Photometric Segmentation: Simultaneous Photometric Stereo and Masking

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3DV 2019
International Conference on 3D Vision
Québec City, Canada
September 16 - 19, 2019

Problem Statement

- **Photometric Stereo (PS) can recover 3D geometry for given images and a mask:** Tedious preprocessing to segment object from background is necessary

PS Images | Segmented Object | Surface Normals

- **Goal:** Given a set of photometric stereo images, simultaneously infer binary mask and geometry.

Two Separate Problems

Segmentation (e.g. Chan-Vese (CV) Active Contours [1])

$$\min_{\mu_1,\mu_2,C} \int_{\text{inside}(C)} \mathcal{P}_1(\mu_1, I(x))\,\mathrm{d}x + \int_{\text{outside}(C)} \mathcal{P}_2(\mu_2, I(x))\,\mathrm{d}x + \nu\,\text{length}(C)$$

- $\mathcal{P}_j(\mu_j, I(x)) = \frac{1}{m}\sum_{i=1}^{m}(\mu_j - I_i(x))^2,\ j \in \{1,2\}$
- PS images $I = \{I_i\}_{i\in\{1,\dots,m\}}$
- mean intensity μ_j, $j \in \{1,2\}$, of back- and foreground
- minimal length curve C

Photometric Stereo (e.g. Image Ratios [3])

$$I_i(x) = \rho(x)\ \langle \mathbf{n}(x), \mathbf{s}_i \rangle\ ,\ i \in \{1,\dots,m\}, \text{ with } \mathbf{n}(x) = \frac{[\nabla z(x), -1]^\top}{\sqrt{|\nabla z(x)|^2 + 1}}$$

- albedo ρ
- depth map z
- lighting vectors $\mathbf{s}_i = [s_i^1, s_i^2, s_i^3]^\top$

$$\underset{\binom{m}{2}\text{ ratios}}{\rightsquigarrow} \quad \frac{I_i(x)}{[\nabla z(x), -1]^\top \cdot \mathbf{s}_i} = \frac{\rho(x)}{\sqrt{|\nabla z(x)|^2 + 1}} = \frac{I_j(x)}{[\nabla z(x), -1]^\top \cdot \mathbf{s}_j}$$

$$\underset{\binom{m}{2}\text{ eqs.}}{\rightsquigarrow} \quad \mathbf{a}_{ij}(x)\nabla z(x) = b_{ij}(x), \text{ with}$$

$$\mathbf{a}_{ij}(x) := \begin{bmatrix} I_i(x)s_j^1 - I_j(x)s_i^1 \\ I_i(x)s_j^2 - I_j(x)s_i^2 \end{bmatrix}^\top \in \mathbb{R}^{1\times 2}$$

$$b_{ij}(x) := I_i(x)s_j^3 - I_j(x)s_i^3 \in \mathbb{R}$$

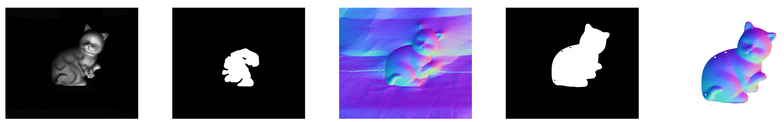
Use $\binom{m}{2}$ linear PDEs and solve for z:

$$\mathcal{P}_{\mathsf{PS}}(z(x)) := \frac{1}{\binom{m}{2}} \sum_{ij} \left(\mathbf{a}_{ij}(x)\nabla z(x) - b_{ij}(x)\right)^2 + \lambda(z(x) - z_0(x))^2$$

$$\min_z \int_\Omega \mathcal{P}_{\mathsf{PS}}(z(x))\,\mathrm{d}x$$

Contribution

Photometric Segmentation
jointly solve segmentation and photometric stereo (PS)



PS images | Segmentation only | PS only | Segmentation + PS

Variational Formulation

$$\min_{z,\phi} \int_\Omega H(\phi(x))\ \mathcal{P}_{\mathsf{PS}}(z(x))\,\mathrm{d}x + \int_\Omega (1 - H(\phi(x)))\ \mathcal{P}_{\mathsf{PS}}(z_0(x))\,\mathrm{d}x + \nu \int_\Omega |\nabla H(\phi(x))|\,\mathrm{d}x$$

Curve Parameterization using Level-Sets [2]

Level-set function: $\phi : \Omega \to \mathbb{R};\ x \mapsto \phi(x) = \begin{cases} > 0, & x \in \text{inside}(C)\ \text{(“foreground”)} \\ 0, & x \in C \\ < 0, & x \in \text{outside}(C)\ \text{(“background”)} \end{cases}$

Heaviside step function: $H : \mathbb{R} \to \{0,1\};\ x \mapsto H(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}$

Numerical Solution

Solve proposed model alternatingly over z and ϕ:

$$z^{(k+1)} = \arg\min_z \int_\Omega H(\phi^{(k)}(x))\mathcal{P}_{\mathsf{PS}}(z(x))\,\mathrm{d}x, \quad \text{(linear least squares problem)}$$

$$\phi^{(k+1)} = \arg\min_\phi \int_\Omega H(\phi(x))\mathcal{P}_{\mathsf{PS}}(z^{(k+1)}(x))\,\mathrm{d}x + \int_\Omega (1 - H(\phi(x)))\mathcal{P}_{\mathsf{PS}}(z_0(x))\,\mathrm{d}x + \nu \int_\Omega |\nabla H(\phi(x))|\,\mathrm{d}x$$

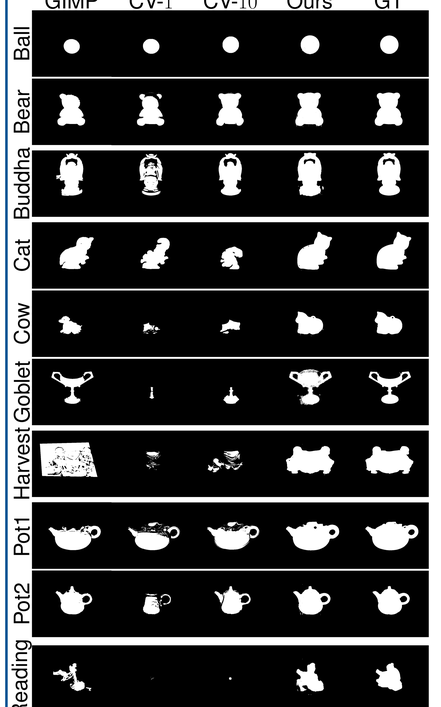
$\phi^{(k+1)}$ update is solved using gradient descent on Euler-Lagrange equation:

$$\delta(\phi(x))\left[\mathcal{P}_{\mathsf{PS}}(z^{(k+1)}(x)) - \mathcal{P}_{\mathsf{PS}}(z_0(x)) - \nu\,\text{div}\left(\frac{\nabla\phi(x)}{|\nabla\phi(x)|}\right)\right] = 0,$$

with $\delta(\phi(x))$ (dirac delta) the derivative of the $H(\phi(x))$.

Experimental Results

Segmentation Comparison



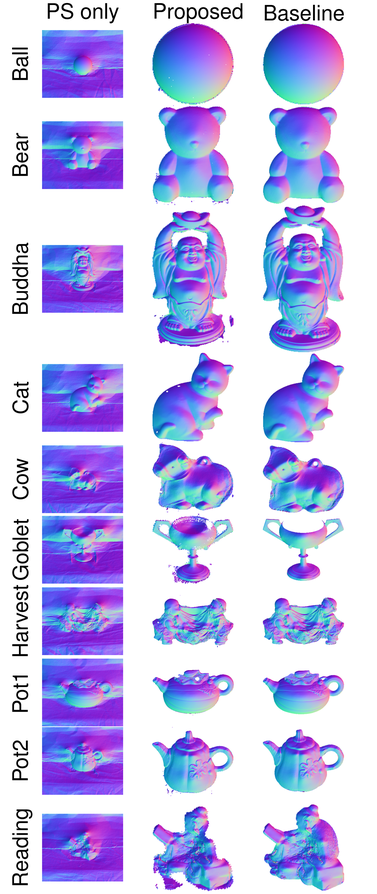
Dataset	GIMP	CV-1	CV-10	Proposed
Ball	0.6958	0.7307	0.8090	**0.9643**
Bear	0.8767	0.8254	0.9391	**0.9827**
Buddha	0.9112	0.7441	0.9074	**0.9320**
Cat	0.8567	0.6719	0.4352	**0.9842**
Cow	0.5536	0.1695	0.3277	**0.9829**
Goblet	**0.8706**	0.0601	0.2734	0.6727
Harvest	0.4830	0.0706	0.2227	**0.9773**
Pot1	0.7930	0.6781	0.7978	**0.9727**
Pot2	0.9145	0.4596	0.8305	**0.9851**
Reading	0.4970	0.0023	0.0114	**0.7748**

Table: IoU of segmentation estimate

Dataset	W/O mask	Proposed
Ball	0.9290	**0.7522**
Bear	0.6211	**0.2974**
Buddha	0.7791	**0.5370**
Cat	0.2068	**0.0868**
Cow	0.9644	**0.6592**
Goblet	6.8144	**6.4709**
Harvest	**0.6204**	0.6816
Pot1	1.7623	**1.5196**
Pot2	0.8353	**0.3747**
Reading	**9.0507**	9.2291

Table: MAE of normals estimate

Normal Comparison



References

[1] T. F. Chan and L. A. Vese. Active contours without edges. *IEEE Transactions on Image Processing*, 10(2):266–277, 2001.

[2] S. Osher and J. A. Sethian. Fronts propagating with curvature-dependent speed: algorithms based on Hamilton-Jacobi formulations. *Journal of Computational Physics*, 79(1):12–49, 1988.

[3] Y. Quéau, R. Mecca, and J.-D. Durou. Unbiased photometric stereo for colored surfaces: A variational approach. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 4359–4368, 2016.