An Optimized Union-Find Algorithm for Connected Components Labeling Using GPUs

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Abstract—In this paper, we report on an optimized union-find (UF) algorithm that can label the connected components on a 2D image efficiently by employing GPU architecture. The proposed method comprises three phases: UF-based local merge, boundary analysis, and link. The coarse labeling in local merge, which makes computation efficient because the length of the label-equivalence list is sharply suppressed, boundary analysis only manages the cells on the boundary of each thread block to launch fewer CUDA threads. We compared our method with the label equivalence algorithm [1], conventional parallel UF algorithm [2], and line-based UF algorithm [3]. Evaluation results show that the proposed algorithm speeds up the average running time by around 5x, 3x, and 1.3x, respectively.

I. INTRODUCTION

Connected components labeling (CCL) is a task to give a unique ID to each connected region in a 2D/3D grid, which means that the input data is divided into separate groups where the elements from a single group share the same ID. As a basic data clustering method, it is employed in numerous research areas like image processing, computer vision, and visual communication [4]. W. Song, et al. [5] presented a motion based skin region of interest detection method using a real-time CCL algorithm to reduce its execution time. A fast 3D shape measurement technique using blink-dot projection patterns that utilizes a CCL algorithm to compute the size and location of each dot on the captured images has been reported [6] [7]. P. Guler, et al. proposed a real-time multi-camera video analytics system [8] employing CCL to perform noise reduction.

On the basis of the fact that parallel devices find countless applications in both industrial and academic areas, some CCL algorithms using GPUs have emerged [9] recently to improve the real-time property of CCL, which is very important for many applications. The CCL algorithms can be classified into two categories, the multi-pass method and one-pass method, according to whether they apply a convergence criterion or not [10]. Tab. I summarizes five typical parallel CCL approaches and a brief explanation is given in the following. Neighbor propagation [1] is the simplest multi-pass approach that scans the neighborhood of a target cell to get the lowest label of a neighboring cell belonging to the same group. Row-column unification [1] enlarges the scan scope by allocating one row to each thread. Label equivalence [1] employs neighbor propagation as the first phase to construct label-equivalence chains, and the following analysis and relabeling phases find the roots of each chain. The resolution of an input image determines the iteration times of neighbor propagation, while the iteration of row-column unification and label equivalence depend on the complexity of an input image. The usual union-find (UF) algorithm [12] is parallelized by dividing the input image into independent 2D blocks; local merge and global merge are introduced to solve the connectivity [2]. Instead of using 2D blocks, a line-based parallel UF algorithm [3] collects the pixels in one row to perform local label unification. Even the computation of each kernel in such one-pass methods is heavier than those of multi-pass approaches; they label an image faster because each kernel only runs one time.

In this study, we propose an optimized UF algorithm that is an improved version of conventional parallel UF [2] with an optimized local merge and lightweight boundary analysis. Its concepts are: (1) row-column unification is performed using shared memory before local UF to reduce the complexity of an initialized local label map; (2) connectivity analysis is conducted only for the cells on the block boundary to decrease the number of required CUDA threads. Compared with the conventional UF [2], our proposed approach can perform local merge more efficiently because the label-equivalence chains are extensively suppressed as a result of the coarse labeling. For the line-based UF [3], it can extract the local label map slightly faster than our method. However, its global merge phase takes much longer because global UF should be applied to all the cells in the input data.

### TABLE I: Classification of the parallel CCL algorithms

| Method                | Scan Mode | Computational cost |
|-----------------------|-----------|--------------------|
| Neighbour Propagation | Multi-Pass | High               |
| Row-Column Unification | Multi-Pass | High               |
| Label Equivalence     | Multi-Pass | High               |
| Conventional UF       | One-Pass  | Low                |
| Line-based UF         | One-Pass  | Low                |
II. ALGORITHM DESCRIPTION

In this section, we outline the three kernels of our method. In the first kernel, UF-based local merge, we perform a coarse labeling before finding the real root of each cell to reduce the computational complexity in each thread. In the last two kernels, boundary analysis and link, we merge individual blocks together to generate a global label map.

Kernel 1 Local UF merge with coarse labeling

Require: Image $I$ of size $N \times M$

Require: Both block dimension and grid dimension are 2D

Require: $label_{sm}[, dBuff_{sm}][, ]$ are on shared memory

Require: $LabelMap[, ]$ is on global memory

1: declare int $x, y, tid, temp, l, g_x, g_y, g_l$
2: declare int $label_{sm}[, dBuff_{sm}][, ]$
3: $x, y \leftarrow 2D$ global thread id
4: if $x < \text{imgWidth}$ & $y < \text{imgHeight}$
5: $tid \leftarrow 1D$ thread id within block
6: $label_{sm}[tid] \leftarrow tid$
7: $dBuff_{sm}[tid] \leftarrow \text{image}[x, y]$
8: call syncthreads()
9: // row scan
10: if $dBuff_{sm}[tid] == dBuff_{sm}[tid - 1]$
11: $label_{sm}[tid] = label_{sm}[tid - 1]$
12: end if
13: call syncthreads()
14: // column scan
15: if $dBuff_{sm}[tid] == dBuff_{sm}[tid - \text{blockdim}.x]$
16: $label_{sm}[tid] \leftarrow label_{sm}[tid - \text{blockdim}.x]$
17: end if
18: call syncthreads()
19: // row-column unification
20: temp $\leftarrow$ tid
21: while $temp != label_{sm}[temp]$
22: temp $\leftarrow label_{sm}[temp]$
23: $label_{sm}[tid] \leftarrow temp$
24: end while
25: // local union find
26: if $dBuff_{sm}[tid] == dBuff_{sm}[tid - 1]$
27: findAndUnion($label_{sm}[, tid, tid - 1]$)
28: end if
29: call syncthreads()
30: if $dBuff_{sm}[tid] == dBuff_{sm}[tid - \text{blockdim}.x]$
31: findAndUnion($label_{sm}[, tid, \text{tid} - \text{blockDim}.x]$)
32: end if
33: call syncthreads()
34: // convert local index to global index
35: $l \leftarrow \text{find}($label_{sm}[, tid])$
36: $l_x \leftarrow l / \text{blockdim}.x$
37: $l_y \leftarrow l \% \text{blockdim}.x$
38: $g_l \leftarrow (\text{blockIdx}.x * \text{blockDim}.x + l_x) + (\text{blockIdx}.y * \text{blockDim}.y + l_y) * \text{imgWidth}$
39: $LabelMap[x, y] \leftarrow g_l$
40: end if

Fig. 1: Input data and initialized local label map.

A. Local merge with coarse labeling

The first kernel, local merge with coarse labeling, consists of three phases: initialization, coarse labeling using row-column unification, and local UF. Its pseudo-code is listed in Kernel 1 by following 4-connectivity.

1) Initialization:

We divide the input image into several rectangular pieces, as shown in Fig. 1(a), and assign each piece to different GPU threads blocks where the threads can cooperate with each other using shared memory and can be synchronized [13]. The cells in each block are indexed by the thread ID within the block. Fig. 1(b) presents an example of an $8 \times 8$ initialized local label map that was allocated on shared memory. Here, the gray cells represent foreground areas, while the white cells represent background areas.

2) Coarse labeling using row-column unification:

In an initialized local label map, as shown in Fig. 1(b), the label of the left cell and the label of the upper cell are always smaller than that of a target cell, while the upper one is always smaller than the left one. Based on this fact, we scan the rows first and then go to column scan. The cell will get the label of its neighboring cell, left or upper, with the same property. Fig. 2 shows the scan models. Unlike the methods that record the entire label-equivalence lists, this method records the lowest label that the label is equivalent to. Its memory access complexity is reduced due to the utilization of shared memory, while the equivalence can be unified by a low number of iteration because the dimension of a thread block is limited by the CUDA runtime system. Fig. 3(a)
Require: Both block dimension and grid dimension are 2D after row-column unification.

...coarsely labeled label map after row-column unification.

Kernel 2 Boundary analysis
Requiere: Image I of size $N \times M$
Requiere: Both block dimension and grid dimension are 2D

```
1: declare int id, $h_x$, $h_y$, $v_x$, $v_y$, pInLine, $p_h$, $p_v$
2: declare bool $b_b$, $b_v$
3: id $\leftarrow$ 1D global thread id
4: // convert 1D global thread id to 2D cell id
5: $h_x$ $\leftarrow$ id $\%$ imgWidth
6: $h_y$ $\leftarrow$ id / (imgWidth $\times$ blockDim.y)
7: pInLine $\leftarrow$ imgWidth $/$ blockDim.x
8: $v_x$ $\leftarrow$ id $\%$ pInLine $\times$ blockDim.x
9: $v_y$ $\leftarrow$ id / pInLine
10: $p_h$ $\leftarrow$ $h_x$ + $h_y$ $\times$ imgWidth
11: $p_v$ $\leftarrow$ $v_x$ + $v_y$ $\times$ imgWidth
12: $b_h$ $\leftarrow$ $h_x$ $<$ imgWidth $\&$ $h_y$ $<$ imgHeight
13: $b_v$ $\leftarrow$ $v_x$ $<$ imgWidth $\&$ $v_y$ $<$ imgHeight
14: // boundary analysis along x-axis
15: if $b_h$ $\&$ image[$h_x$, $h_y$] $==$ image[$h_x$ - 1, $h_y$]
16: findAndUnion(LabelMap, $p_h$, $p_h$ - 1);
17: end if
18: // boundary analysis along y-axis
19: if $b_v$ $\&$ image[$v_x$, $v_y$] $==$ image[$v_x$, $v_y$ - imgWidth]
20: findAndUnion(LabelMap, $p_v$, $p_v$ - imgWidth);
21: end if
```

3) Local UF:

UF, expressed by `findAndUnion` in Kernel 1 is a data structure that divides a set of elements into a number of disjoint subsets by using `find` and `merge` operations. The `find` is an iterative search to extract the root of a label-equivalence list and return its label. The `merge` is a unification to assign the root label to the elements belonging to the subset.  

...provides two equivalence lists in the local label map after row-column scan. Fig. 3(b) shows the coarsely labeled label map after row-column unification.

Kernel 2 Boundary analysis

Compressed sharply, which enables local UF to run efficiently. The final step of this kernel is an ID conversion that converts the local index to a global index. Fig. 4(a) presents a converted global label map.

B. Boundary analysis

In the boundary analysis phase, we only perform UF for the cells on the block boundary (those marked on Fig. 4(a)) to launch fewer threads. Assuming the resolution of an input image is $N \times M$ and the block configuration of the Kernel 1 is $\{b_z, b_y, 1\}$, the number of cells on the block boundary along $x$-axis and $y$-axis is $\{P_x, P_y\}$ can be determined as follows:

$$P_x = \lceil N / b_x \rceil \times M,$$

$$P_y = \lceil M / b_y \rceil \times N.$$

Here, $\lceil x \rceil$ means the largest integer smaller or equal to $x$.

To integrate the boundary analysis along $x$- and $y$-axis into one kernel, max$\{P_x, P_y\}$ threads spawned by Kernel 2 should be invoked. Fig. 4(b) shows how to analyze the connectivity in the $x$-direction: the cell on the boundary merges with its upper cell by using UF if they have the same property. The union along the $y$-direction works in the same manner.

C. Final link

After analyzing the connectivities of the cells on the block boundary, the independent local label maps are associated as...
an entirety. We compute the final global label map in the same way as that reported in [2] and [3].

III. EVALUATION EXPERIMENTS

To demonstrate the effectiveness of our proposed algorithm, we run it and the other three parallel methods, label equivalence (LE) [2], conventional parallel UF [2], and line-based UF [3], on a PC equipped with an NVIDIA GeForce GTX 1070 for the images shown in Fig. 5. For the line-based UF method, its thread blocks are configured as \( [512, 1, 1] \), while the configuration of the other three methods is \( [32, 16, 1] \).

Tab. II shows the comparison results for the execution times of these algorithms with images of different size. Here, we run each algorithm 100 times and take their extreme value as well as average value. It can be seen that the optimized UF can label a \( 512 \times 512 \), \( 1024 \times 1024 \), \( 2048 \times 2048 \), and \( 4096 \times 4096 \) binary image in around 0.14, 0.40, 1.10, and 3.40 ms respectively, while the other methods take longer to accomplish CCL. From an analysis of these results, it can be deduced that the one-scan methods, UF, line-based UF, and our proposed method, work more efficiently than LE, one of the typical multi-scan methods. Meanwhile, it indicates that our method outperforms the other two methods. Compared with UF, the speedup ratio increases with the increase in image resolution. It is about 3.4 times faster for a \( 4096 \times 4096 \) binary image. For the line-based UF, the speedup ratio is quite stable and is around 1.30 for all the images.

IV. CONCLUSIONS

In this paper, we introduced an optimized parallel UF algorithm for fast CCL using GPUs. Our algorithm employs a coarse row-column unification to reduce the computation complexity of local merge and launches a low number of threads for block-to-block connectivity analysis. As a result, the proposed method can efficiently perform CCL on GPUs in a single scan. We verified its performance on NVIDIA GeForce GTX 1070 and compared the execution time with those of three other methods. Experimental results show that the running time of CCL improved greatly compared with the latest method. The efficiency makes the proposed method suitable for many real-time applications.

TABLE II: Execution time in millisecond for different images

| Images (size) | LE min | LE max | LE mean | UF min | UF max | UF mean | Line UF min | Line UF max | Line UF mean | ours min | ours max | ours mean |
|--------------|--------|--------|---------|--------|--------|---------|-------------|-------------|-------------|----------|----------|----------|
| lena (512 × 512) | 0.06 | 0.26 | 0.17 | 0.13 | 0.13 | 0.13 | 0.13 | 0.13 | 0.13 | 0.13 |
| lena (1024 × 1024) | 1.61 | 3.98 | 2.97 | 1.29 | 1.29 | 1.29 | 1.29 | 1.29 | 1.29 | 1.29 |
| lena (2048 × 2048) | 5.13 | 9.65 | 5.65 | 1.45 | 1.45 | 1.45 | 1.45 | 1.45 | 1.45 | 1.45 |
| lena (4096 × 4096) | 18.40 | 11.49 | 18.10 | 11.71 | 18.64 | 11.56 | 18.64 | 11.56 | 18.64 | 11.56 |
| peppers (512 × 512) | 0.78 | 0.27 | 1.06 | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 |
| peppers (1024 × 1024) | 2.61 | 1.02 | 2.13 | 0.98 | 2.13 | 0.98 | 2.13 | 0.98 | 2.13 | 0.98 |
| peppers (2048 × 2048) | 6.06 | 1.50 | 6.47 | 1.71 | 6.25 | 1.54 | 6.25 | 1.54 | 6.25 | 1.54 |
| peppers (4096 × 4096) | 18.20 | 11.49 | 22.24 | 12.97 | 18.79 | 11.59 | 18.79 | 11.59 | 18.79 | 11.59 |

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