The Performance of 3D Multi-slice Branched Surface Reconstruction on CPU-GPU Platform

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Abstract: In this paper, a CPU-GPU algorithm to generate composite contour for 3D branching surface is presented. The composite contour is generated based on the data points from based and branched contours and located in between the two contours. Distance calculation is one of the processes in composite contour generation which consumes the most CPU time, therefore, this process is chosen to be executed on the GPU. The developed composite contour generation method on the CPU-GPU platform is then applied on CT images of Stanford bunny and human pelvic with three different number of curve points per segment. These samples generate 12 composite contours in total. The performance of the developed algorithm is measured based on the processing time and the speedup. The result shows that the CPU-GPU algorithm has improved the speedup as high as 150 times.

1 INTRODUCTION

In medical imaging, the studied object such as organs are typically stored as 2D contours with evenly spaced cross sectional images called slices (Sunderland et al., 2015). Two commonly used multi-slice images are Computed Tomography (CT) and Magnetic Resonance Images (MRI). CT scan plays a significant role in a wide range of applications such as medical diagnosis, security, and manufacturing (Ziabari et al., 2018).

In medical diagnosis, the reconstructed 3D image from CT scan must be in high resolution to assist clinical examinations (Kainz et al., 1901) for example to get the precise location as well as the size of tumour (Sentana et al., 2018). The 3D visualization of the image must be easily understood for treatment planning and further analysis (Ge, 2018; Sunderland et al., 2015). The challenges in handling CT scan images are the amount of data to be considered and the branched contours in some image slices. The amount of data is in terms of the number of pixels in each image slice which is usually $256 times 256$ or $512 times 512$, and the number of image slices which can exceed a hundred slices. Thus, the 3D image reconstruction process requires a powerful processor to ensure the process can be run efficiently with a sufficient amount of data within the optimal processing time.

CT scan images of real-life objects such as hand, heart and bone cannot avoid a branching contour situation where the number of contours in a slice is not the same as the adjacent slice (Sunderland et al., 2015). This situation is also known as multi-furcating surfaces (Joshi and Bhatt, 2019).

Graphical Processing Unit (GPU) was originally developed to calculate the 3D graphics in Central Processing Unit (CPU). Presently, the use of GPU has been expanded to be used in scientific calculation to save computational time (Hosokawa et al., 2015). Each GPU consists of hundreds of cores that calculate the given tasks in parallel. Thus, it is suitable for a huge number of calculations which cannot be afforded by CPU to accelerate the calculation process and increase the accuracy of the result (Kainz et al., 2015). On the other hand, a small amount of data should be processed in the CPU only to avoid idle time in GPU.

Since CPU and GPU have different abilities to process the data, numerous research have been carried out to combine these two processors in the same algorithm, for example in generating 2D font (Abdul Hadi, 2019) and 3D image (Hadi, 2018; Hadi and Alias, 019a). This algorithm is named as CPU-GPU and hybrid computing (Sentana et al., 2018). The illustration of GPU is given in Figure 1

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(Alias and Kamal, 2017)

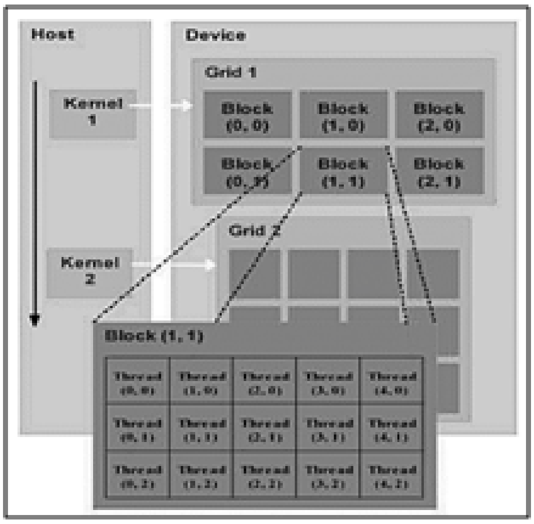


Figure 1: The GPU illustration

The host and device in Figure 1 is the CPU and GPU, respectively. Each task is assigned to the device through a kernel from the host. A GPU consists of a number of grids with each grid containing a certain number of blocks, and each block having hundreds of threads. A thread communicates with another thread in a block by high- speed shared memory, and other blocks by global memory (Alias et al., 2016; Hadi and Alias, 019b).

In this paper, the CPU-GPU algorithm is developed in the branching surface reconstruction process. Details of the method is will be discussed in section 2. The performance of the developed algorithm is then analyzed in section 3. This paper is concluded in section 4.

2 MATERIALS AND METHOD

2.1 CT Scan Images

This study employs two sets of CT scan images obtained from (Kels and Dyn, 2011) which are Stanford bunny and human pelvic. The Stanford bunny data, consisting of 254 slices, is the most widely used data in 3D image reconstruction provided by Stanford Computer Graphics Laboratory, Stanford University ("Computer Graphics at Stanford University," n.d.). Human pelvic data consists of 257 slices but only bottom part of the pelvic, which consists of 141 slices is considered in this work. All considered images have undergone the pre-processing stage to convert the original grayscale images to binary images.

The number of branching cases in both datasets are three for bunny and nine for pelvic. An example of branching case for each dataset are shown in the following figure.

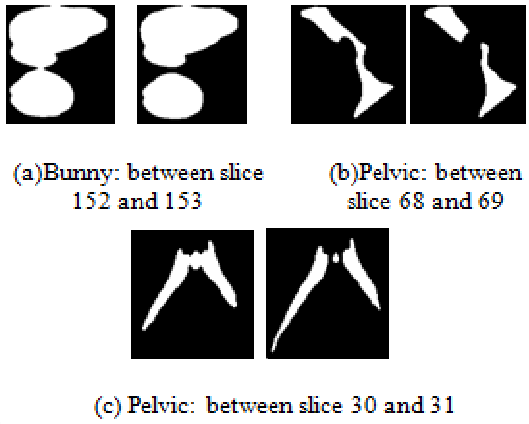


Figure 2: CT images with branching cases

In Figure 2, there are two types of branching cases: (a) and (b) one-to-two case, and (c) is one-to-three case. This makes the 3D surface of the image discontinuous at the branching slice. The reconstructed surface with discontinuous surface at the branching slice is shown in Figure 3.

The branching slices have divided the 3D image to five parts for bunny, and twelve parts for pelvic. Therefore, to join these parts, a new contour known as composite contour is introduced to fit in between the separated part of the image.

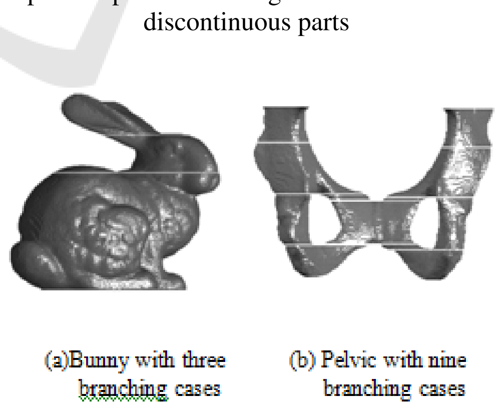


Figure 3: 3D surface with discontinuous branching parts

2.2 Composite Contour Generation

Composite contour is a generated contour using curve points from based and branched contours and located in between those contours. The flowchart of composite contour generation is as follows:

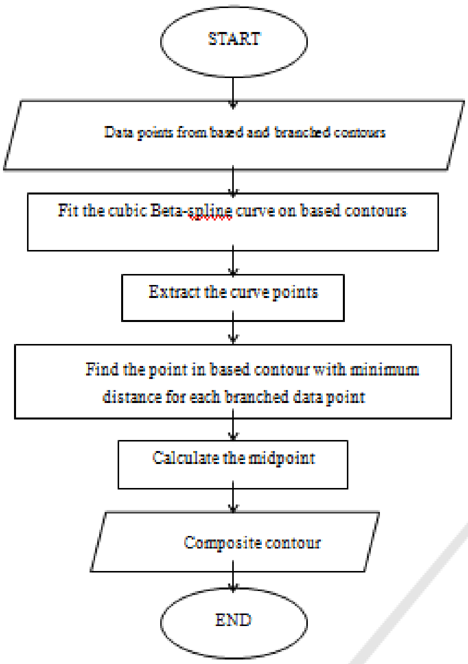


Figure 4: The flowchart for composite contour generation

The first step is the cubic beta-spline curve fitting to all data points in the based contours. Beta-spline is a reliable curve developed by Brian A. Barsky in 1981 (Barsky, 1981) based on G2 condition. This condition makes the beta-spline curve always continuous and smooth, independent of the distribution of the control points. The equation of cubic beta-spline curve (Hadi, 2018) is as follows:

$$F(t) = [T][M][V] \tag{1}$$

$[T]$ is the matrix of parameter t with 0<t<1, $[V]$ is the set of 4×4 control points, and $[M]$ is the beta-spline basis function (refer (Halim et al., 2018)). Then, the required ith curve points for each curve can be extracted by F(t_i). After that, distances between each data points in the branched contours to the curve points in the based contours are calculated. The pair of points (based-branched) with the minimum distance is selected as the potential composite contour data points. Finally, the midpoint between each pair of points is appointed as the data point for the composite contour.

Figure 5 shows the datapoints of based and branched contours, and the generated composite contour.

The number of extracted curve points in the branched contour must be sufficient to ensure the accuracy of the generated composite contour. Fewer curve points produces a smaller number of data points in the composite contour and less accurate reconstructed image. However, the processing time to calculate the distance between each branched data point to each based curve points is also increased. Therefore, this study has employed the GPU to handle the process.

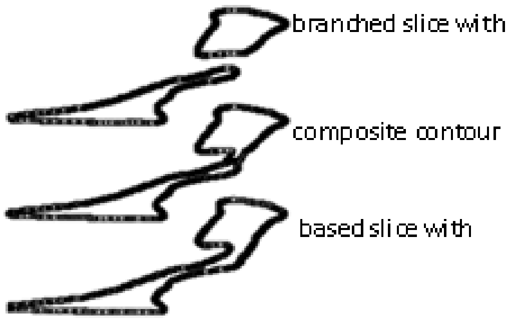


Figure 5: Based, branched and composite data points

2.3 Composite Contour Generation on GPU

Basically, the GPU is employed at the chosen step in the CPU process. From the flowchart in Figure 3, only one process is executed on the GPU, which is the distance calculation process. The earlier processes are executed on the CPU, and the extracted curve points are transferred to the GPU to calculate the required distance. Finally, the calculated distance is gathered in the CPU to calculate the midpoint. The generated composite contour is treated as other contours to fit beta-spline surface. The equation of beta-spline surface is extended from the cubic beta-spline curve equation in (1) with parameters u and v as follows:

$$S(u,v) = [T][M][V][M]^T[U] \tag{2}$$

where $[V]$ is the 16×4 control points. The performance of the developed algorithm is discussed in the following section.

3 RESULT

The employed CPU is Intel (R) XEON (R) (2.10GHz) with 2 processors, and the GPU is NVIDIA Tesla K20c running on Windows 10 64-bit. The performance is measured in terms of the processing time for the whole composite contour generation process and speedup. The data for bunny and pelvic is combined in the same analysis

3.1 Processing Time

Processing time is the time taken for a process to be completed. This paper compares processing time between CPU-alone and the developed CPU-GPU algorithm for different number of curve points per curve segment. There are twelve branching cases for bunny and pelvic, and the processing time is combined and compared in Figure 6.

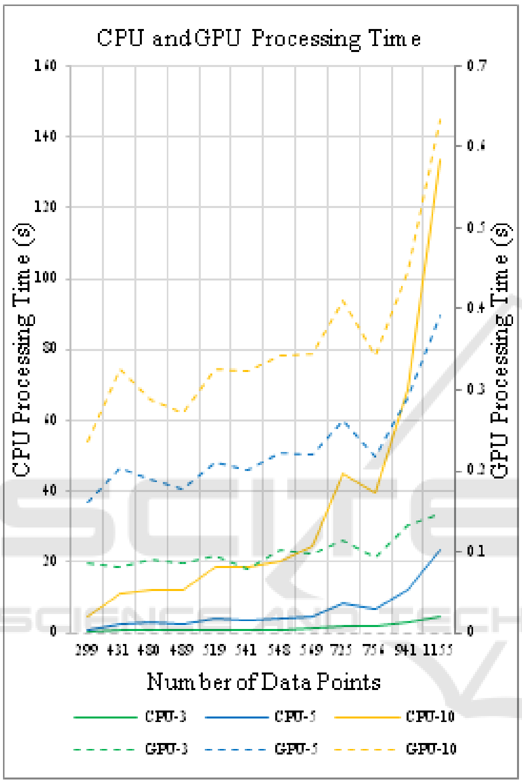


Figure 6: CPU and GPU processing time for different number of curve points

CPU-3, CPU-5 and CPU-10 (represented by solid lines) are the CPU-alone execution time for 3, 5 and 10 curve points per curve segment, respectively. GPU-3, GPU-5 and GPU-10 (represented by dashed lines) are the time consumed by the CPU-GPU algorithm. The number of curve segments for each branching case is presented at the x-axis. Processing time for GPU is the total execution time including the communication between CPU and GPU.

Based on Figure 6, both CPU and GPU processing time are increased with the increment of the number of curve points. For 1155 data points for example, the increment of curve points from 3 to 10 points per segment has increased the CPU processing time 24× from 4.59s to 110.41s. Although the GPU processing time has also increased, which is only 4.97× which is still low. This shows that the GPU can still afford more data compared to the CPU. Furthermore, the sudden increment in CPU time suggests that the CPU has reached its limit.

3.2 Speedup

The speedup is calculated as time for CPU per time for GPU to show how fast the GPU is as compared to the CPU. The speedup for the developed CPU-GPU algorithm is shown in Figure 7.

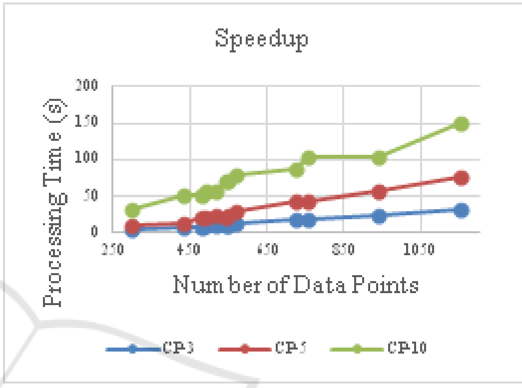


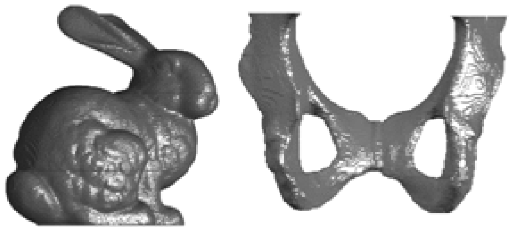
Figure 7: Speedup for three different number of curve points per segment

From Figure 7, all three curves have almost linear shape curves. This shows that the speedup of the developed algorithm is getting better when larger number of data points is considered. The position of CP-10 curve is also higher than CP-5 and CP-3 which shows that the speedup is better when the number of curve points per segment is increased. This is because the GPU has hundreds of threads to do the task. The best speedup from the figure is 150 for CP-10 which shows that the GPU has accelerated the processing time 150×.

3.3 Reconstructed 3D Images

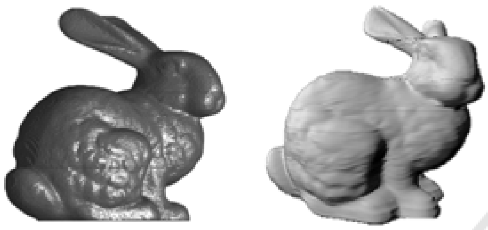
The developed algorithm is applied on two datasets of CT scan images: bunny and pelvic. The reconstructed surface with branching slice has been shown in Figure 3.

Figure 8 shows the same reconstructed 3D images as in Figure 3 but with composite contour. Based on the figure, separated parts for both figures have been joined smoothly using cubic beta-spline surface. Stanford bunny is a widely used data for 3D image reconstruction. Thus, the comparison of the reconstructed bunny in this paper is compared to a previous similar work by (Abdul Hadi et al., 2013), as shown in Figure 9.



(a) Bunny with composite contours (b) Pelvic with composite contours

Figure 8: reconstructed surface with composite contours



(a) The generated bunny using CPU-GPU (b) The generated bunny from previous work

Figure 9: The reconstructed surface with composite contours

Figure 9(a) shows the generated bunny using the method developed in this paper, and Figure 9(b) is the generated bunny using CPU-alone by (Abdul Hadi, Ibrahim, Yahya, & Md Ali, 2013). In Figure 9(a), the texture on the bunny body and paws are clearer. This is because Figure 9(a) consists of 500 surface points per slice, while Figure 9(b) has only 75 surface points per slice due to the memory limitation of the CPU.

The CPU limitation also has disadvantage in generating composite contour. Thus, some branching part for example ear in Figure 9(b) is not smoothly joined and can be obviously seen.

4 CONCLUSION

In this paper, an algorithm for generating composite contour on the CPU-GPU platform has been developed. The composite contour occurs when the adjacent image slices have different number of contours. The decrement of the processing time and the improvement of the speedup of the developed algorithm suggest that the CPU-GPU platform is suitable to be employed in the composite contour generation since the process involves huge number of data points.

The capability of GPU also allows the number of surface points to be high enough to produce the smoothed and accurate surface. Furthermore, the fitted cubic beta-spline surface has high continuity (G2) to confirm the continuity of the surface.

For future research, more process will be considered to be executed on the GPU. Further analysis of the performance will also be studied to ensure the quality of the developed method.

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