transmission. Given the two-dimensional structure of the image, this paper also configures the block in the kernel as a two-dimensional structure. To obtain the best energy transfer performance, this paper tests all the possible combinations of the two dimensions. Then point-to-point high-frequency mode is used for inductive transmission of energy.

2. Image Transmission and Unit Processing Algorithm

2.1. Image Transmission in Network

From the perspective of image processing, capsule endoscopy image processing is a part of the network computing system and a supplement to cloud computing in the application of edge networks [7]. At present, the research on image processing of capsule endoscopy mainly focuses on the application of image processing architecture, resource virtualization, task unloading algorithm, and deep learning in the image processing system of capsule endoscopy [8]. As a computing-intensive task, deep learning needs a lot of computing resources, while the resources in the edge network are limited, so how to deploy the deep learning task to the capsule endoscopy image processing environment is worth studying [9]. The deep learning model on the terminal node is segmented, and the computing subtasks are unloaded to the edge server, to reduce the computing burden of the terminal node. However, network congestion occurs from time to time, which may cause the subtasks to be lost or exceed the deadline of the task [10]. In general, the edge server has more abundant resources, so this paper can consider putting the computing-intensive tasks on the edge server [11].

In this paper, multiple adaptive instance normalization (adain) residual network blocks are used in the generator to form the middle area, and the output of the image domain controller is used as the input style information of the residual network block. Adain is used to fuse the image content feature information and style feature information, preserve the original image content information, and increase the style diversity [12]. Adain is an improvement based on in, which aligns the mean and standard deviation of image content information and style information, to better fuse different image domain information. X is the content information of the image, y is the style information:

$$\mathrm{AdaIN}_{jh} = \int_0^{\infty} dF_h(y) \int_0^{y} (y-x)\, dF_j(\mathrm{IN}) \quad (1)$$

$$\mathrm{Y_j} = \frac{\frac{1}{2u_j} \sum_{i=1}^{n_j} \sum_{r=1}^{n_j} \left| y_{ji} - y_{jr} \right|}{n_j^2} \quad (2)$$

2.2. Wireless Transmission Unit Processing Algorithm

The convolution operation of the down sampling of the selective transmission unit leads to the reduction of the image resolution. It is difficult to effectively increase the detailed feature information of the transferred image domain only by transferring the features extracted from the down sampling to the up sampling through the jump connection [13]. To solve this problem, this paper introduces the selective transmission unit (stu) to selectively transmit the features extracted from the down sampling to the up sampling according to the input relative attribute labels, to form fusion features, increase the detailed information of the migrated image domain, and reduce the chances of the irrelevant image

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domain [14]. Stu is an improvement based on Gru. The model input is:

$$\mathrm{STU}_{jh} = \frac{\sum_{Z=1}^{h_j}\sum_{r=1}^{n_h}\left|y_{ji} - y_{hr}\right|}{\mathrm{GRU}_j n_h (u_j + u_h)} \quad (3)$$

$$\mathrm{GRU}_{nb} = \sum_{j=2}^{k}\sum_{h=1}^{\mathrm{Tconv}-1} G_{jh}(\mathrm{LZ}_j s_h + p_h \mathrm{IR}_j)\mathrm{Conv}_{jh} \quad (4)$$

IR is the repeat gate, LZ is the update gate, which is the splicing operation, tconv is the convolution, conv is the convolution, which is the Hamiltonian product, and E is the matrix addition:

$$\mathrm{E}_t = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh}(p_j s_h + p_h s_j) D_{jh}(1 - D_{jh}) \quad (5)$$

Due to the lack of detailed features in single scale discrimination, the overall migration image is slightly distorted; Multiscale overemphasizes the details of the background, resulting in obvious changes in the background and other irrelevant image domains of the whole migration image; Dual scale discrimination can identify the authenticity and category of the input image cooperatively, improve the accuracy of image detail feature determination, and improve the quality of the transferred image [15].

3. Wireless Power Transmission Experiment of Endoscope

3.1 Methods

In this paper, a wireless energy transmission system for capsule endoscopy is constructed based on the high-power and low-loss transmission of image processing technology. The image processing technology is researched, and the image processing and wireless transmission are combined to achieve efficient image processing in wireless transmission by improving the merging method of image processing.

3.2 Wireless Energy Transmission for Endoscope

Because of the two-dimensional structure of the image, this paper also configures the block in the kernel as a two-dimensional structure. To obtain the best energy transfer performance, this paper tests all possible combinations in two dimensions (the test range of each dimension is from 1 to 1024, but the maximum number of threads in a block is 1024, so some combinations such as 256 * 8 are illegal combinations). Each thread in the GPU (graphics processing unit) implementation needs to read pixels, find the tag of the corresponding element in the root array with the pixel value as the subscript, and write different values to the pixels according to the tag. The image data and the root array are located in the global memory, so the algorithm performance is more sensitive to the global memory access efficiency.

There are two sources of input image data in the GPU merging process: the intermediate result filled by CPU (central processing unit) and the intermediate result filled by GPU. The work of the merging stage is to divide the pixels in the images filled with different tags into three categories according to the results of the union search algorithm: those connected with the image boundary, those not connected with the image boundary, and the original contour of the image, and then fill them into the background color, foreground color or remain unchanged. The image is divided into several blocks from top to bottom by CPU merging, and each thread is responsible for the inversion of pixels in an image. The GPU merge implementation starts a thread for each pixel, and the number of threads is determined by the image resolution. The biggest difference between the two is the number of pixels. The best number of seed/thread is 110 when the CPU is filled, so each pixel can be represented by 8bit; the best number of seed/thread is 32768, and the bit length is 16bit. The difference of image capacity between the two is one time, and the difference of root array length (equal to the number of seeds) is 300 times. Therefore, there are great differences in data transmission efficiency and GPU global memory access performance, resulting in different average speedups for the same algorithm. In this paper, the transmission unit effect evaluation experiments are carried out for 160000 to 200000 iterations. When the number of iterations reaches 200000, the model enters into a state of complete convergence, so 200000 iterations are selected as the final number of iterations. To achieve the best migration effect, this paper selects the dual scale discrimination and selects the original image and the

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average pooled image as the input of the discriminator.

4. Results and Discussion

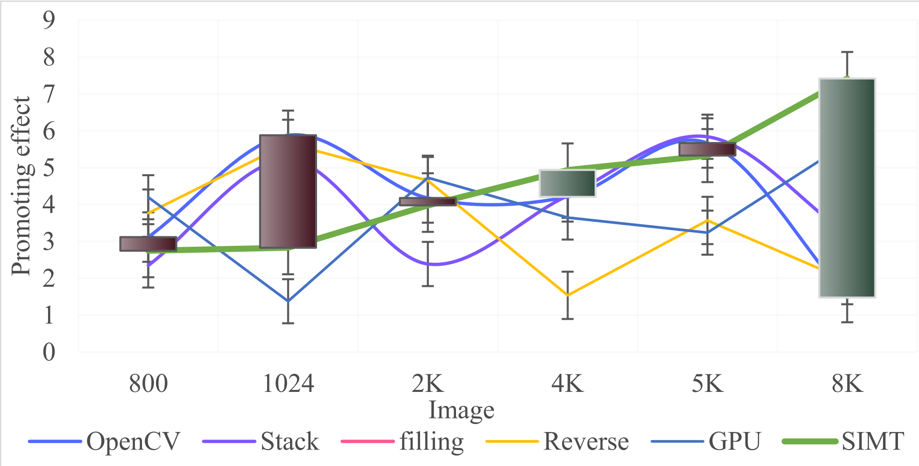

Figure 1: Speedup of serial implementation

This paper tests the performance of various schemes on the experimental platform, and calculates the speedup ratio of each scheme relative to the serial implementation, as shown in Figure 1. It can be seen that the performance of the parallel algorithm in the high-resolution image is much higher than that in low-resolution images. This is because the amount of data is small, and the benefits of multithreading are not enough to make up for the overhead of thread management. The speedup ratio of GPU + GPU combination is only slightly higher than 1, because the complex logical structure of the filling process is not suitable for the SIMT execution model of GPU. The combination of CPU + CPU and CPU + GPU achieves more than 3 times of speedup, which is higher than the performance of OpenCV implementation, so it has practical value. As the standard of speedup calculation, the serial algorithm uses a single thread and single stack to complete filling and inversion; as a measure of effectiveness, OpenCV uses functions to fill and invert images respectively.

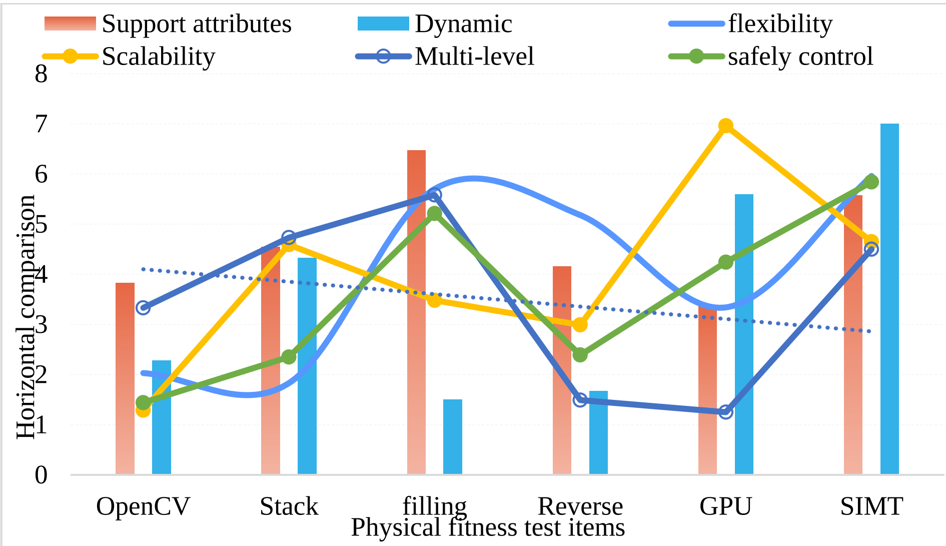

Figure 2: Time-consuming initialization and union search algorithm

As shown in Figure 2, no matter which combination, the time-consuming of seed initialization and search algorithm only account for a very small proportion, and the time-consuming filling process is dominant. In the combination without GPU, the merge / reverse process takes the second place; in the combination using GPU, data transmission takes the second place of time-consuming, and merge / reverse process takes the third place. In practical application scenarios, such as pipeline work piece detection, it is often necessary to process batch images.

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Table 1: Batch image processing time

Item	OpenCV	Stack	Filling	Reverse	GPU	SIMT
Support attributes	3.83	4.54	6.47	4.16	3.38	5.57
flexibility	2.03	1.83	5.7	5.18	3.34	5.96
Dynamic	2.28	4.32	1.5	1.67	5.59	7
Scalability	1.29	4.59	3.48	2.99	6.96	4.65
Multi-level	3.33	4.73	5.58	1.49	1.25	4.5
Safely Control	1.44	2.35	5.21	2.39	4.24	5.84

For the combination of filling and merging running on the same device, the batch image processing time is the superposition of single image processing time, as shown in Table 1. The combination of CPU and GPU run on heterogeneous platforms. For batch tasks, it has additional advantages, which makes it possible to further optimize the combination. The filling phase of the combination runs on the CPU, while the merging phase runs on GPU. For batch filling tasks, by reasonably arranging the execution sequence between two adjacent image processing steps, the combination can be optimized, heterogeneous platforms can be built as pipelines to further improve the processing efficiency.

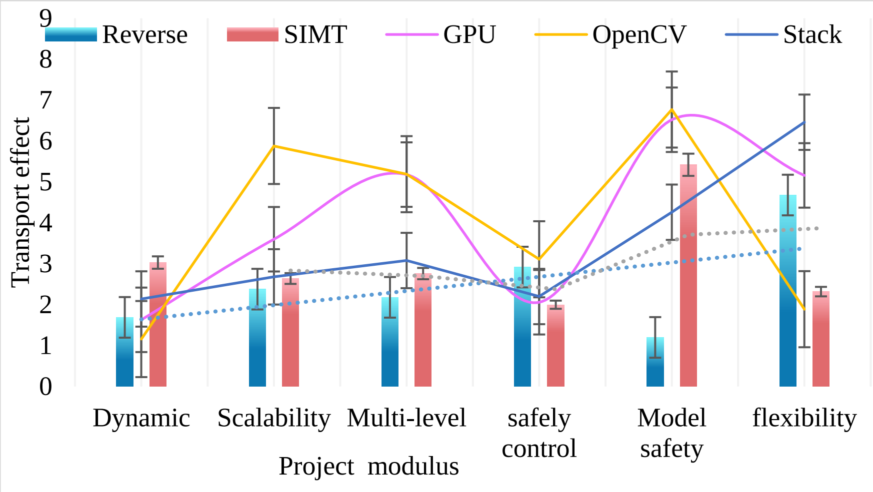

Figure 3: Transmission efficiency of the model

As shown in Figure 3, the wireless energy transmission system based on image processing technology in this paper can transmit energy at the frequency of 50 Hz-60 Hz, the loss rate is between 11% - 19%, and the overall efficiency has a small fluctuation in different modes. Compared with wired power transmission, this system has only a small loss increase, but its efficiency is more than 30% higher than that of battery. And after 100 groups of image testing, this system takes a short time and can meet the wireless power transmission effect of capsule endoscopy. Compared with the single image filling/inversion two-stage serial implementation, the pipeline model can achieve an average performance improvement of 14.21% in the case of batch processing. The CPU is used in the filling phase of the combination, and the optimal seed / thread number range is 70 - 110. 8 bits are used to represent a pixel. Compared with the implementation of the GPU filling phase, it reduces the cost of data transmission between CPU and GPU.

5. Conclusion

The image processing architecture of capsule endoscopy depends on different applications. For the application of target detection in capsule endoscopy image, to effectively use various computing resources of edge network system, this paper carries out the research of target detection based on the edge network architecture of "terminal network layer edge server layer cloud layer", and designs the application architecture, and the wireless communication environment is unstable, which is easy to cause data loss. Therefore, in the terminal network layer, the collected image will be initially detected for saliency, and then the different detection areas in the image will be compressed with different compression rates to reduce the energy loss of network transmission. In the edge server layer, the deep learning algorithm is implemented to recognize the image uploaded by the terminal node, and the data that need to be further mined and stored for a long time is uploaded to the cloud through the core network.

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