Improved Photometric Stereo through Efficient and Differentiable Shadow Estimation

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Introduction

Traditional photometric stereo approaches have faced limitations due to lack of considering accurate shadow estimation under different object geometry and varying lighting conditions. We propose a fast and accurate shadow estimation algorithm based on a dynamic programming-based sampling method with a differentiable temperature function. The proposed method can be easily used to improve existing photometric stereo methods for better estimation of shadow estimation results.

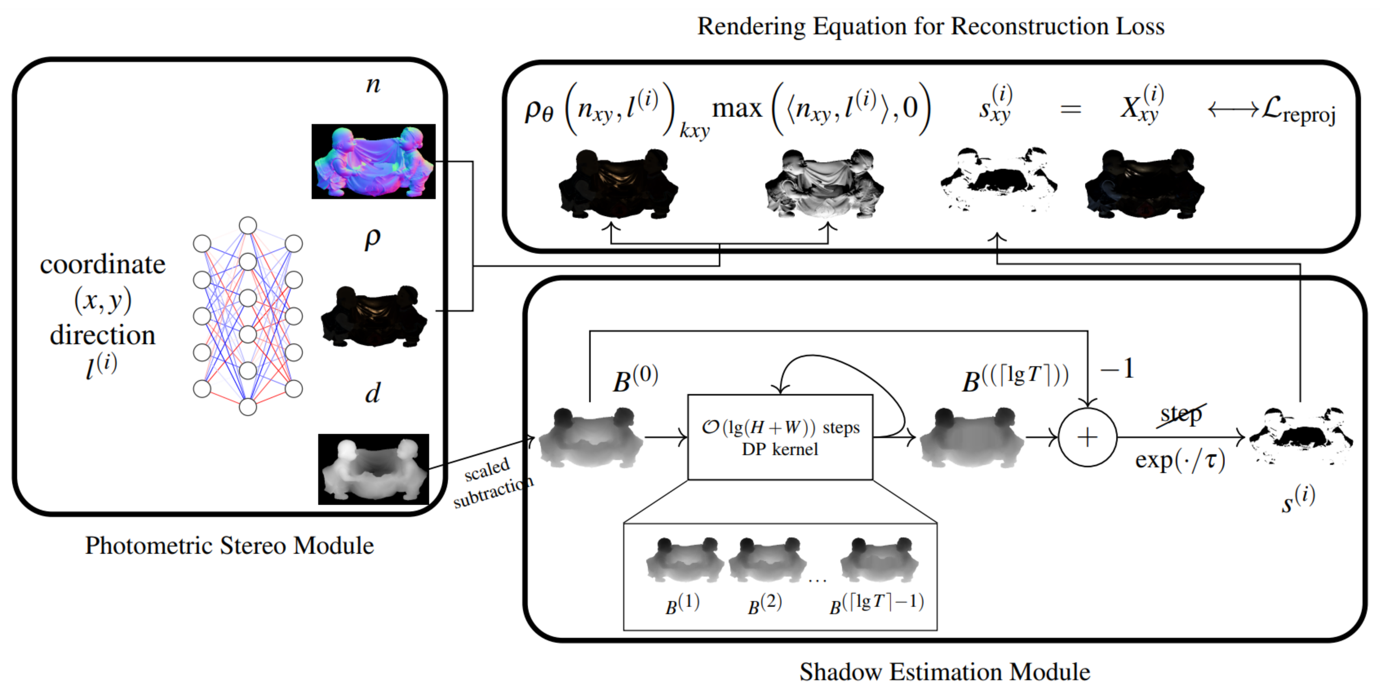


Figure 1. Overview of our contribution.

The results demonstrate that our method consistently outperforms other state-of-the-art unsupervised methods in terms of mean angular error (MAE) while remaining competitive with supervised techniques.

The Formulation

We start with the formulation of our central problem.

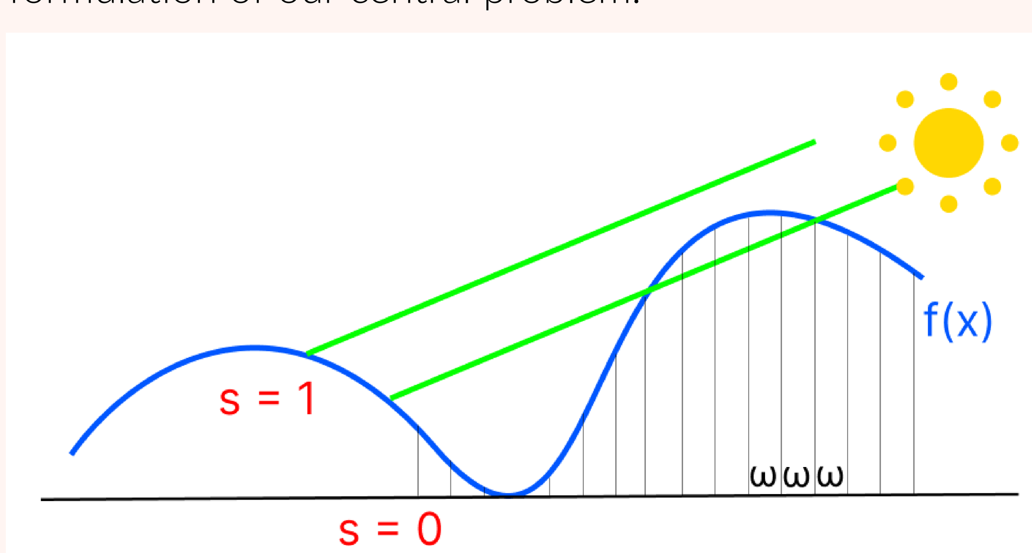


Figure 2. The central problem in our paper.

$$s(x) = \text{step}\left(\min_{t \in \mathbb{R}_+} [f(x) + lt - f(x+t)]\right) \tag{1}$$

By discretization with ω per step, we can use sampling to find if a pixel is in shadow, resulting in a linear time algorithm per pixel.

From Linear Time to Logarithm Time

We alias $F[i] = f(iw)$, $B[i] = ilw - F[i]$ and write down the problem reduction.

$$S[i] = \text{step}\left(\min_{i \le j < N} [F[i] + (j-i)lw - F[j]]\right) \tag{2}$$

$$= \text{step}\left(\left[\min_{i \le j < N} B[j]\right] - B[i]\right) \tag{3}$$

This translates to a reversed prefix minimum problem.

Parallel Prefix

To tackle this, we can scan the array B from end to start. Moreover, we propose an improved approach. Let $B^{(0)}[i] := B[i]$. Then, we can iteratively calculate $B^{(l)}[i]$ using parallel prefix [2]:

$$B^{(l+1)}[i] := \min\left(B^{(l)}[i], B^{(l)}[i+2^l]\right) \tag{4}$$

$$= \min\left(B^{(l-1)}[i], B^{(l-1)}[i+2^{l-1}], B^{(l-1)}[i+2\cdot 2^{l-1}], B^{(l-1)}[i+3\cdot 2^{l-1}]\right) \tag{5}$$

$$\vdots \tag{6}$$

$$= \min_{0 \le t < 2^l} B^{(0)}[i+t] \tag{7}$$

	Naive sampling, parallely	Naive DP approach	ours
Total Queries	$\Theta(N^2)$	$\mathbf{\Theta(N)}$	$\Theta(N \log N)$
Parallelable	Yes	No	Yes
Parallel Acceleration	$\Theta(N)$	$\Theta(N)$	$\mathbf{\Theta(\log N)}$

Table 1. Summary of Improvement

A Softened Approximation

To make the process differentiable, we replace the $\text{step}(\cdot)$ by $\exp(\cdot/\tau)$. We further let τ trainable.

$$s(iw) \approx \exp\left(\frac{B^{(\lceil \lg T \rceil)}[i] - B^{(0)}[i]}{\tau}\right), \tag{8}$$

We provide a numerical error upper bound for this estimation:

$$\underbrace{\frac{w}{\tau} \sup_{t \in \mathbb{R}_+} |l_z - z'(t)|}_{\text{dominant when } \tau \text{ is small}} + \underbrace{\exp\left(\frac{\min_{t \in \mathbb{R}_+} z(0) + tl_z - z(t)}{\tau}\right)}_{\text{dominant when } \tau \text{ is large}} \tag{9}$$

Quantitative Results

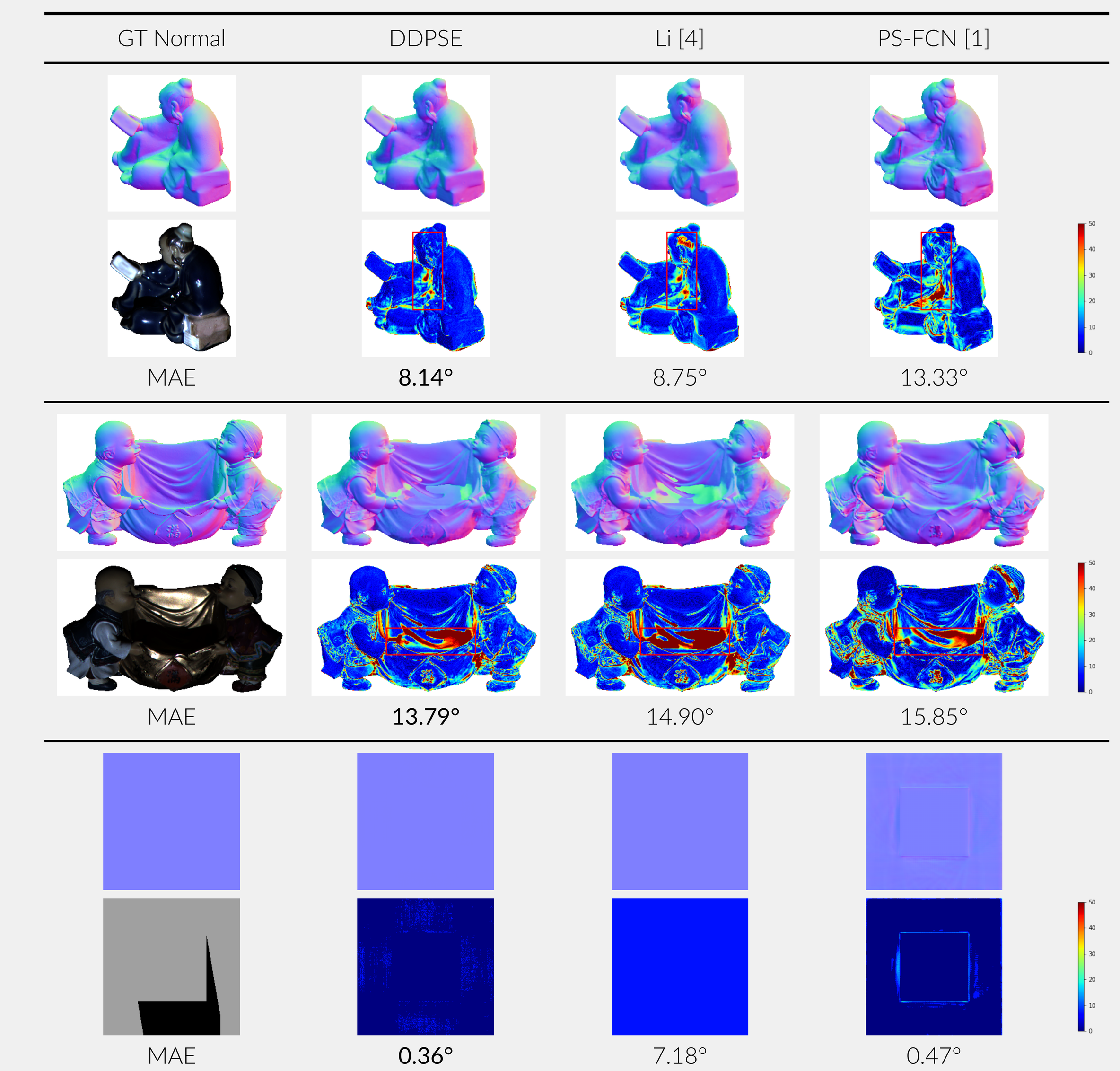
Table 2. We compare our method with other state-of-the-art method in the MAE metric. The bold font means the best normal estimation accuracy.

Methods	Ball	Bear	Buddha	Cat	Cow	Goblet	Harvest	Pot1	Pot2	Reading	Avg
TM18 [5]	**1.47**	5.79	10.36	5.44	6.32	11.47	22.59	6.09	7.76	11.03	8.83
BK21 [3]	3.78	5.96	13.14	7.91	10.85	11.94	25.49	8.75	10.17	18.22	11.62
L2 [6]	4.10	8.40	14.90	8.40	25.60	18.50	30.60	8.90	14.70	19.80	15.40
Li22 [4]	2.43	3.64	8.04	4.86	4.72	6.68	14.90	**5.99**	**4.97**	8.75	6.50
DDPSE (ours)	2.00	**3.61**	**7.48**	**4.75**	**4.64**	**6.53**	**13.79**	6.11	5.51	**8.14**	**6.26**

Experimental Results

We compare our method with prior works.

Table 3. Qualitative comparison results on normal estimation.



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