

GPU-ACCELERATED SNAKE

GPU IMPLEMENTATION OF A REGION-BASED SEGMENTATION ALGORITHM (SNAKE) FOR LARGE IMAGES

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Image segmentation

Definition, goal

- Dividing an image into two homogeneous regions.
- Reducing the amount of data needed to code information.
- Helping the human perception in certain cases.

Image characteristics

- 16 bit-coded gray levels,
- **•** From 10 Mpixels to more than 100 Mpixels,
- Very noisy.

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Algorithm basics : criterion

- The goal is to find the most likely contour Γ (number and positions of nodes).
- The criterion used is a *Generalized Likelihood*.

In the Gaussian case, it is given by

$$
GL = \frac{1}{2} \left[n_B \cdot \log \left(\widehat{\sigma_B}^2 \right) + n_T \cdot \log \left(\widehat{\sigma_T}^2 \right) \right]
$$

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 $\mathbf{A} = \mathbf{A} \oplus \mathbf{B} \quad \mathbf{A} = \mathbf{B} \quad \$

where $\widehat{\sigma}_{\Omega}$ is the estimation of the deviation σ for the region Ω .

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Algorithm basics : criterion

• Parameters estimation is done by 1-D sums on along the contour.

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• Every pixel coordinates are needed.

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Snake algorithm in action

• 150 Mpixels image. Initial contour: 4 nodes. \bullet

 $A \equiv \mathbf{1} \times \mathbf{1} \times \mathbf{1}$

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Snake algorithm in action

• End of first iteration: no more move can be of interest.

 $\Box \rightarrow \neg \leftarrow \Box \Box$

 $\mathbf{A} = \mathbf{A} \cdot \mathbf{B} + \mathbf{A} \cdot \mathbf{B}.$

Snake algorithm in action

• Nodes added in the middle of segments.

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 $\mathbf{A} = \mathbf{A} \oplus \mathbf{A} \oplus \mathbf{A} \oplus \mathbf{B}$

Snake algorithm in action

• End of second iteration.

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 $\mathbf{y} = \mathbf{y} + \mathbf$

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Snake algorithm in action

• End of fourth iteration

 $\Box \rightarrow \neg \leftarrow \Box \Box$

 $\mathbf{y} = \mathbf{y} \oplus \mathbf{y}$, $\mathbf{y} \oplus \mathbf{y}$

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Snake algorithm in action

- End of seventh iteration.
- Fast segmentation.
- **•** Efficient with noise.

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 $\mathbf{A} = \mathbf{A} \oplus \mathbf{A} \oplus \mathbf{A} \oplus \mathbf{B}$

- This SNAKE algorithm has proved to be fast and robust.
- **Images to be processed are becoming larger and larger.**
- To be user-friendly, process must be done in less than 1 second.
- **GPU are cheap and can bring impressive speedups.**
- GPU are easy to embed in a simple PC (in a aeroplane,...)

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GPU design : key points

- The parallelism of a modern GPU lays on a SIMT paradigm (Single Instruction Multiple Threads): the same instruction is processed by a great number of threads at a time (up to 2^{16}).
- Threads are compounded in independants blocks with no possible synchronization between blocks.
- **•** Threads in a block share a small amount of shared memory (16-48 KBytes).

[Context](#page-2-0)

[Conclusion](#page-19-0)

- There are restrictive conditions to be fullfilled in order to make efficent accesses to global and shared memory.
- Data transfers between CPU and GPU are slow.

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 $\mathbf{A} = \mathbf{A} \oplus \mathbf{B} \quad \mathbf{A} = \mathbf{B} \quad \$

GPU implementation: parallelization

- **•** Every 16 segments for every node are processed in parallel.
- Fits GPU specific parallelism: each segment pixel is processed by a thread.
- Criterion values are obtained after several reduction stages.
- All nodes are possibly moved in one step.

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GPU implementation: first results

- Global speedup around x7-x8 (Nvidia C2050) for image sizes from 15 to 150 Mpixels.
- **•** First iterations have higher speedups:
	- several large segments,
	- \bullet few inactive threads in the grid.

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 $A \equiv 3$ and B

GPU implementation: smart init (reasons)

- The target shape is often far from initial contour,
- It causes the very first iteration to be much more time-consuming than the other ones.
- It's fast on GPU to find a rectangle near the target. But it needs to overrule the 'one thread/one pixel' principle.

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GPU implementation: smart init (process)

- Realize a periodic sampling of a few hundreds of J-coordinates.
- Evaluate in parallel every possible rectangle of diagonal $(0, j_L) - (H, j_H)$.
- Select the one with the best GL criterion.
- \bullet *j_L* and *j_H* are now considered as constants.

GPU implementation: smart init (process)

 \bullet Given *j_l* and *j_H*.

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- Realize a periodic sampling of a few hundreds of I-coordinates.
- **•** Evaluate in parallel every possible rectangle of diagonal $(i_L, j_L) - (i_H, j_H)$.
- Select the one with the best GL criterion.

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GPU implementation: improvement

- Global speedup around x10 (Nvidia C2050) for image sizes from 15 to 150 Mpixels and a 'small enough' target.
- Less than 0.6 s for the 150 Mpixels image of the example.
- A real-life 10 Mpix S.A.R. picture after 3 iterations in less than 50 ms .

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Conclusion, future works

- Interesting speedups
- Original algorithm is not GPU-friendly
- **•** Future works:
	- Finding a more suited structure to describe the contour.
	- Switching to a statistical model independant from a PDF: the potts model.
	- Benefit from recent features of CUDA v4 (overlapping, multiple kernels).
	- Extend to a multiple targets algorithm, based on this single target elementary piece of code.

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