Numerical Reflectance Compensation for Non-Lambertian Photometric Stereo

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Abstract—The surface normal estimation from photometric stereo becomes less reliable when the surface reflectance deviates from the Lambertian assumption. The non-Lambertian effect can be explicitly addressed by physics modeling to the reflectance function, at the cost of introducing highly nonlinear optimization. This paper proposes a numerical compensation scheme that attempts to minimize the angular error to address the non-Lambertian photometric stereo problem. Due to the multifaceted influence in the modeling of non-Lambertian reflectance in photometric stereo, directly minimizing angular errors of surface normal is a highly complex problem. We introduce an alternating strategy, in which the estimated reflectance can be temporarily regarded as a known variable, to simplify the formulation of angular error. To reduce the impact of inaccurately estimated reflectance in this simplification, we propose a numerical compensation scheme whose compensation weight is formulated to reflect the reliability of estimated reflectance. Finally, the solution for the proposed numerical compensation scheme is efficiently computed by using cosine difference to approximate the angular difference. The experimental results show that our method can significantly improve the performance of state-of-the-art methods on both synthetic data and real data with small additive costs. Moreover, our method initialized by results from the baseline method (least square based) achieves state-of-the-art performance on both synthetic data and real data with significantly smaller overall computation, i.e., about 8 times faster as compared to state-of-the-art methods.

Index Terms—Photometric stereo, Angular error, Numerical reflectance compensation, Non-Lambertian.

I. INTRODUCTION

PHOTOMETRIC stereo [1] is an important 3D reconstruction technique, which is able to provide a highly detailed 3D surface structure through the recovery of the surface normal. The surface normal estimates can be used to reconstruct delicate 3D surface at micron scale (e.g., [2]), to improve high-level visual problems like face recognition (e.g., [3]), to provide useful cues for biometrics (e.g., [4], [5]), and to benefit emerging techniques like 3D printing (e.g., [6]).

The distortion in the surface normal estimation brought by the complex interaction between illumination and surface reflectance is the biggest difficulty in preventing photometric stereo from being practical. Such an issue is usually addressed by explicitly integrating the Bidirectional Reflectance Distribution Function (BRDF) into the photometric stereo pipeline (e.g., [7]) or by adding robust terms into the conventional Lambertian image formation model to tolerate the non-Lambertian phenomenon (e.g., [8]). However, the former type of solution usually introduces highly nonlinear terms so that the optimization becomes rather complicated, while the latter type of solution often relies on some statistical priors in which the Lambertian component is required to be dominantly observed so that its ability to deal with generally unknown reflectance is quite limited. There are also approaches exploring the general properties of BRDFs (e.g., [9]), but it is difficult to estimate such prior information on real data with noise. Furthermore, these methods cannot always ensure the efficient computation and accurate estimation at the same time.

In this paper, we present a method to achieve accurate normal estimates to unknown general reflectance by optimizing angular error (refer to Section III-B for the definition) [10]. We firstly argue that angular error based optimization can be more accurate to formulate the photometric stereo problem. However, multifaceted influence in the modeling of unknown reflectance makes the inverse problem, i.e., formulation of angular error itself complicated, which results in difficulty in solving angular error based optimization. In order to address this problem, we introduce an alternating strategy in which reflectance can be temporarily regarded as known, and the angular error can be reformulated as a more flexible formulation, i.e., the difference between two angles. This alternating strategy can help to reformulate and minimize angular errors but it is inevitably influenced by less accurate estimation of surface reflectance. In order to reduce the adverse impact of such inaccuracy, we propose a numerical compensation scheme using compensation weight to account for the inaccurately estimated reflectance. Finally, the solution for proposed numerical compensation scheme is efficiently computed by using cosine difference to approximate the angular difference. Experimental results detailed in this paper indicate that our method can achieve state-of-the-art performance with a considerable advantage in the computational speed.

Our method does not make any assumption on the mathematical form or the physical properties of the reflectance, and it applies a purely numerical term in a pixel-wise manner. Hence, our approach is expected to be applicable to different types of non-Lambertian reflectance theoretically. We evaluate the effectiveness of our approach using synthetic data from
the MERL database [11] and real data from the ‘DiLiGenT’ dataset [12]. Our contributions can be summarized as follows:

- This paper attempts to reformulate non-Lambertian photometric stereo problem using the angular error. The advantage of this formulation is that its solution is not explicitly restricted by the physical properties of the surface which is generally complex and unknown for most practical applications.
- We propose a numerical compensation scheme to address angular error based optimization. The compensation weight for our solution is judiciously adopted to reflect the reliability or accuracy of the estimated reflectance.
- We show the proposed method can achieve significantly improve the performance of state-of-the-art methods on both synthetic data and real data with small additive costs. Besides, our method initialized by baseline method outperforms state-of-the-art methods with significantly smaller overall computation. We also show that the performance advantage is particularly evident when the number of input images is small.

II. RELATED WORK

Since the introduction of classic photometric stereo [1], which assumes Lambertian reflectance with known directional light sources under an orthographic camera, researchers have extended this classic method to accommodate more realistic reflectance, lighting, and camera models. Our paper focuses on the photometric stereo problem for generally unknown reflectance and therefore we only summarize recent works on this topic, and we refer the readers to survey papers in [13], [14], [12] for other generalizations of photometric stereo.

The real world reflectance could be addressed using physics-based modeling. The classic Lambertian reflectance model could be replaced with more sophisticated reflectance models. Georgiades [15] adopted the Torrance-Sparrow model [16], and Chung and Jia [17] and Goldman et al. [7] chose the Ward model to explicitly represent the non-Lambertian effect. Drbohlav et al. [18], [19] assumed specular-spike reflectance and provided solutions by detecting specular spots in the images. By exploring more general physics properties of surface reflectance, photometric stereo has been extended for a broader range of real world materials. Alldrin et al. [20] employed bi-variate approximations of isotropic reflectance. Chandraker et al. [21] derived the theory of photometric surface reconstruction with image derivatives for isotropic reflectance. Ikehata et al. [22] used a smooth, bivariate Bernstein polynomials function to model the surface reflectance. Shi et al. [23] presented a bi-polynomial reflectance model to describe the low-frequency component of the surface reflectance. La et al. explored intensity profile similarity [24] and BRDF symmetry [25] to solve for uncalibrated photometric stereo with isotropic BRDF.

Another category of the methods incorporates statistical approaches to address the non-Lambertian components in a numerical way. Wu and Tang [8] developed a robust estimation framework using expectation maximization. Sunkavalli et al. [26] selected shadow-free images using RANSAC even without knowing the lighting direction. Yu et al. [27] developed a method which satisfies the Lambertian constraint to obtain the maximum subset of images. Wu et al. [28] explicitly added sparse corruptions and formulate the optimization as the problem of recovering a low-rank matrix. Ikehata et al. [29] extended this method by explicitly forcing the rank-3 Lambertian constraint. Samejima et al. [30] adopted IRLS to accelerate its speed with a little sacrifice of the performance. Tozza et al. [31] formulated the problem using differential equations to deal with the mixture of diffuse and specular reflectance.

The approaches based on the modeling of physical reflectance can be more effectively used for the non-Lambertian materials, but they usually involve highly nonlinear or even non-convex optimization. While for numerical approaches, most methods assume there is a dominant Lambertian component, which is not true for many real-world materials. Recently, deep learning based approaches [32], [33] have shown to offer impressive performance on public benchmark dataset. Key limitation of these methods lies in the requirements of lots of training data, generated from various non-Lambertian materials and shapes. In this paper, we propose a numerical approach, but without assuming the dominance of the Lambertian component. The proposed approach is able to achieve the general modeling ability with an alternating computation.

We firstly introduce our motivation of using angular error based optimization to address the photometric stereo problem in Section III. A numerical compensation scheme aiming to solve the angular error based optimization is then proposed in Section IV. The performance of our method is reported in Section V.

III. MOTIVATION

In this section, we formulate the solution for the photometric stereo problem using the optimization of angular error. In Section III-A we briefly introduce the classical solutions for photometric stereo methods which attempts to minimize the projection error. We then argue that the optimization of angular error offers more attractive and feasible solution than the optimization of projection error for the photometric stereo problem in Section III-B. Finally, a quadratic angular error based optimization for the photometric stereo problem is presented in Section III-C.

A. Classical Formulation of Photometric Stereo Problem

We adopt the camera-centric coordinate system as most photometric stereo methods. For a pixel with surface normal \( \mathbf{n} \in \mathbb{R}^3 \) illuminated by a directional lighting \( \mathbf{l} \in \mathbb{R}^3 \), its irradiance value \( I \) is denoted as

\[
I = \epsilon(\mathbf{n}, \mathbf{l}, v) \max(\rho(\mathbf{n}, \mathbf{l}, v)\mathbf{l}^\top \mathbf{n}, 0),
\]

where \( \rho(\mathbf{n}, \mathbf{l}, v) \) is a general BRDF term, \( v \) is the viewing direction vector, \( \max \) addresses the attached shadow, and \( \epsilon(\mathbf{n}, \mathbf{l}, v) \) is the visibility term for cast shadow.

Given \( m \) different lightings stacked in the matrix \( \mathbf{L} = (l_1, l_2, \ldots, l_m) \in \mathbb{R}^{3 \times m} \) and the corresponding intensity...
profile \( \mathbf{I} = (I_1, I_2, \ldots, I_m)^T \in \mathbb{R}^m \) observed for a pixel with surface normal \( \mathbf{n} \), the general photometric stereo problem solves \( \mathbf{n} \) for the current pixel via a \( \ell^2 \)-norm optimization
\[
\min_{\mathbf{n}, \mathbf{R}} \| \mathbf{I} - \mathbf{R} \circ \mathbf{L}^T \mathbf{n} \|_2, \quad (2)
\]
where \( \mathbf{R} = (R_1, R_2, \ldots, R_m)^T \in \mathbb{R}^m \) as surface reflectance which includes the general BRDF and both attached and cast shadow related terms. ‘\( \circ \)’ denotes element-wise multiplication.

**B. Projection Error and Angular Error**

For each pixel, the optimization (2) attempts to minimize the measurement error resulting from the difference between \( I_i \) and the projection from \( \mathbf{n} \) to \((\mathbf{R}, \mathbf{l}_i)\). This difference is defined as the projection error in this paper. The direction of the estimated surface normal w.r.t. ground truth normal is widely used in the literature to measure the accuracy. In this paper, the angle between the estimated surface normal and the ground truth surface normal is defined as angular error. Since projection length measurement and angular degree measurement are not equivalent, inconsistency exists between surface normal optimization using the projection error and evaluation using the angular error.

The problem resulting from such inconsistency can be intuitively interpreted from the illustration in Figure 1.\(^1\) Can be observed from this figure, the quantitative value of projection error, i.e., \( I_i - R_i \mathbf{l}_i^T \mathbf{n} \), heavily relies on the values of reflectance \( R_i \) and angle \( \arccos(\mathbf{l}_i^T \mathbf{n}) \). However, it is not the case for angular errors represented by the orange sectors. Therefore, it is quite reasonable to argue that two estimated surface normals \( \mathbf{n}_1, \mathbf{n}_2 \) with same angular error \( \arccos(\mathbf{n}_1^T \mathbf{n}_2) \overset{\sim}{=} \arccos(\mathbf{n}_1^T \mathbf{n}_2) \), but totally different projection errors.

These two kinds of error are fundamentally different. If such difference is uniformly varying from different observations or from different \( i \), the optimizations based on them separately will offer the same solution. However, such uniformity is not plausible because the reflectance is unpredictable and the angles between illumination directions and unknown surface normal can be arbitrary. Hence, the optimizations based on them will result in different optimal solutions. Since criterion to evaluate the accuracy of the photometric stereo solution is the angular error, the optimization based on angular error is expected to be more effective and judicious.

**C. Angular Error based Formulation**

Photometric stereo problem is essentially an optimization problem aiming to estimate optimal solution for true value from multiple measurements. All measurement errors are expected to be optimally minimized. For optimizations based on projection error, this true value is essentially the quantitative value of projection from vector \((R_i, \mathbf{n})\) (\( \mathbf{n} \) here is true surface normal) to vector \( \mathbf{l}_i \). The measurement error or projection error \( e_{proj}(i) \) is the difference between a measured value \( I_i \) and the true value
\[
e_{proj}(i) = I_i - R_i \mathbf{l}_i^T \mathbf{n}. \quad (3)
\]

For optimizations based on angular error, the true value is our optimization target \( \hat{\mathbf{n}} \), while the measured value \( \mathbf{n}_i \) is determined by \( I_i \) and \( \mathbf{l}_i \) according to Equation (1). The measurement error or angular error \( e_{ang}(i) \) can be expressed as
\[
e_{ang}(i) = \arccos(\mathbf{n}_i^T \hat{\mathbf{n}}). \quad (4)
\]

Generally, for given \( I_i \) and \( \mathbf{l}_i \), there are several possible unit vectors \( \hat{\mathbf{n}} \) satisfying Equation (1) even with known BRDFs model. These \( \hat{\mathbf{n}} \) are expected to be distributed on a complex cone-like structure \( \mathbf{C}_i \) (blue cone in Figure 1). Obviously, the measurement error here is the minimum difference between \( \mathbf{n} \) and all possible \( \hat{\mathbf{n}} \). Then \( \mathbf{n}_i \) (red vectors in Figure 1) in Equation (4) can be expressed as follow\(^2\),
\[
\mathbf{n}_i = \min_{\hat{\mathbf{n}}} \arccos(\hat{\mathbf{n}}^T \mathbf{n}), \quad \hat{\mathbf{n}} \in \mathbf{C}_i. \quad (5)
\]

Then the quadratic angular error based optimization for photometric stereo can be formulated as
\[
\min_{\mathbf{n}} \| e_{ang} \|_2, \quad (6)
\]

where \( e_{ang} = (e_{ang}(1), e_{ang}(2), \ldots, e_{ang}(m))^T \in \mathbb{R}^m \). The angular error based optimization can be translated as the problem of finding the intersection of several cones. However, since the shape of \( \mathbf{C}_i \) can hardly be formulated, it is quite difficult to explicitly formulate angular error \( e_{ang} \) which makes the presented angular error based optimization (6) intractable.

**IV. PROPOSED NUMERICAL COMPENSATION SCHEME**

In order to explicitly formulate the angular error, we introduce an alternating strategy in which reflectance can be temporarily regarded as a known variable during the optimization of the surface normal, resulting in a simpler shape of \( \mathbf{C}_i \) and a more flexible formulation of \( e_{ang}(i) \). However, the inaccurately estimated reflectance in the alternating strategy will inadvertently deviate the optimization from our original target. In order to reduce the adverse influence from such deviation, we propose a numerical compensation scheme using compensation weight to reflect and offset the reliability or accuracy of estimated reflectance in Section IV-A. The formulation of our compensation weight is detailed in Section IV-B. In Section IV-C, efficient solution for the proposed numerical compensation scheme is developed by using cosine difference to approximate the angular difference. Finally, our whole algorithm is summarized in Section IV-D.

\(^1\)When both surface reflectance and surface normal are unknown, the cone-like structure, where the normals are expected to be distributed, can become rather complex (depending on the number of lobes and dominant projection directions of the BRDFs [9], [22]). We simplify such a complex structure and instead use a right circular cone here for better illustration and comprehension.

\(^2\)It appears that \( I_i = R_i \mathbf{l}_i^T \mathbf{n} \), as illustrated in Figure 1, but this equality can hardly be true because \( R_i = \rho(\mathbf{n}, \mathbf{l}_i, \mathbf{v}) \) is expected to be different from \( \rho(\mathbf{n}, \mathbf{l}_i, \mathbf{v}) \) in practice.
A. A Numerical Compensation Scheme

Explicit formulation of \( e_{\text{ang}}(i) \) is difficult because the shape of the cone-like structure \( C_i \) is expected to be complex. Even if the formulation of reflectance is known, e.g., using Cook-Torrance reflectance model [34] to fit specular component, inferring the shape of \( C_i \) is an inverse problem and its explicit formulation is hard to achieve. However, once the value of reflectance \( R_i \) is known, the shape of \( C_i \) becomes a right circular cone as shown in Figure 1. Consequently, \( e_{\text{ang}}(i) \) can be explicitly formulated. Such benefits have motivated us to adopt the alternating strategy.

To be more specific, when \( R_i \) is fixed, vectors \( \mathbf{n}, \mathbf{l}_i \), and \( \mathbf{n}_i \) are coplanar. This coplanar relationship can be directly derived using simple algebraic geometry. Based on such coplanarity, the angular error \( e_{\text{ang}}(i) \) in Equation (4) can be reformulated as

\[
e_{\text{ang}}(i) = \arccos(\mathbf{n}_i^T \mathbf{n}) \\
= |\arccos(l_i^T \mathbf{n}_i) - \arccos(l_i^T \mathbf{n})| \\
= |\arccos(I_i^T \mathbf{n}_i) - \arccos(I_i^T \mathbf{n})|. 
\]  

(7)

Equation (7) converts the angular error calculation, whose originally formulation is difficult to optimize, to a tractable one by temporarily assuming the reflectance is known.

Adopting the alternating strategy to optimize \( \mathbf{n} \) is able to provide an estimated reflectance, however, the estimated reflectance may not be accurate. Such inaccuracy will inevitably impact the estimation of the surface normal. As shown in Figure 1, if the estimated \( R_i \) is slightly different from the true \( R_i \), the shape of the right circular cone \( C_i \) will be inaccurate. Therefore, directly optimizing angular error using the alternating scheme will make the reformulation (7) less reliable and inevitably deviate us from the objectives of the (ideal) angular error based optimization.

In order to retain the benefits from the alternating strategy, i.e., using more flexible angular error formulation in (7), at the same time reduce the impact of inaccurate \( R_i \), we penalize the estimated reflectance \( \hat{R}_i \) according to its reliability. Hence, combining Equation (6) and Equation (7), our numerical compensation scheme for angular error based optimization problem can be formulated as follows,

\[
\min_{\mathbf{n}} \sum_{i=1}^{m} (\omega_i (\arccos(l_i^T \mathbf{n}) - \arccos(l_i^T \mathbf{n}))^2, 
\]

(8)

where \( \omega_i \) is the compensation weight which reflects and offsets the reliability of \( \hat{R}_i \). Angular error \( e_{\text{ang}}(i) \) is compensated with larger weight \( \omega_i \) if \( \hat{R}_i \) is more reliable and more accurately estimated. The detailed formulation of \( \omega_i \) will be explained in the next section.

B. Quantification of Compensation Weight \( \omega_i \)

As detailed earlier, our idea is to weight the contribution from surface reflectance according to their reliability. Since the true value of \( \mathbf{R} \) is always unknown in a general photometric stereo problem, we introduce an indirect way to reflect its reliability or accuracy.

Assuming that the true surface reflectance \( \mathbf{R} \) is known, photometric stereo problem in Equation (2) can be reformulated as

\[
\min_{\mathbf{R}} \| \mathbf{R} \circ (\cos(\mathbf{\theta}) - \cos(\mathbf{\theta}^0)) \|_2 \quad \text{with} \quad \mathbf{\theta} = \arccos(\mathbf{I} \circ \mathbf{R}) \quad \text{and} \quad \mathbf{\theta}^0 = \arccos(\mathbf{L}^T \mathbf{n}),
\]

(9)

where \( \mathbf{\theta} \) and \( \mathbf{\theta}^0 \) are vectors of length \( m \), \( \circ \) denotes element-wise division. Trigonometric functions are extended to operate with vectors in our deduction, unless otherwise explicitly stated.

Considering function \( f(\theta_i) = \cos(\theta_i) \), its first-order Taylor expansion at \( \theta_i^0 \), \( i = \{1, 2, \ldots, m\} \) can be approximated as

\[
f(\theta_i) - f(\theta_i^0) \approx -\sin(\theta_i^0) \delta_i, \quad \delta_i = \theta_i - \theta_i^0. 
\]

(10)

Its second-order Taylor expansion at \( \theta_i^0 \) is

\[
\delta_i \approx -\frac{f(\theta_i) - f(\theta_i^0)}{-\sin(\theta_i^0) - \cos(\theta_i^0) \delta_i}. 
\]

(11)

Substituting the \( \delta_i \) from Equation (11) into Equation (10), Equation (9) can then be approximated as

\[
\min_{\mathbf{R}} \| \mathbf{M} \circ \mathbf{R} \circ (\cos(\mathbf{\theta}) - \cos(\mathbf{\theta}^0)) \|_2, 
\]

(12)

where \( \mathbf{M} \in \mathbb{R}^m \) and \( M_i \) is

\[
M_i = \frac{\sin(\theta_i^0)}{\sin(\theta_i^0) + \frac{\cos(\theta_i^0) \delta_i}{2}} = \frac{1}{1 + \frac{\cos(\theta_i^0) \delta_i}{2 \sin(\theta_i^0)}}. 
\]

(13)

If we have known true surface reflectance \( \mathbf{R} \), \( M_i \) is expected to be one. But we only have an estimated \( \mathbf{R} \), considering \( M_i \) is a continuous function of \( R_i \), therefore, we use how \( M_i \).
deviates from 1 to represent the reliability of the estimated \( \hat{R}_i \). According to Equation (13), the difference between \( M_i \) and 1 is determined by the numerical difference between \( \sin(\theta_i^0) \) and \( \cos(\theta_i^0) \delta_i \). Therefore, we simply use absolute value for the reciprocal of the \( \theta \)-relevant term (constant term ‘2’ has been ignored) in Equation (13) as our compensation weight\(^4\)

\[
\omega_i = \left| \frac{\sin(\theta_i^0)}{\cos(\theta_i^0) \delta_i} \right|.
\]  

(14)

A larger \( \omega_i \) indicates \( M_i \) is closer to 1, thus \( \hat{R}_i \) is expected to be more reliable and more accurately estimated. It should be noted that \( \delta_i \) here does not represent angular error \( e_{ang}(i) \) unless \( \hat{R}_i \) is equal to true reflectance \( R_i \).

According to Equation (14), the compensation weight can be assigned larger value with larger \( \theta_i^0 \) and smaller \( \delta_i \). Such an assignment can be intuitively explained by the following two reasons:

- Even though \( \delta_i \) cannot accurately represent the angular error \( e_{ang}(i) \), however, there exists a strong correlation, i.e., smaller \( \delta_i \) is expected to achieve smaller angular error \( e_{ang}(i) \) and offer better estimation of the surface reflectance.
- When \( \theta_i^0 \) is large, the observed intensity \( I_i \) from the corresponding pixels will always remain small according to Equation (1). This indicates low-intensity pixels are expected to have a better estimation of the surface reflectance\(^5\). Therefore our compensation weight is consistent with the observations in earlier work, e.g., the works [23], [35] indicate that the surface normal can be accurately obtained by analyzing the low-frequency reflectance/low-intensity observations\(^6\).

It should be noted that the idea of compensation weight is fundamentally different from that in [23], [35] even they share the similar spirit.\(^6\) Our compensation weight aims to reflect and offset inaccurately estimated reflectance instead of analyzing low-frequency reflectance. This is validated by the consistent performance improvement observed in our experiment using a small number of input images, for which it is not possible to perform the low-frequency analysis.

C. Computing Solution for Our Formulation

We presented angular error based optimization for formulating photometric stereo problem in Equation (8). However, the non-linear operation \( \text{arccos} \) in this formulation can significantly increase the computational complexity. Therefore, we introduce an efficient solution for the optimization in (8) by incorporating a reasonable approximation. Considering \( \text{arccos}(x), x \in [-1, 1] \) is continuous and monotonic function, we have

\[
\min_{n}(\text{arccos}(\frac{I_i}{R_i}) - \text{arccos}(l_i^T n)) = \min_{n}(\frac{I_i}{R_i} - l_i^T n).
\]  

(15)

\(^4\)When dividing by zero, we practically use a small value \((10^{-10})\) instead of zero to avoid infinite.

\(^5\)Note that the influence from the shadows has been neglected by selecting a threshold.

\(^6\)Please refer to our supplementary materials for experimental validation.

We then incorporate following approximation for the optimization in (8),

\[
\min_{n} \sum_{i=1}^{m} (\omega_i(\text{arccos}(\frac{I_i}{R_i}) - \text{arccos}(l_i^T n)))^2
\approx \min_{n} \sum_{i=1}^{m} (\omega_i(\frac{I_i}{R_i} - l_i^T n))^2.
\]  

(16)

Above approximation essentially uses cosine difference, instead of direct difference, between two angles for each term. Such approximation can retain key characteristics of the angular error, i.e., independent of scale term \( R_i \). Consequently, the operations for the approximations in (16) are linear and the complete objective function of our numerical compensation scheme can be reformulated in a matrix form,

\[
\min_{n, \omega} \| \omega \circ (I \circ R - L^T n) \|_2, \quad s.t. \quad \| n \|_2 = 1,
\]  

(17)

where \( \omega = (\omega_1, \omega_2, \ldots, \omega_m)^T \in \mathbb{R}^m \) in which \( \omega_i \) is defined in Equation (14).

Note that even though our final formulation in (17) is a weighted version of the formulation for projection errors, it essentially evaluates angular errors. Such an objective is achieved from the reformulation in Equation (7), in which angular error defined in Equation (4) can be more flexibly expressed with known reflectance. Weights \( \omega \) here are used for the compensation so that the terms with less accurate reflectance are penalized and make the reformulation in (7) more reliable. In the next section, we detail an iteratively alternating strategy to compute \( \omega \), surface normal, and reflectance.

D. Iteratively Alternating Strategy

It is useful to note that our derivation above does not make any assumption on the mathematical form or the physical properties of the reflectance. Therefore, some assumptions are required to solve the ill-posed problem of Equation (17).

In order to make the solution computationally feasible, we simply adopt the constraints introduced by Lambertian formulation, i.e., \( R_i \) are the same for different \( i \). However, it does not necessarily mean that our method follows the Lambertian assumption. The estimated reflectance values by enforcing the Lambertian assumption is just a ‘reflectance proxy’ but not the reflectance estimated based on Lambertian assumption or any other assumption with a physical meaning.\(^7\) Despite such arguments, in order to underline the effectiveness of our solution for constraints introduced by other reflectance models, we also report the results using bi-polynomial reflectance model [23], [35] in our experiment.

Considering the complex formulation of \( \omega \), it is not easy to directly optimize the minimization in (17) even with alternating strategy to compute \( n \) and \( R \). Hence, we adopt an iterative strategy to alternating optimize \( \omega \), \( n \), and \( R \). We use results from other methods to initialize the alternating strategy and they are represented as \( n_0 \).

\(^7\)Note that the value of our ‘reflectance proxy’ and that of estimated reflectance can be numerically equal to each other only if the compensation weight is 1.
Algorithm 1: Estimating surface normal $n$.

**Input:** intensity profile $I$.
illumination directions matrix $L$.
initial surface normal $n_0$.

**Output:** the estimated surface normal $n$.

1: initialize $n = n_0$ and set $\omega = 1$;
2: compute $R$ by Equation (18);
repeat
3: compute $\omega$ by Equation (14);
4: update $R$ by Equation (18);
5: update $n$ by Equation (19);
until max #iterations or convergence.

**Solving for $R$.** Fixing $n$ as the given initial input $n_0$, $R$ is firstly optimized by following minimization with $\omega = 1$,

$$
\min_{R} \|\omega \circ (I \circ R - L^T n)\|_2.
$$

(18)

Note that only if $\omega = 1$, the value of our reflectance proxy is equal to that of reflectance estimated based on Lambertian assumption. Then $\omega$ is computed using Equation (14). And $R$ are further updated using Equation (18).

**Solving for $n$.** When both $R$ and $\omega$ are fixed from the previous steps, computation of the surface normal $n$ in Equation (17) becomes a weighted least squares problem, which has a closed form solution as

$$
\omega = [\omega // \omega // \omega],
\hat{n} = (I \circ R - L^T n)^+ = (#L \circ \omega^T)(\omega \circ I)^T,
\bar{n} = \frac{n}{\|n\|_2},
$$

where ‘//’ denotes the operation to concatenate vectors column-wisely to form a matrix. It should be noted that there is a constraint for $n$ to be unit length, i.e., $\|n\|_2 = 1$. We relax this constraint and get the approximate results as several excellent photometric stereo methods did [23], [22], [30], [29], [35]. A convergence analysis is provided in our experiment section.

Our complete algorithm is summarized in Algorithm 1, for only one pixel. Since both $R$ and $n$ have closed form solutions during each iteration, our algorithm is computationally simpler as compared to most of the photometric stereo methods.

V. EXPERIMENTS AND RESULTS

We use both synthetic and real data to perform the quantitative evaluation for our method in terms of the mean angular error. Our experiments are mainly performed using five representative and state-of-the-art methods, i.e., LS [1], IW12 [29], SM16 [30], IA14 [22], and ST14 [23] (note that [23], [35] are the same method). They are used to initialize our alternating strategy and their comparative performances are reported. These five methods are used to initialize our algorithms, with ‘*’ after each method name indicating our results from the corresponding initial method, i.e., LS*, IW12*, SM16*, IA14*, ST14*. The results from our method are achieved after 10 iterations, unless otherwise explicitly stated. The implementation of our methods on the following experiments is made publicly available [36] to ensure reproducibility.

### A. Synthetic Data

The MERL BRDF database [11], which contains 100 different measured BRDFs, is used to conduct our synthetic experiment. The synthetic experiment setup is similar to those in [9], [23], [35], i.e., synthetic irradiance values are rendered with 1620 normal directions uniformly sampled from 36 longitudes and 45 latitudes, illuminated under 100 randomly distributed lighting directions for all 100 materials.

1) Improvement over Lambertian Methods: The LS (least squares method) [1] should be one of the simplest photometric stereo methods and it is used as the most popular baseline. IW12 [29] is believed to be one of the most efficient methods. LS holds the Lambertian assumption for the whole observation matrix while IW12 holds the Lambertian assumption only for a low-rank observation matrix. Complete results by our method initialized using these two methods are shown in Figure 2. The average errors over 100 materials are shown in Table I.

From the figures and the table, it can be found that our method shows a consistent and significant improvement over these two initial methods, i.e., from 10.18$^\circ$ to 0.966 for LS, and from 5.046 to 1.009 for IW12. Moreover, they both achieve the state-of-the-art performance, especially for LS* (0.966), which is initialized by the simplest photometric stereo method.

2) Improvement over SM16: Even though performance using SM16 [30] is not expected to be comparable to that from IW12 as introduced in Section II, performance comparison with SM16 is discussed separately. Because it shares the similar weighted formulation as ours. The main difference between our methods and SM16 is mainly on two sides:

- The object of weighted form in SM16 is to accelerate the speed of L1 optimization in IW12 [29] with a little sacrifice of performance. However, our weighted formulation is to improve normal estimation performance.
- The formulations of the weights are quite different between these two methods. The weight in SM16 is indeed the reciprocal of the projection error, however, our weight in Equation (14) is to reflect and balance the inaccurately estimated reflectance aiming to a better approximation to angular error based optimization.

SM16 employs the results from LS as their initialization. Therefore, a fair comparison between our method and SM16 should be LS* and SM16 which is shown in Figure 2 and Table I. As can be found from the figure and table, LS* significantly outperforms SM16, i.e., 0.966 over 6.435.

In order to show our method and SM16 are different in nature and to emphasize our method is insensitive to the initialization, we also show the performance of SM16+. As can be found from the figure and table, SM16+ (0.996) can still achieve the state-of-the-art performance.

3) Improvement over Non-Lambertian Methods: Inspired by the significant improvement from Lambertian methods, we also evaluate our method initialized using non-Lambertian
methods. IA14 [22] and ST14 [23], [35] are two empirical-based modeling methods to fit BRDFs to address the non-Lambertian component. They both achieve state-of-the-art performance as reported in a recent benchmark evaluation [12].

ST14 was proposed by incorporating the idea of extracting low-frequency reflectance. It was argued that using position thresholds is effective to extract low-frequency reflectance [12]. However, our experimental results (LS: 11.63, ST14:11.74) using position thresholds ($T_{\text{low}} = 40, T_{\text{high}} = 60$) do not illustrate encouraging performance. Therefore, both ST14 and ST14+ use the setting $T_{\text{low}} = 25$ i.e., 25 lowest intensity observations (among 100), to fit the bi-polynomial model and estimate the surface normal, which is the same setting as in [23], [35], are incorporated in our experiments.

As can be observed from the average error results in Figure 3 and Table I, our method can still improve the performance using these two non-Lambertian methods. The smallest average error is achieved using ST14+, i.e., 0.776. The improvement of IA14+ over IA14 is consistent and significant, i.e., 1.046 over 3.013.

The number of materials whose performance is improved by ST14+ is not as large as that from IA14+. The main reason is that we simplify our implementation with the Lambertian assumption to compute $\mathbf{R}$ in (18). However, ST14 carefully considers the non-Lambertian effect with 25 lowest intensity observations. Such difference sometimes adversely affects our optimization when using ST14 as initialization. Even so, our method can still outperform ST14 on the average error.

In summary, our method consistently achieves state-of-the-art performance with all the five methods as initialization. It is expected to have the potential to improve other photometric stereo methods.

4) Without Low-Frequency Reflectance Constraint: Several studies in the literature [12], [23], [35], [22] has indicated that the idea of low-frequency reflectance is quite effective for the photometric stereo problem.

Note that ST14+, which achieves the best performance among all the methods according to our experiments, has also incorporated such low-frequency setting. In order to better emphasize the effectiveness of our method, we investigate the performance of ST14+ without considering $T_{\text{low}}$. More specifically, we perform our algorithm with all the intensity observations, i.e., $T_{\text{low}} = 100$. That is, all the 100 intensity observations are used to compute surface reflectance $\mathbf{R}$ and
A polynomial model is used to compute surface reflectance in this experiment. More specifically, the bi-or biquadratic model incorporates non-Lambertian assumption, the bi-polynomial order to ascertain our approach can also be generalized to introduced by Lambertian assumption in Equation (5). With Non-Lambertian Assumption: As outlined in Section IV-D, we simplify our implementation using the constraint introduced by Lambertian assumption in Equation (18). In order to ascertain our approach can also be generalized to incorporate non-Lambertian assumption, the bi-polynomial or biquadratic model [23], [35] was adopted to fit surface reflectance in this experiment. More specifically, the bi-polynomial model is used to compute surface reflectance $R_i$ instead of using Equation (18) and the remaining steps in Algorithm 1 are kept the same. Considering the fact that ST14 also incorporates the bi-polynomial model, we use the results from ST14 to initialize our algorithm in this experiment.

Figure 3 and Table I show our results using bi-polynomial model and the results are labelled as ‘ST14+ non-Lamber.’ It can also be observed from Table I that the improvement in the average error from ‘ST14+ non-Lamber.’ over ST14 is not as significant as that from ST14+. The reason is ST14 has already achieved small optimization error with the constraint of using bi-polynomial model. The error can hardly be further optimized with the same reflectance model assumption. However, the improvement is still observable over ST14, i.e., 0.880 over 1.093. Moreover, as compared to ST14, ‘ST14+ non-Lamber’ consistently improves the performance of all the 100 different materials. It has the advantages of robustness and stability over ST14+. Such consistency indicates that our approach is also expected to incorporate other non-Lambertian methods for further performance improvement, which is suggested for the further extension of this work.

6) Convergence: Figure 4 shows the average results over 100 materials with increasing number of iterations. It can
TABLE I: Total number (T.N.) of materials with performance improved, average error over 100 materials, and the corresponding computational time from the mentioned methods (per-pixel).

<table>
<thead>
<tr>
<th>Method</th>
<th>T.N.</th>
<th>Error</th>
<th>Time (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>LS [1]</td>
<td>/</td>
<td>10.18</td>
<td>0.076</td>
</tr>
<tr>
<td>LS+ (iter=10)</td>
<td>98</td>
<td>0.966</td>
<td>0.076+0.921</td>
</tr>
<tr>
<td>LS+ (iter=1)</td>
<td>99</td>
<td>1.407</td>
<td>0.076+0.092</td>
</tr>
<tr>
<td>IW12 [29]</td>
<td>/</td>
<td>4.046</td>
<td>11.92</td>
</tr>
<tr>
<td>IW12+ (iter=10)</td>
<td>100</td>
<td>1.009</td>
<td>11.92+0.092</td>
</tr>
<tr>
<td>IW12+ (iter=1)</td>
<td>100</td>
<td>1.496</td>
<td>11.92+0.092</td>
</tr>
<tr>
<td>SM16+ (iter=10)</td>
<td>98</td>
<td>0.996</td>
<td>6.311+0.092</td>
</tr>
<tr>
<td>SM16+ (iter=1)</td>
<td>100</td>
<td>1.499</td>
<td>6.311+0.092</td>
</tr>
<tr>
<td>IA14 [22]</td>
<td>/</td>
<td>3.031</td>
<td>1.573</td>
</tr>
<tr>
<td>IA14+ (iter=10)</td>
<td>99</td>
<td>1.046</td>
<td>1.573+0.921</td>
</tr>
<tr>
<td>IA14+ (iter=1)</td>
<td>100</td>
<td>1.702</td>
<td>1.573+0.092</td>
</tr>
<tr>
<td>ST14+ (iter=10)</td>
<td>66</td>
<td>0.776</td>
<td>7.772+0.718</td>
</tr>
<tr>
<td>ST14+ Tlow=100</td>
<td>65</td>
<td>0.775</td>
<td>7.772+0.921</td>
</tr>
<tr>
<td>ST14+ non-Lamber.</td>
<td>100</td>
<td>0.880</td>
<td>7.772+2.321</td>
</tr>
<tr>
<td>ST14+ (iter=1)</td>
<td>76</td>
<td>0.746</td>
<td>7.772+0.072</td>
</tr>
</tbody>
</table>

Fig. 4: The average error for 100 materials during 20 iterations from LS+, IW12+, SM16+, IA14+, ST14+, ST14+ Tlow = 100, and ST14+ non-Lamber, respectively. The Y-axis shows average angular errors in degrees; the X-axis shows the iteration number.

be observed that even though our algorithm is initialized by different photometric methods or different settings, and with some proper approximations, the results can always converge after about 10 iterations. Moreover, the convergence speed is much faster in the first a few iterations, especially for the methods like LS+, IW12+, SM16+, IA14+, in which the average errors from their initial methods are relatively large. It can also be observed that the errors have little fluctuation in the first a few iterations for ST14+ and ‘ST14+ Tlow = 100’. However, they get stable after 10 iteration. This phenomenon can be largely attributed to the simple assumption made in Equation (18) while ST14 and ‘ST14+ non-Lamber.’ fit the non-Lambertian or bi-polynomial model to solve R.

Considering the performance and computation, the number of iterations for our method was also fixed to 10. Inspired by the faster convergence speed in the first a few iterations, the performance with only one iteration is also reported. As shown in Table I, our algorithm with only one iteration can also achieve state-of-the-art performance. For example, result from LS+ (1.407) with only one iteration is much better than that from IW12 (5.046), SM16 (6.435), and IA14 (3.013), and is comparable to ST14.

7) Computation: It should be noted that, during each iteration, all the optimizations in our approach have the closed form solutions. Considering the fast convergence of our algorithm shown above, our method can not only offer the superior performance advantage but is also computationally simpler so that it can significantly improve the performance from existing methods with small additive costs.

The per-pixel computational time of all the related methods is reported in Table I, on a Windows PC with 2.8 GHz CPU using Matlab implementation. As can be found from Table I, our method (LS+ with ten iteration) outperforms state-of-the-art photometric stereo methods (e.g., ST14) with a huge computational advantage (0.997 ms v.s. 7.772 ms). It is useful to underline that our method (LS+, with one iteration) which uses very small computational time (0.168 ms), can still achieve the state-of-the-art performance which is far better than the baseline.

8) With Small Number of Images: Several photometric stereo methods need large number of input images to perform BRDFs modeling or statistical analysis, their performance always drops down when the number of input images is small. However, according to our numerical compensation theory and inspired by our result in Section V-A4, our method is expected to work well even if when the number of input images is small.

Considering the performance reported in Table I, one Lambertian based method (LS) and two non-Lambertian based methods (IA14, ST14) are used to initialize our algorithm in this experiment. The experiment is conducted with the number of input images is 4, 8, 12, 16, 20, 24, 28, 32 respectively. The illumination directions are randomly set. Such randomness will impact the estimated results especially when the number of input images is small. In order to achieve reliable results, we report the average results under 100 different illumination conditions for each number of input images. The performance of LS, LS+, SM16, IW12, IA14, IA14+, ST14, and ST14+ are compared in this experiment. The average errors over 100 materials for 100 different illumination conditions are detailed in Figure 5. The corresponding quantitative results of their average errors over 100 different illumination conditions (average over 100 materials × 100 illumination conditions) are reported in Table II.

It can be found from Figure 5 and Table II, LS achieves slightly better performance than that from IW12, SM16, IA14, ST14 when the number of input images is 4. The reason is when the number of input images is small, the empirical-based models (BRDFs) or statistical models always fail to fit a proper reflectance and therefore the performance is unpredictable and...
Fig. 5: The errors distributions for all the related methods under 100 different randomly selected illumination conditions. The X-axis shows the labels of 100 different illumination condition ordered by their corresponding errors from LS, and the Y-axis shows the average angular errors in degrees over 100 materials in MERL dataset. Subfigures (a)-(h) illustrates the errors distributions when the number of input images is 4, 8, 12, 16, 20, 24, 28, 32 respectively. The legend labels in (b)-(h) are consistent with that in (a).
sensitive to illumination, and sometimes even not comparable to LS. With the number of input images increasing, the performance of IW12, SM16, IA14, ST14 become better. These methods have the advantage when the number of input images is large.

In contrast, our methods, LS+, IA14+, ST14+, can consistently achieve the best performance under different numbers of input images. Moreover, when the number of input images is relatively larger, our method can be more advantageous, i.e., LS+ achieves 2.816 average errors when the number of input images is 28, which is better than that from IA14 (3.013) in which the number of input images is 100 as shown in Table I. As can be found from Figure 5, when the number of input images is larger than 4, the performance advantage using our methods is superior under almost all the 100 random illumination configurations. Besides, even though the results from IA14 are not good and unstable when the number of input images is small, i.e., 4, 8, 12, 16, our method IA14+ can still achieve the state-of-the-art performance. The performance using ST14+ is slightly better than that from LS+ when the number of input images is larger than 4. The reason is when the number of input images is larger, ST14 can get better results against LS. Therefore, ST14+ is fed with better initialization as compared to LS+ so that it achieves better performance.

B. Real Data

We use the real-world data from the ‘DiLiGenT’ dataset [12] to quantitatively evaluate our approach. It contains ten objects with different scales of non-Lambertian reflectance under 96 lighting directions. It is argued that better performance can be achieved with position thresholds [12]. However, according to our experiment, the overall performance (LS: 11.63, ST14:11.74) with position thresholds ($T_{\text{high}} = 60$, $T_{\text{low}} = 40$) is not encouraging [10]. Similar phenomenon can also be justified from the observations in [12], i.e., performance with position thresholds (LS with $T_{\text{high}} = 60$, $T_{\text{low}} = 40$) is not comparable to that with $T_{\text{low}}$ only (ST14 with $T_{\text{low}} = 40$). Therefore, we judiciously incorporate the setting $T_{\text{low}} = 40$ for ST14 and IA14, which is the same setting as in [12] for the experiments in real data. Inspired by the convergence analysis for synthetic data, the iteration number is also set as 10 for real data.

1) Overall Performance: Besides five representative methods discussed above, we also report the overall performance of our approach initialized using three additional methods for real data. These methods are denoted as GC10 [7], HS15 [37], and SH17 [38], with $+$ after each method name indicating our results from the corresponding initial method.

Table III shows the angular error from our methods and initial methods for all 10 objects in the ‘DiLiGenT’ dataset. Figure 6 provides a complete example of error maps for object Goblet from all the discussed methods. These figures intuitively show how our method improves the original normal...
estimation in various regions of the objects, especially for the regions without cast shadows or occlusion near the boundaries of real data.

The results from methods ST14 and IA14 were achieved with setting $T_{\text{low}} = 40$, i.e., only 40 low-frequency intensities images (out of 96 images) are used to perform normal estimation. Therefore, to ensure fairness in the comparison, we also report our method initialized by LS with the same setting.

As can be observed from Table III that our method outperforms the original ones for most of the cases. To be more specific, 72 out of 80 (8 methods with 10 objects) cases are improved. Our method shows more significant improvement on methods like IW12, SM16, and LS, for objects like ‘BEAR’, ‘CAT’, and ‘BUDDHA’. This observation is consistent with those from the experiments in synthetic data. Since these methods assume the diffuse reflectance component is entirely Lambertian, they leave a relatively larger space for our method to improve. The performance drops down slightly on the ‘HARVEST’ and ‘READING’ data which has lots of cast shadows or occlusion near the boundaries [39].

The overall improvement in real data is not as significant as that on synthetic data. The key reason is that there are lots of unpredictable cast shadows or occlusion near the boundaries of real data. Our method is designed to be a pixel-wise solution like most of the state-of-the-art photometric stereo methods [23], [35], [22], [9], [37], [38], and is therefore
Fig. 7: From left to right columns: angular error maps (in degrees) from LS [1], LS+, IW12 [29], SM16 [30], IA14 [22], IA14+, ST14 [23], [35], and ST14+. From top to bottom rows: angular error maps using 4, 12, 20, and 28 images respectively.

TABLE IV: Average angular errors (in degrees) for different numbers of input images on ‘DiLiGenT’ dataset. Each average angular error is computed from 50 different illumination conditions over 10 objects. The best results for different illumination conditions are highlighted in blue.

<table>
<thead>
<tr>
<th>Image Number</th>
<th>4</th>
<th>8</th>
<th>12</th>
<th>16</th>
<th>20</th>
<th>24</th>
<th>28</th>
<th>32</th>
</tr>
</thead>
</table>

It can be observed from the error maps that the estimation accuracy heavily degrades at the edge regions which are heavily influenced by the cast shadow or occlusion near the boundaries. The quantitative results in Table III also supports such analysis. The performance is relatively worse on the objects with larger region affected by shadows or occlusion near the boundaries (BUDDHA, HARVEST, READING) and the performance bottlenecks for most of the methods are mainly due to these cast shadows or occlusion near the boundaries.

2) With Small Number of Images: Similar protocols as detailed in Section V-A2 for the MERL dataset were incorporated in this set of experiments. For each of the numbered input images, we performed experiments using 50 randomly selected illumination conditions. The average of the errors from these 50 illumination conditions (10 objects × 50 illumination conditions) are reported in Table IV.

It can be observed from this table that when the number of input images is 4, which is the smallest number of input images for photometric stereo optimization, the state of art methods fail to outperform the baseline method LS. With the number of input images increasing, the performance using these methods becomes better. Our methods LS+, IA14+, ST14+ consistently achieve the best performance over other methods. The results are consistent with the observation from synthetic data. An example of error maps for object POT1 is shown in Figure 7 for sample comparison.

VI. CONCLUSIONS AND FUTURE WORK

In this paper, we argue that the angular error based formulations are more effective and judicious than projection error based ones, due to the fact that the evaluation criterion is based on angular error metric in photometric stereo. The proposed approach attempts to address the non-Lambertian photometric stereo problem based on the minimization of angular error. In order to ensure the efficient solution for the angular error based optimization problem, we introduced an alternating strategy to reformulate the angular error. A numerical compensation scheme is proposed to reduce the adverse impact of inaccurately estimated reflectance and make the reformulation more reliable. The solution for the numerical compensation solution scheme is efficiently achieved by using the cosine difference to approximate angle difference. Our experimental results show that our approach consistently improves several state-of-the-art methods on both synthetic data and real data, with small additive costs, especially when the number of the input image is small. Moreover, the state-of-the-art performance is achieved by our method initialized using the baseline method, with much less overall computation as compared to those from state-of-the-art methods.

Limitations and future works: 1) Despite our effects with the reasonable approximations in Section IV-C for the angular error, our final approach cannot directly optimize the angular error. A more judicious optimization, which can
directly optimize the angular error, is suggested as future work. 2) As discussed in [39], the shadows and occlusion near the boundaries pose more challenging than speckularity and interreflection in real data. Therefore, the inclusion of such factors, i.e., shadow and occlusion near boundaries, in the angular error based formulation is expected to further improve results for real data and is suggested as a further extension of this work. 3) Real data is always expected to be accompanied by noise. Even though our approach is able to achieve state-of-the-art performance on real data, robustness for such random noise is not explicitly investigated. A more robust formulation of the reflectance model that considers such random noise based on angular error is another area of future work.

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