GPU-based Parallel Algorithm for TCPM External Force Field

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Abstract

With the development of technology, the contour extraction for High-definition images is a major problem at present. The snake model is a contour extraction algorithm which has many advantages. Its improved models include the GVF snake, CPM , TCPM,and so on. The external force field of snake model has a great influence on the performance. In order to save the computation time ,The GPU-based parallel algorithm Of TCPM external force field is introduced.Firstly, the principle of the original snake model, GVF snake, CPM and TCPM are interpreted. The computation of external force field in the TCPM can be simplified to the two-dimensional discrete convolution l. The parallel algorithm of TCPM external force field was proposed and optimized. Two sets of experiments were introduced to conform the acceleration effect of the parallel algorithm. The result shows that the parallel algorithm of the TCPM external force field has achieved a good acceleration effect, and should be worthy of application and promotion.

Keywords

Snake models;GVF snake;TCPM;CUDA;High-definition images processing.

1. Introduction

The advancement of technology in recent years has turned the contour extraction of high-definition images to a hot issue at present, such as medical image processing and the chromatographic method in reverse engineering. One common feature of this type of contour extraction is that there are high requirements on the speed of image processing. In 1988, an innovated contour extraction method—snake model was proposed by Kass[1].Compared with the traditional method, Snake model has some unique advantages. Firstly, the snake model creatively integrates the high-level information and the underlying information in an digital image. Second, the snake model can control the processing effect of the algorithm externally by artificially changing the parameters. However, the traditional snake model proposed by Kass itself has some drawbacks: (1) the traditional snake model must be initialized near the target contour. (2) the traditional snake model has poor convergence to the boundary concavities of the object Based on these difficult, some improvements for the external force field of the snake model have been introduced. On the basis of the gradient force of image as external force, an expansion force in normal direction of active contour was increased by Cohen and called balloon force model[2]. With the introduction of expansion force, the curve initialized farther away from the target edge also has the tendency to convergent to the object. However, its drawback is that the initialization must be completely inside or outside the object . In 1997, Gradient Vector Flow (GVF) model was proposed by XU[3].The GVF model has an significant improvement that the image gradient force is diffused to the further region of image by the diffusion equation in fluid mechanics[4]. Hence the advantages of the GVF model over a traditional snake are its insensitivity to initialize and the ability to move into boundary concavities. However, the GVF snake can not converge to deeper concavities. Some scholars have also improved the external force field of the snake model from other physical models. Park proposed the virtual electric field (VEF) model by introducing the electrodynamic model and taking the Coulomb force between the charged particles as the external force[5].Then the further model—charged particle model (CPM) was proposed by Jalba[5]. The CPM can be regarded as a system of charged particles moving in an electrostatic field.In CPM the external force includes Coulomb force and Lorentz force .When reach to the boundary of image, the charged particles can continue to move into the deep concavities owing to the Coulomb force from other charged particles in active contour. However, the CPM model also has some disadvantages such as it is not a standard active contour model. In addition, the external force in the CPM is composed of the changing Coulomb force and the static Lorentz force, and the computation of Coulomb force is more very time-consuming. After giving full study of CPM, a new type model —Truncated Charged Particle Mode (TCPM) was proposed by Tang and is applied to parametric active contours [7].In TCPM the computation of the external force of the CPM model is simplified by the truncation method. Furthermore only the static Lorentz force is carried out in the computation of the external force field so that the computational time was greatly saved.

In recent years, GPU-based parallel computation has developed rapidly. In 2007,a new parallel software CUDA was launched by NVIDA and make parallel programming easier.At present, there are relatively few research on parallel computation for snake models. However, the image external force of the snake model has a great influence on the initialization of the contour and the convergence to the boundary concavities. The computation of the external force of the snake model may greatly affect the whole time efficiency of the snake l algorithm. If the external force field computation of the snake model can be accelerated by the parallel programming, it will lay a good foundation for saving the whole computation time of snake models, and is applied to medical and industrial in practical. The parallel algorithm proposed in this paper will focus on the external force field of the TCPM . First, the original snake model and its modified principles are reviewed in the paper. Then, a parallel algorithm of TCPM external force field is proposed and optimized. Finally, the experiment is introduced to confirm the speedup of the parallel algorithm of the TCPM external force field.

2. Snake model and its improved models

2.1 Traditional snake model

A normalized parametric curve $\boldsymbol{c(s)} = (x(s), y(s))$, $s \in [0,1]$ was introduced into the original snake model proposed by Kass to represent the active contour, and then a minimization energy of the parametric curve is defined as

$$E_{snake} = \int_0^1 E_{int} + E_{ext}\boldsymbol{ds} \tag{1}$$

The internal energy of the curve E_{int} can be expressed as following

$$E_{int} = \frac{1}{2}(\alpha \,|\, \boldsymbol{c_s(s)} \,|^2 + \beta \,|\, \boldsymbol{c_{ss}(s)} \,|^2) \tag{2}$$

The internal energy E_{int} is mainly responsible for the control of the geometric topological properties of the curve during the convergence. $|\boldsymbol{c}_s(s)|$ and $|\boldsymbol{c}_{ss}(s)|$ represent the continuity and the curvature of the active contour change respectively. Therefore setting the coefficient α in equation (1) can change the continuity in the convergence process , while setting the coefficient β can change the curvature during the curve motion such as maintaining the curve smooth.

The effect of the curve external energy E_{ext} is to drive the active contour to converge to the object. In the original snake model, it is generally assumed that $E_{ext} = -|\nabla \boldsymbol{I}(x, y)|^2|$ or $E_{ext} = -|\boldsymbol{G}_\sigma * \nabla \boldsymbol{I}(x, y)|^2$. $\boldsymbol{I}(x, y)$ is the input image and $\boldsymbol{G}_\sigma$ is the Gaussian smooth convolution kernel with a standard deviation σ . The function of the Gaussian smooth convolution kernel is to increase the scope of the external energy in image, and enlarge the curve initialization range. The original snake model defines the convergence condition of active contour as the minimization of the energy. According to the functional extreme principle, E_{snake} in formula (1) takes the minimum value by solving the following Euler equation

$$\frac{\partial}{\partial s}\left(\alpha\frac{\partial \boldsymbol{c}}{\partial s}\right)-\frac{\partial^2}{\partial s^2}\left(\beta\frac{\partial^2 \boldsymbol{c}}{\partial s^2}\right)-\nabla E_{ext}=0 \tag{3}$$

2.2 GVF model

For the sensitive initialization and poor convergence to the boundary concavities in original snake model, XU has proposed the GVF model, in which the condition of contour convergence is transform to the following force balancing condition

$$\boldsymbol{F_{int}}+\boldsymbol{F_{ext}}=0 \tag{4}$$

The convergence process of GVF snake can be regarded as the interaction of external force and internal force of the active contour, and then the force balance is achieved in the object. The external force field of GVF is defined to be the vector field $\boldsymbol{F}(x,y)=[u(x,y),v(x,y)]$, and can be calculated by the following minimum energy function.

$$\varepsilon=\iint \mu(u_x^2+u_y^2+v_x^2+v_y^2)+|\nabla f|^2|\boldsymbol{F}-\nabla f|^2\,dxdy \tag{5}$$

Where f is the edge of the input image calculated by the edge operator. According to the variational principle, the external force field can be obtained by the following Euler equations.

$$\mu\nabla^2 u-(u-f_x)(f_x+f_y)^2=0 \tag{6}$$

$$\mu\nabla^2 v-(v-f_x)(f_x+f_y)^2=0 \tag{7}$$

Equations (6) and (7) are equivalent to a set of diffusion equations which spread the image gradient force further. Therefore, the GVF model has a large capture range for active contour and possesses ability to move into boundary concavities. However , the GVF also has some defects, such as the long computation time of the external force and the failure to converge to the deep concavities in the object.

2.3 CPM and TCPM

In view of the shortcomings of the GVF model, some scholars have attempted to introduce mechanical model to improve external force field of snake model. The charged particle model(CPM) proposed by Jalba can be seen as negatively static charged particles on the object which attracting positively free charged particles. The external force is mainly consist of the Lorentz force generated by static particle in the object and the Coulomb force among the free charges, specifically expressed as follows:

$$\boldsymbol{F}_L(\boldsymbol{s}_i)=q_i\sum_{k:\boldsymbol{R}_k\neq\boldsymbol{s}_i}^{M}\frac{e_k}{4\pi\varepsilon_0}\frac{\boldsymbol{s}_i-\boldsymbol{R}_k}{|\boldsymbol{s}_i-\boldsymbol{R}_k|^3} \tag{8}$$

$$\boldsymbol{F}_C(\boldsymbol{s}_i)=q_i\sum_{j\neq i}^{N}\frac{q_j}{4\pi\varepsilon_0}\frac{\boldsymbol{s}_i-\boldsymbol{s}_j}{|\boldsymbol{s}_i-\boldsymbol{s}_j|^3} \tag{9}$$

In Equation (8) and (9), M and N are respectively the amounts of static particles and free particles, S is the position vector of the active charged particle, R is the position vector of the fixed charged particle on the object, e is the electric quantity of charged particles on the object, q is the electric quantity of the free particles. When converging to the target, the CPM has the ability to move into depressed concavities due to the Coulomb force. However, as Coulomb force is dynamic in convergence process, it is time-consuming in computing the force field of CPM. In addition, the CPM is a deformable template rather than a standard snake model [6]. The TCPM proposed by Tang introduces truncation method to simplify the computation time of the CPM. A particle (pixel) on the edge of the map will influence or interact with pixels inside a fictitious box as show in Figure 1,given that the truncation scope is 7. In addition,the Coulomb force is a dynamic force, meanwhile the Lorentz force is much greater than the Coulomb force in the CPM. Therefore, the Coulomb force is ignored in the TCPM. In this way, the time of computing the external force field is greatly saved .

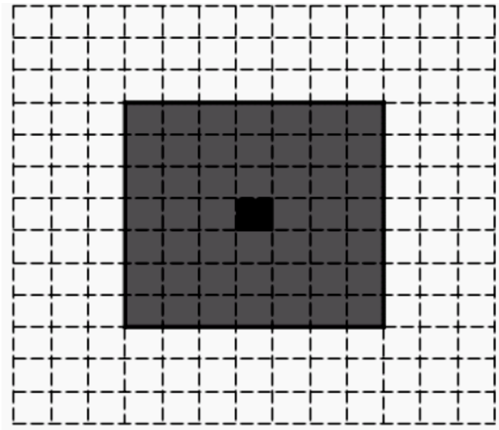


Figure1 the truncation scope in TCPM model(7×7)

The external force field of the TCPM can be calculated as follows. Set the pixel coordinates as (m, n)

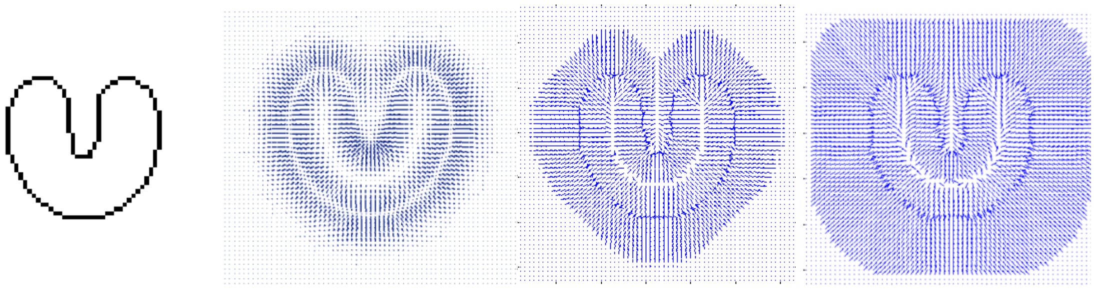
$$\boldsymbol{F}_L(m,n) = -\sum_{\substack{k=-s \\ k\neq 0}}^{s}\sum_{\substack{l=-s \\ l\neq 0}}^{s} ce_1e_2\left(\frac{k}{(k^2+l^2)^{3/2}} + \frac{l}{(k^2+l^2)^{3/2}}\boldsymbol{i}\right)\times h(m+k,n+l) \qquad (10)$$

$h(x,y)$ is defined as

$$h(x,y) = \begin{cases} & \text{when (x, y) is at the target contour} \\ & \text{when (x, y) is at other positions} \end{cases}$$

It has been proved that the TCPM has similar effect with the GVF snake, such as large initialization range and ability to move into the boundary concavities.As shown in Fig. 2 is the external force field of the original snake model, GVF model and TCPM respectively in 64×64 U-shape image

The greatest advantage of the TCPM is that its computation time has been greatly saved compared with the GVF model. Table 1 shows the speed of several algorithms in different external forces about a 64×64 U-shape image.The computation of the TCPM external force field is more than 20 times faster than the GVF model. If the parallel acceleration can be performed,, the computation speed of the external force field can be further improved and the above achievement will lay a foundation for the speedup of the whole snake mode algorithm.



a) 64×64 U-shape b) traditional snake model c) GVF model d) TCPM model image

Figure 2 the comparison between several external force of snake models

Table 1 the computation time of several snake models in U-shape image

Type	Computing time(ms)
Original snake	2.31
GVF	74.42
TCPM	3.25

3. Proposed method

3.1 Simplify of TCPM

As it can be seen from equation (10) that the TCPM can be transformed into a two-dimensional discrete convolution of the input image, and the vector discrete convolution kernel is as follows

$$\boldsymbol{g(x, y)} = \begin{cases} (-\frac{x}{(x^2+y^2)^{3/2}}, -\frac{}{(\quad)} & \text{other circumstances} \\ 0 & x=0, y=0 \end{cases} \tag{11}$$

Moreover, the two-dimensional discrete convolution model is suitable for parallel acceleration. The direct convolution method will be used to parallel algorithm of TCPM external force..The preliminary parallel algorithm flow chart is shown in Figure 3.

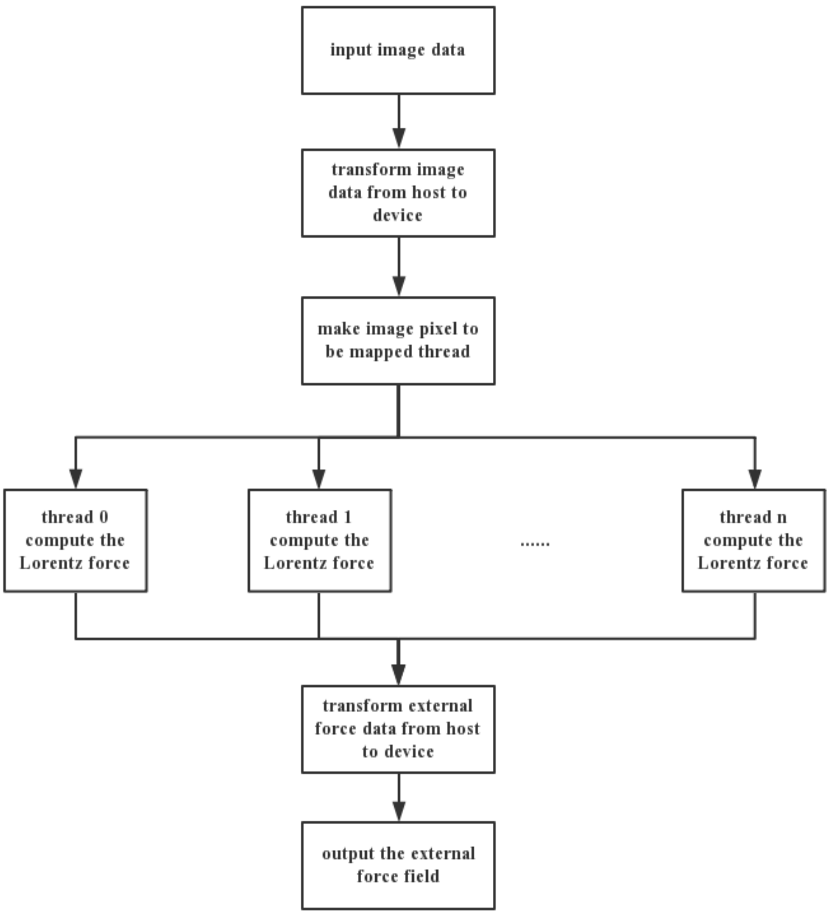


Figure3 parallel algorithm flow chart of TCPM external force field

3.2 Optimization of parallel algorithms

The optimization of parallel algorithms for two-dimensional discrete convolution has been studied deeply[8]. For the original two-dimensional discrete convolution method as proposed above, the algorithm will be optimized from the following two aspects: the convolution kernel and the data of GPU memory in CUDA parallel program.

Firstly, taking a 7×7 vector convolution kernel as an example, both x and y component kernel computed by Equation (11) are partial symmetry, as shown in Fig. 4 and Fig. 5

Therefore, symmetry can be used not only to reduce the operation times in the two-dimensional convolution by extracting the common factors but also to reduce the number of data reading in the convolution kernel.

Secondly, the optimization method focus on GPU memory can be used in parallel program to further save the time of computation. GPU memory mainly includes global memory, shared memory,

-0.0393	-0.0427	-0.0316	0	0.0316	0.0427	0.0393
-0.0640	-0.0884	-0.0894	0	0.0894	0.0884	0.0640
-0.0949	-0.1789	-0.3536	0	0.3536	0.1789	0.0949
-0.1111	-0.2500	-1.0000	0	1.0000	0.2500	0.1111
-0.0949	-0.1789	-0.3536	0	0.3536	0.1789	0.0949
-0.0640	-0.0884	-0.0894	0	0.0894	0.0884	0.0640
-0.0393	-0.0427	-0.0316	0	0.0316	0.0427	0.0393

Figure 4 convolution kernel in x direction

-0.0393	-0.0640	-0.0949	-0.1111	-0.0949	-0.0640	-0.0393
-0.0427	-0.0884	-0.1789	-0.2500	-0.1789	-0.0884	-0.0427
-0.0316	-0.0894	-0.3536	-1.0000	-0.3536	-0.0894	-0.0316
0	0	0	0	0	0	0
0.0316	0.0894	0.3536	1.0000	0.3536	0.0894	0.0316
0.0427	0.0884	0.1789	0.2500	0.1789	0.0884	0.0427
0.0393	0.0640	0.0949	0.1111	0.0949	0.0640	0.0393

Figure 5 convolution kernel in y direction

constant memory, and texture memory. Among them, the global memory has the maximum capacity but a high latency; the constant memory has a small capacity but an excellent read-only mechanism and low latency. All the threads in the kernel can access the constant memory. In a discrete two-dimensional convolution program, the data in the convolution kernel is less and read repeatedly. Therefore, the data in the vector convolution kernel can be located in the constant memory.

The shared memory also has low access latency. However, only threads in the same block can access the data in the shared memory . In the parallel program of the TCPM external force field, the size of the convolution kernel is large, so the total capacity limit of whole shared memory on GPU will be exceeded when the kernel function have a bit more active blocks. So the optimal solution adopted in the parallel computation of the TCPM external force field will focus on the convolution kernel and the constant memory . The main kernel function codes are as follows, where dma1, dma2 are the two components of the vector convolution kernel, a is the input image, and b and c are two components of the output external force field.

```
__constant__ float dma1[],dma2[];
__global__ void conv2ver1(float *a,float *b,float *c,int n1,int n2,int m1,int m)
{
   int i=blockIdx.x*blockDim.x+threadIdx.x;
   int j=blockIdx.y*blockDim.y+threadIdx.y;

   float temp1=0.0;
   float temp2=0.0;
   int k,q,kk,qq;
   for(k=0;k<m1+1;k++)
   {
         for(q=0;q<m1;q++)
         {
               kk=j+k;
               qq=i+q;                    temp1+=dma1[k*m1+q]*(a[kk*n2+qq]-
       a[kk*n2+qq+m-q]+a[(kk+m-k)*n2+qq]-a[( kk+m-k) *n2+qq+m-q]);

               kk=kk-j+i;
               qq=qq-i+j;
       temp2+=dma2[q*(m1+1)+k]*(a[qq*n2+kk]+a[qq*n2+kk+m-k]-a[(qq+m-q)*n2+kk]
       -a[(qq+ m-q)*n2+kk+m-k]);
         }
   }
   b[j*n1+i]=temp1;
   c[j*n1+i]=temp2;
}
```

4. Experiment and results

Two sets of experiments were introduced to test. The first set of experimental objects is six U-shaped images with increasing pixel size for confirming the acceleration effect about the optimized parallel algorithm of the TCPM external force field. The second set of experiments focused on the medical MRI heart images, for comparing the computation time of the GVF force field algorithm on CPU, TCPM external force field algorithm on CPU and parallel TCPM external force field algorithm on GPU respectively.

Hardware in the experiments are as follows: i5-4740 CPU, GTX780 GPU with a computation capacity of 3.5, and 8G RAM. GTX780 has 2304 CUDA cores, 12 SMX and 4 groups of GPC. It also has 64 KB constant memory and 3GB global memory. All test program were performed on CUDA5.5 and Opencv2.4.9.

For the different U-shaped images with increased pixel sizes, the computation time of the TCPM model algorithm on CPU, the original TCPM external force field parallel algorithm, and the parallel algorithm after convolution kernel optimization and constant memory optimization are tested respectively. Truncation scope were 31, 47, and 63 . The results are shown in Table 2 to Table 4

Table2 the comparison of computation time between several algorithms when the truncation scope is 31

Size of image	Algorithm on CPU(ms)	The original parallel algorithm(ms)	The parallel algorithm after optimized(ms)
256×256	27.47	1.75	0.89
256×512	38.02	3.44	1.79
512×512	61.87	6.66	3.55
512×1024	100.47	13.64	7.49
1024×1024	173.02	27.90	15.69
1024×2048	318.98	57.28	32.74

From the above experimental data from Table 2 to table 4, it shows that the parallel algorithm has the best acceleration effect when the truncation range is 31. Compared with the serial algorithm, the optimized parallel algorithm achieves a maximum speedup which is 30.86. When the truncation range is 47, the highest speedup which is 16.5 has been achieved. When the truncation range is 63, the optimized parallel algorithm have achieved the highest speedup which is 10.5.In addition, compared to the original parallel algorithms, the optimized parallel algorithms can achieve the speedup which is more than 1.5, indicating that the optimization method is effective.

Table3 the comparison of computation time between several algorithms when the truncation scope is 47

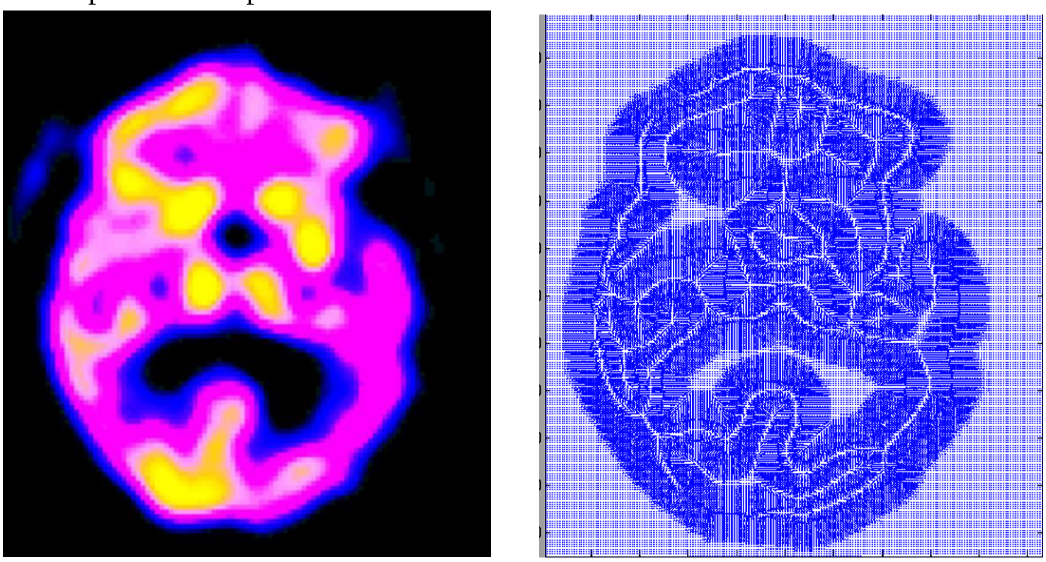
Size of image	Algorithm on CPU(ms)	The original parallel algorithm(ms)	The parallel algorithm after optimized(ms)
256×256	30.14	3.78	1.82
256×512	41.02	7.34	3.56
512×512	71.26	14.21	6.97
512×1024	119.41	28.53	14.19
1024×1024	204.58	57.63	29.22
1024×2048	372.15	116.30	59.83

Table4 the comparison of computation time between several algorithms when the truncation scope is 63

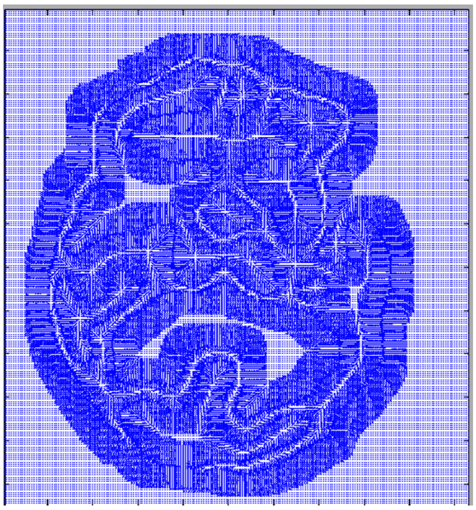
Size of image	Algorithm on CPU(ms)	The original parallel algorithm(ms)	The parallel algorithm after optimized(ms)
256×256	32.81	6.49	3.12
256×512	45.63	12.73	6.03
512×512	78.25	24.81	11.89
512×1024	130.34	49.53	23.83
1024×1024	231.82	99.29	48.38
1024×2048	428.14	199.60	98.10

The experimental result also shows that the acceleration effect is better when the truncation scope is small, and the acceleration effect is poor when the truncation range is large. Although the convolution kernel has optimized, the time-consuming of the parallel algorithm for two-dimensional discrete convolution has a square growth when the size of convolution kernel increases. In the experiment, the convolution algorithm of TCPM external force on CPU is calculated with the fiter2D function in Opencv. When the convolution kernel is small, the fit2D function uses direct convolution method. When the convolution kernel is large, the FFT method is used, which has a better computation time performance than the direct convolution method [9]. Therefore, the FFT method for two-dimensional discrete convolution will be introduced and deeply studied in the future.

From the discussion above, in the U-shaped image of different sizes, the optimized parallel algorithm of TCPM external force field has achieved good acceleration effect when the truncation scope is 31, 47, and 63 respectively.It shows that the parallel algorithm can replace the serial algorithm of TCPM external force certainly. At the same time, in order to test the acceleration effect of the parallel algorithm on the specific image, the medical image will be introduced.. As shown in FIG. 6 there are the 690×618 heart MRI image, its TCPM model external force field and GVF field respectively. The data was obtained from the computation of GVF field on CPU, the computation of TCPM external force on CPU and the optimized parallel algorithm of TCPM external force field. The smoothing coefficient μ in the GVF model is set to 0.1, the number of iterations is set to 90, and the TCPM has a truncation scope of 61. Experimental results are shown in Table 5.



a)690×618 heart MRI image b)its GVF field



c)TCPM external field

Figure 6 the MRI image of heart and its extern force field of snake models

Table5 The comparison of several algorithms about the heart MRI image

Algorithm of GVF field on CPU(ms)	Algorithm of TCPM external force field on GPU(ms)	Optimized Algorithm of TCPM on GPU(ms)
5512.25	121.54	20.82

From the result in Table 5, it shows that the serial algorithm of the TCPM external force has about 40 times faster than the GVF field algorithm on CPU. Meanwhile, the optimized TCPM external force field parallel algorithm has 6 times faster than the serial algorithm. We can draw a conclusion that t the TCPM external force parallel algorithm has also achieved great acceleration performance in the medical image, indicating that the optimized TCPM external force field parallel algorithm can be applied in high-definition image possessing,.

5. Summary

The TCPM external force field has the similar effects with the GVF field, while it has a much faster computation speed than the GVF. For further improvement of time-consuming in snake model, a new parallel algorithm of TCPM external force field is proposed.By the two sets of experiments the effect of TCPM external force parallel algorithm is conformed to be worthy of application to high-definition image processing. In the future the FFT method for dimensional discrete convolution will be deeply studied in order to solve the difficult that when the truncation scope is large the acceleration effect of parallel algorithm will be bad.

Acknowledgments

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