Real-time Image Segmentation

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Overview

Problem Definition

Binary Image Segmentation

Energy functional

$$E_1(u) := \int_{\mathbb{R}^N} |\nabla u| + \lambda \int_{\mathbb{R}^N} |u(x) - f(x)| \, dx$$

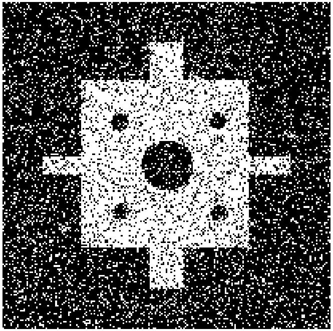
Functional derivative

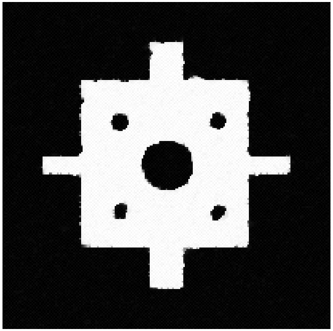
$$\frac{\delta E_1}{\delta u} = -\operatorname{div}\left(\frac{\nabla u}{|\nabla u|}\right) + \lambda \frac{u - f}{|u - f|}$$

Gradient descent solver

Tony F. Chan, Selim Esedoglu and Mila Nikolova (2005)
Finding the Global Minimum for Binary Image Restoration

Sample Result


Noisy binary image.


Restored binary image.

Grayscale Image Segmentation

Euler-Lagrange equation

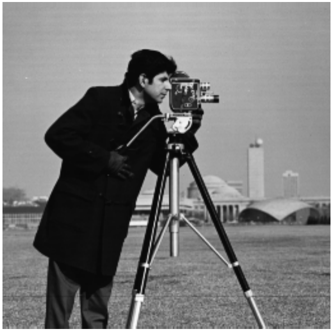
$$\mathrm{div}\left(\frac{\nabla u}{|\nabla u|}\right) - \lambda\, s(x) - \alpha\, \nu'(u) = 0$$

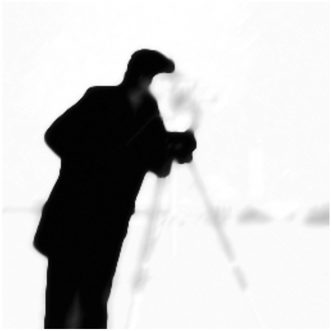
where $s(x) = (c_1 - f(x))^2 - (c_2 - f(x))^2$, and $\alpha\,\nu'(u)$ forces u into $[0;1]$.

Gradient descent solver

Tony F. Chan, Selim Esedoglu and Mila Nikolova (2004)
Algorithms for Finding Global Minimizers of Image Segmentation and Denoising Models

Sample Result


Grayscale input image.


Segmentation (without thresholding).

Primal-Dual Method

Motivation: Gradient descent solver has slow convergence.

Primal variable $u \in \mathcal{C}$

$$u : \Omega \to [0; 1]$$

Dual variable $\xi \in \mathcal{K}$ $\quad (\xi \sim \mathrm{grad}\, u)$

$$\xi : \Omega \to \{(x, y) : x^2 + y^2 \leq 1\}$$

Algorithm:

$$\begin{aligned}
\xi^{n+1} &= \Pi_{\mathcal{K}}(\xi^n - \sigma \nabla \bar{u}^n) \\
u^{n+1} &= \Pi_{\mathcal{C}}(u^n - \tau(\mathrm{div}\xi^{n+1} + s)) \\
\bar{u}^{n+1} &= u^{n+1} + (u^{n+1} - u^n) = 2u^{n+1} - u^n
\end{aligned}$$

$\Pi_{\mathcal{C}}$ and $\Pi_{\mathcal{K}}$ clamp the range to fit $\mathcal{C}$ and $\mathcal{K}$ respectively.

Result

- A single iteration is costlier than for the gradient descent solver, but we could reduce iteration count from 2000 to 160.
- Huge impact on performance.

CUDA Implementation

- Update kernels calls from CPU to have synchronization
- Update ξ and update u implemented as two kernels
- Image arrays for u^{n-1} and u^n swapped after each iteration
- Branching to avoid invalid memory accesses

CUDA Implementation

- Swapping images after each iteration makes things difficult
- Cannot be used in gradient calculation. Can be used in divergence calculation
- Texture memory used on intermediate results ξ_x and ξ_y
- Improves the FPS by 12%

OpenGL Interoperability

What is Interoperability?

- Mapping OpenGL Resources to CUDA, to enable CUDA to read/write
- Can be used to show output from CUDA kernel, straight from GPU saving time and bandwidth

How to use OpenGL Interop?

- Set current threads OpenGL context to use for OpenGL interop with CUDA **device**.

```
cudaGLSetGLDevice(device);
```

- Create OpenGL Pixel Buffer, and register to use as CUDA buffer.

```
gl.glGenBuffers(1, &pixels);
gl.glBindBuffer(GL_PIXEL_UNPACK_BUFFER, pixels);
size_t size = w * h * 4 * sizeof(unsigned char);
gl.glBufferData(GL_PIXEL_UNPACK_BUFFER, size, 0,
    GL_DYNAMIC_DRAW);
cudaGraphicsGLRegisterBuffer(&pixels_CUDA, pixels,
    cudaGraphicsMapFlagsWriteDiscard);
```

How to use OpenGL Interop?

Inside the Display Loop,

- Before starting kernel, map pixel buffer to a CUDA pointer.

```
cudaGraphicsMapResources(1, &pixels_CUDA, 0);
cudaGraphicsResourceGetMappedPointer(&d_pixels, &size,
     pixels_CUDA);
```

- Pass CUDA pointer as parameter for kernel. The kernel writes to the buffer in **RGBA8** format.
- After kernel execution, unmap pixel buffer.

```
cudaGraphicsUnmapResources(1, &pixels_CUDA, 0);
```

- Draw buffer

```
glDrawPixels(w, h, GL_RGBA, GL_UNSIGNED_BYTE, 0);
```

Demo

Thank you for your attention.