Backscatter Compensated Photometric Stereo with 3 Sources

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Abstract

Photometric stereo offers the possibility of object shape reconstruction via reasoning about the amount of light reflected from oriented surfaces. However, in murky media such as sea water, the illuminating light interacts with the medium and some of it is backscattered towards the camera. Due to this additive light component, the standard Photometric Stereo equations lead to poor quality shape estimation. Previous authors have attempted to reformulate the approach but have either neglected backscatter entirely or disregarded its non-uniformity on the sensor when camera and lights are close to each other.

We show that by compensating effectively for the backscatter component, a linear formulation of Photometric Stereo is allowed which recovers an accurate normal map using only 3 lights. Our backscatter compensation method for point-sources can be used for estimating the uneven backscatter directly from single images without any prior knowledge about the characteristics of the medium or the scene. We compare our method with previous approaches through extensive experimental results, where a variety of objects are imaged in a big water tank whose turbidity is systematically increased, and show reconstruction quality which degrades little relative to clean water results even with a very significant scattering level.

1. Scattering and Shape

Applying Photometric Stereo (PS) in murky media has had limited success so far, since the measured light carries information not only about the scene orientation but also about the medium itself. Specifically, light gets attenuated and scattered by the medium’s particles, adding a strong unwanted signal to the measured brightness, the so-called backscatter component. Figure 1 illustrates the severity of this effect on image quality, dictating special treatment if any effective photometric task is to be considered.

In this paper we formulate PS within a scattering environment by estimating and taking account of the strong uneven backscatter created from point sources close to the camera. We describe that the camera-lights baseline, which is irrelevant in pure air, is crucial in scattering media. Thus we relax the assumption of [12] that all lights are far away from the camera and investigate how this affects the varying backscatter from every source. As we describe, the additional ambiguity that is introduced by the backscatter makes a direct solution of the PS equations ineffective and hence we propose both a calibrated and an automatic way for estimating the unknown backscatter directly from the measured images. This gives further potential for single-image restoration in turbid media under directional lighting.

As we show, the backscatter compensation yields a linear PS solution that estimates the scene normals and a scaled version of the albedo. In our practical approach, only 3 sources are required as for PS in pure air, in a symmetric arrangement around the camera. We demonstrate our results through extensive experiments in a big water tank where the camera and light sources are both immersed into the turbid medium and separated by a small distance. We evaluate the performance of our method over a wide range of controlled scattering levels by adding milk of gradually increasing quantity and show that our method outperforms related approaches, compensating effectively for the backscatter effect and yielding shape recovery results similar to those in clean water even for high levels of water turbidity.

Related Work: A large amount of work has focused on modelling image formation within scattering environments with diffuse illumination in haze and fog [6, 11, 16], or sub-sea [3, 14]. There the lighting term is constant and equally illuminates all the particles of the medium between
the camera and the scene. As the depth of the imaged scene increases, the volume of illuminated particles increases as well. This implies that under diffuse illumination backscatter is directly associated with scene depth, and this can be used for estimating a rough depth map of the scene.

However, in Shape from Shading methods illumination is provided by artificial directional sources. This is also the case for deep sea underwater vehicles which carry a camera and light sources at a small offset \[8\] \[13\] \[17\]. Here, due to the limited beam angle of the sources, only some of the medium’s particles are illuminated depending to their position from the source \[5\] \[13\]. Moreover, backscatter is saturated after a small depth from the source \[17\], after which it cannot serve the purpose of a depth prior as in diffuse lighting. These characteristics require careful backscatter modelling and compensation when directional sources are employed, as it happens with Photometric Stereo.

Instead of compensating for the backscatter effect, some previous approaches have aimed to minimize its impact by changing the hardware setup \[8\], using active methods \[2\] \[5\] or fusing multiple images \[18\]. Nevertheless, in typical imaging conditions where a camera and a conventional light are carried by the same body at a small offset, backscatter was still shown to be the main effect degrading image quality \[10\] \[17\]. In \[17\], it was measured using using polarizing hardware, while in \[9\] \[10\] it was estimated directly from a low-pass filtered version of the captured image.

As we show in this paper, the effect of backscatter on photometric-based shape recovery is highly significant. Related works \[13\] \[19\] neglected backscatter under the assumption that the water murkiness level is low or a special setup has been employed for its minimization. In \[11\], the decreasing effectiveness of PS due to the presence of an additive light component was also described, yet no further effort was made to model or remove its effect. PS in a scattering medium was studied in \[12\], suggesting that a non-linear system of at least 5 equations should be solved. The problem can be reduced to a 4-source linear solution if the scattering is isotropic and the sources are symmetric. Although effective shape reconstruction was achieved, the sources in the setup of \[12\] were outside water and distant from the camera. By adopting this type of setup, the backscatter saturation that occurs as depth increases and its non-uniformity on the image sensor were neglected.

2. Light Propagation Model

When illumination comes from an artificial source, due to Inverse Square Law (ISL) its intensity \(I_k\) is inversely proportional to the distance \(d\) travelled. In turbid media, light is further attenuated exponentially with distance:

\[
I_d = \frac{I_k}{d^2} e^{-cd}, \tag{1}
\]

where \(c\) is the total attenuation coefficient of the medium which describes the light loss per unit distance \[8\], modelled as \(c = a + b\). \(a\) and \(b\) denote the medium’s absorption and scattering coefficients. \(b\) reflects the superposition of all scattering incidents around a unit volume particle and can be calculated by integrating the angular scattering function of the medium \(\beta(\theta)\) over all the directions around the particle: \(b = 2\pi \int_0^\pi \beta(\theta) \sin(\theta) d\theta\). We employ the low-order representation of \[12\] defining \(\beta(\theta)\) as \(\beta(\theta) = \frac{a}{4\pi}(1 + g \cos \theta)\), where \(g \in (-1, 1)\).

Consider a camera and an artificial point-light source both located on the same plane in a scattering medium and separated by a small distance \(h\) as in Figure 2. We define a coordinate system whose \(xy\) plane coincides with the camera’s image sensor, and \(z\)-axis coincides with the camera’s optical axis. As in related works \[12\] \[13\] \[17\], we assume that the size of the imaged object is small with respect to its distance (depth) \(z_O\) from the camera, such that we can use an orthographic camera model. The total irradiance due to light source \(k\) that is measured by a pixel with coordinates \((x, y)\) on the image sensor is the sum of the direct and backscatter components, denoted as \(D_k(x, y)\) and \(B_k(x, y)\), respectively \[1\]. For simplicity we omit the pixel \((x, y)\) coordinates notation in the following derivations.

### Direct Component

The direct component is the light beam travelling distance \(\sqrt{h^2 + z_O^2}\) from the source to the scene that then gets reflected and travels a distance \(z_O\) to the camera sensor. Considering the attenuation of \[1\], the incident component on the scene is \(I_k e^{-c\sqrt{h^2 + z_O^2}}\). We assume here that the surface is Lambertian with a constant albedo \(\rho\) and unit normal vector \(\mathbf{n}\), while light direction is denoted by unit vector \(\mathbf{s}_k\). The scene-reflected light will be then attenuated again by \(e^{-cz_O}\) before it reaches the sensor. Hence, the total direct component is:

\[
\hat{D}_k(x, y, z_O) = I_k e^{-c\sqrt{h^2 + z_O^2}} e^{-cz_O}. \tag{2}
\]

\[1\]As in the prior art, we adopt the single scattering model. We ignore forward scattering phenomena \[19\] and focus on the backscatter which was shown to have the dominating impact on image quality \[17\] \[10\].
\[ D_k = \frac{I_k}{h^2 + z_O^2} e^{-c(z_O + \sqrt{h^2 + z_O^2})} \varrho \mathbf{n} \cdot \mathbf{s}_k. \] (2)

**Backscatter Component:** Consider now a differential scattering volume at distance \( z \) across the Line-Of-Sight (LOS) of the sensor pixel. As before, the scattering volume is illuminated by \( I_k = \frac{I_k}{h^2 + z_O^2} e^{-c(z_O + \sqrt{h^2 + z_O^2})} \). This backscatters through angle \( \theta \) a light component equal to \( \beta(\theta) I_k \), which is attenuated by \( e^{-cz} \) until it reaches the sensor. Thus, replacing \( \beta(\theta) \) by \( \frac{b}{4\pi} (1 + g \cos \theta) \), and \( \cos \theta \) by \( \frac{z}{\sqrt{h^2 + z^2}} \), the differential backscatter component that reaches the sensor pixel is
\[ dB_k(z) = \frac{b I_k}{4\pi} (1 + g \frac{z}{\sqrt{h^2 + z^2}}) e^{-c(z + \sqrt{h^2 + z^2})} \frac{z}{h^2 + z^2}. \]

In order to estimate the total backscattered light, we have to integrate over all depth positions \( z \) along the pixel’s LOS where differential volumes of particles are illuminated from the source and backscatter part of this light towards the sensor. Thus, it should be emphasized here that the lower limit of the integral does not equal 0 as in [12], but the minimum depth position on the LOS where the particles are illuminated, denoted by \( z_k \) in Figure 2, \( z_k \) corresponds to the intersection point between the pixel’s LOS and the limited beam angle of the illumination source. The maximum limit of the integral equals the scene depth \( z_O \) which is the final point on the LOS where particles receive and backscatter light towards the sensor. Finally, the total backscatter component on pixel \((x, y)\) due to the source \( k \) is given as
\[ B_k = \int_{z = z_k}^{x = z_O} \frac{b I_k}{4\pi} (1 + g \frac{z}{\sqrt{h^2 + z^2}}) e^{-c(z + \sqrt{h^2 + z^2})} \frac{z}{h^2 + z^2} dz. \] (3)

There exists no closed-form solution for the integral. However, it was shown that it is a smooth function that is straightforward to evaluate numerically [15].

### 3. Photometric Stereo in a Scattering Medium

In pure-air PS, the product \( \varrho \mathbf{n} \cdot \mathbf{s}_k \) yields a system of linear equations that can recover the normals and albedo for every pixel using at least 3 sources. Based on the image formation model of Section 2 within a scattering medium the total measured intensity \( E_k \) for every pixel/source equals the sum \( D_k + B_k \). The equation is non-linear and has a complicated form. Increasing the number of sources is a common practice to determine the PS problem when further unknowns are added. Narasimhan et al. [12] showed that within turbid media where sources are far away from the camera at least 5 sources are required for determining the non-linear system of equations. Otherwise, for a 4-source symmetric setup and isotropic medium (\( g = 0 \)), the backscatter for each pixel should be equal for all 4 sources: \( B_{ki} = B_{kj} \) \( \forall i, j \in \{1, 2, 3, 4\} \), and thus can be eliminated by subtracting pairs of measured intensities: \( E_{ki} - E_{kj} = D_{ki} - D_{kj} \). Let us examine the problem for our case, where, in addition to the considerations of [12], the limited beam angle of the \( k_i \) source next to the camera that leads to \( z_k \neq 0 \) and ISL are also considered. The medium coefficients \( b, c \) and \( g \) are constants-global unknowns within a uniform scattering medium. The unknown values for every pixel are: the albedo \( \varrho \), the normal vector \( \mathbf{n} \) and \( \mathbf{s}_k \) are considered as 3 unknowns together since \( \mathbf{n} \) is a unit vector, and the depth variables \( z_O, z_k \). At a first glance the total number of unknowns for each pixel are 5 plus 3 global unknowns, and thus 6 sources would be enough to determine all of the unknowns for every pixel.

**Figure 3:** The LOS of a sensor pixel intersects the beam angle of each light source \( k_i \) at a different depth \( z_k \). Thus, each source creates a distinct backscatter component on the sensor (illustrated by backscatter images \( B_1 \) and \( B_2 \)).

#### 3.1. Backscatter Variation for Each Source - \( z_k \)

In fact, contrary to the rest of the parameters, \( z_k \) does not have a single value for every pixel \((x, y)\) since it differs for each source (Figure 3). When a pixel is closer to a light source \( k_i \), its LOS will intersect the beam angle of \( k_i \) at a smaller depth point \( z_k \) than it will intersect the other sources. Thus, for this source the integration path between \( z_k \) and \( z_O \) will be larger than for other sources, adding a higher backscatter value \( B_i \) to the pixel. This holds for every pixel, and hence every source finally creates an uneven backscatter component on the sensor according to its position with respect to each pixel. The synthetical backscatter images (using (3)) of Figure 3 illustrate this non-uniformity due to varying \( z_k \) for every pixel/source. In order to estimate \( z_k \) we would have to calculate the exact intersection point of each pixel’s LOS with the beam angle of every source. Such a task would be very difficult since the precise 3D position, rotation and beam angle of the source should be known. Note here that \( z_k \), as opposed to scene depth \( z_O \) which might be far away from the camera-lights setup (as...
in orthographic projection), is only a few cm away from the sensor \(^2\) where the backscatter function \((3)\) is highly variant and hence small errors in calibration of \(z_k\) are expected to have a strong impact on backscatter estimation \cite{10}.

Due to the varying \(z_k(x, y)\) for every pixel-source combination, increasing the number of sources also increases the number of the unknowns. This leaves the problem underdetermined regardless of the number of sources. Furthermore, due to this variation the linear solution of \cite{10} that assumes that backscatter for every pixel would be equal for every source \(B_k = B_k\) does not hold, as \(z_{k_l} \neq z_{k_j}\).

### 3.2. Linear Solution with 3 Sources

Since the extra ambiguity due to \(z_k\) lies solely in the additive backscatter term, we suggest that the whole backscatter component is estimated for each pixel-source and subtracted from the measured brightness without having to determine the exact value of \(z_k\) (Section 3). This would leave us with the direct component for every source, given by \((2)\). The albedo and the attenuating factor can be combined into a scene-depth dependent function defined as 

\[
\varrho_{sc}(z_O) = \frac{1}{1+2z_O} e^{-\varrho z_O/\sqrt{z_O^2+5}}
\]

for every pixel.

Thus, after subtracting the estimated backscatter we end up with the direct component that carries the shape information of the scene and a scaled version of the albedo \(\varrho_{sc}(z_O)\):

\[
E_k(x, y) - B_k(x, y) = I_k g_{sc}(z_O(x, y)) \cdot n \cdot s_k.
\]

Given that the light intensity and direction are known for each source, we can estimate the unit normal vector \(n\) and scaled albedo \(g_{sc}(z_O)\) of the surface patch, given at least 3 light sources. Since \(E_k(x, y)\) is the measured intensity, the problem now becomes estimation of the varying backscatter component \(B_k(x, y)\) for every pixel \((x, y)\) and source \(k\).

### 3.3. Backscatter Variation with Scene Depth \(z_O\)

As \((3)\) indicates, backscatter is a function of both the minimum lighted depth \(z_k\) and the scene depth \(z_O\). These two values determine the integration path (pointing arrows in Figure 3), whose length determines the intensity of the backscatter. According to Section 3.1, pixels that are positioned closer to a source will have a bigger integration path due to smaller \(z_k\). Let us now examine the upper limit \(z_O\).

Contrarily with cases of diffuse or distant from camera illumination \cite{6} \cite{12}, backscatter for point-sources is saturated after a small depth value due to ISL \cite{17}. Figure 4a shows the backscatter function for increasing scene-depth when ISL is considered. It equals 0 below the minimum lighted depth \(z_k\) and then exhibits a rapid increase until it reaches saturation, while it is smoothly increased with scene depth when ISL is omitted. The saturation indicates that backscatter dependence on \(z_O\) can be safely omitted after \(z_{sat}\), where the scattered light by the particles becomes negligible: \(B_k(z_O) = B_k(\infty), \forall z_O \in [z_{sat}, \infty] \) (Figure 4b). \(z_{sat}\) is within the small range of 0.5 – 1.5m from the camera \cite{17} \(^3\), which indicates that in typical orthographic PS setup (Section 5) backscatter will be saturated, and \(z_O\) can be replaced by \(\infty\) in the backscatter function term.

Interestingly, according to numerical evaluations using \((2)\) and \((3)\), even for \(z_O < z_{sat}\) backscatter variation with scene depth can be omitted when the total measured brightness \(E_k\) is considered. For the small depths below \(z_{sat}\) we expect the intensity of the illuminating light, and the direct component \(D_k\) to be very high due to ISL. Figure 4c shows the respective direct component over the varying depth \(z\), along with the absolute values of the backscatter component of Figure 4a. For small depths where backscatter isn’t still totally saturated, the measured brightness seems to be dominated by the direct component intensity. In order to estimate the impact of the backscatter variation with scene depth with respect to the actual measured brightness \(E\), we calculate the ratio \(\frac{B(z)}{E(z)}\) within a varying scene depth range \(z\), and the ratio \(\frac{B(\infty)}{E(\infty)}\) which approximates the backscatter by its saturation value even for scene depths below \(z_{sat}\) where it is still unsaturated. Figure 4d indicates that these two differ with a small error value \(\epsilon(z)\) at every depth.

This is negligible at a depth point smaller than \(z_{sat} \) \(^4\).

\(^2\)Typical values of \(z_k \in [10-30cm]\) were approximated in \cite{17}.

\(^3\)This range limit coincides with the one we found through numerical evaluations using \((3)\).

\(^4\)We consider as negligible any value smaller than 1/255 that is the minimum sensing capability of the majority of imaging sensors (8-bit).
Using (4), we have run extensive numerical simulations for a wide range of its unknown values \((b, c \in (0 - 2m^{-1}), z_0 \in (0.1 - 10m), z_k \in (0.01 - 0.5m))\) and the error \(\epsilon\) for any \(z_0 > 0.5m\) was measured to be as low as 0.02 brightness values. The respective error for any \(z_0 > 1m\) which is the imaging range in our PS setup was below 0.005 brightness levels which is similar to sensor or quantization noise level. Considering also that in PS applications we expect a much smaller scene depth range than the one used in the numerical simulations, due to ISL we can safely neglect the backscatter dependence on any scene depth \(z_0 > 0.5m\) and replace \(z_0 = \infty\) in (3).

4. Backscatter Estimation

Previous Work: The task of estimating the backscatter component when directional sources are employed has drawn limited attention compared with the respective cases of diffuse lighting [6-13]. The work of Mortazavi and Oakley [9-10] was the only work we found estimating this directly from the image brightness. The dependence of backscatter on \(z_k\) and its saturation with scene depth were omitted in this work and as it was assumed, the measured backscatter was proportional to a low-pass filtered version of the image \(B(x,y) \approx \gamma \bar{E}(x,y)\). \(\bar{E}(x,y)\) was used for extracting the illumination variation of the image by suppressing any high-frequency details and thus a recursive Gaussian filter with a large parameter \(\sigma\) was used. As we show next, the assumption that backscatter follows a low-pass filtered version of the image is unrealistic in many cases, overestimating the backscatter and introducing high errors in PS.

Proposed Calibrated Method: As it was described in Section 3 for point-light sources next to the camera backscatter is saturated, and thus the varying integration path that results in an uneven backscatter for every pixel-source combination is attributed to \(z_k\). Thus, the backscatter component can be estimated by capturing images when the camera looks at \(x_0\), directly measuring the saturation value \(B_k^\infty(x,y)\) of every pixel\(^5\). In a finite tank, this can be done using a flat matte black canvas to produce \(D = 0\).

Proposed Automatic Method: As \(z_k(x,y)\) varies smoothly for every pixel due to its clear geometrical meaning (Section 3.1), the respective backscatter function is also smooth. Specifically, \(B_k(x,y)\) would have its maximum at the pixel position which is closest to the source \(k\) and then smoothly decrease for the rest of sensor pixels (Figure 3). This smoothness gives us insight that knowing the backscatter intensity of only a few pixels, we can approximate the whole smooth backscatter function over the sensor:

\[
B_k \approx f_k(X, \alpha),
\]

where \(X\) is the set of all pixel coordinates \((x,y)\), and \(\alpha\) are the unknown parameters of the model that approximates \(B_k\). Due to the smoothness of the function and its unique maximum on image border, we found that a 2D quadratic function \(f_k(x,y) = \alpha_0 + \alpha_1 x^2 + \alpha_2 y^2 + \alpha_3 xy + \alpha_4 x + \alpha_5 y\) can estimate with negligible errors the true \(B_k\) function of (3)\(^6\). A set of at least 6 points with known backscatter component are needed in order to define the 6 unknown coefficients of \(\alpha\), although more pixels would be necessary for robustness, as described in Section 5.

Figure 5a shows the true backscatter function \(B_k(x,y)\) simulated using the model of (3), and the resulting fitted quadratic function \(f_k\) using the backscatter values of only 6 points.

\[\text{Figure 5: (a) Simulated ground-truth backscatter and fitted quadratic function using 6 random points. (b) Automatic backscatter estimation for a murky-water object image.}\]

The problem now comes to the selection of at least 6 backscatter pixels that are the input for our regression. Potential candidates are pixels that correspond either to dark scene points, i.e. \(g(x_B, y_B) = 0\), or to infinite depth points \(z_O(x_B, y_B) = \infty\). From (2), the respective direct component for these pixels will be 0 and hence the measured brightness corresponds to the actual backscatter intensity:

\[E_k(x_B, y_B) = D_k(x_B, y_B) + B_k(x_B, y_B)\]

In order to select a potential set of backscatter pixels for which \(D_k(x_B, y_B) = 0\), we divide the image into a number of \(N \times N\) blocks and choose the pixel with the lowest intensity in each block (Figure 5b). In reality, not all of the selected points have zero direct component, which introduces a number of outliers. For this purpose, we exploit a RANSAC approach which iteratively evaluates a 6-point set out of the selected pixels. We also take advantage of the physical characteristics of our model in order to facilitate the outlier rejection. Specifically, given that backscatter for each source has its maximum on a border pixel that is closer to the source, we reject solutions that estimate the maximum of \(f_k\) on non-border pixels. Furthermore, in our case the outliers should be always additive to our model \(f_k\) since they correspond to a positive direct component: \(f_k + D_k, D_k > 0\). Thus, we penalize solutions that have outliers below the fitted function, by adding the absolute

\[^5\text{The calibration should be done separately for every source creating a backscatter lookup table for each pixel-source combination.}\]

\[^6\text{The selection of the quadratic function for the regression is supported by ground-truth comparison of real data in Section 5.}\]
number of these outliers to the RANSAC score count. Figure [5b] shows the resulting estimated function \( f_k \), together with the inliers and outliers of our RANSAC approach. This procedure yields an automatic backscatter estimation for each light source, which requires no prior knowledge about the characteristics of the source, the medium or the scene.

5. Experiments

Our experimental setup (Figure 3) consists of a rectangular-frame pool with a water volume of 5000L. Both the underwater lights and the camera were placed in the water, imitating the setup of an underwater robotic vehicle. Specifically, 4 lights were on the corners of a square baseline with side length 0.4m around the camera. The camera is a Nikon D60 with a AF-S Nikkor 35mm f/1.8G lens. The imaged objects are matte, their size (each dimension) is within 10 – 15cm, and they were all captured at approximately 1.2m depth, enforcing the orthographic assumption. To simulate the scattering effect, we made a linear scale of 15 turbidity steps ranging from totally clean up to heavily murky, by adding milk to the water (Figure 9).

![Image 6](image6.png)

Figure 6: Top row: Calibrating the camera in clean water. Bottom row: Imaged man-made objects.

![Image 7](image7.png)

Figure 7: (a) Backscatter estimation error according to the number of backscatter pixels (x-axis). (b) Backscatter estimation error for the Head, Turtle, Deer, Gnome, Ladybug and Sphere objects (x-axis).

**Backscatter Estimation:** The backscatter component for all 4 sources and 15 scattering levels was first measured through the calibration step by placing a matte black canvas at 2m depth in our setup. In order to examine how well the quadratic function can fit to the ground-truth backscatter given only a small number of its points, we estimated the RMSE between the real and the estimated function (Figure 7a) after selecting a different random combination of its points (x-axis). Regardless of the number of blocks, the error was as low as noise variation when at least 8 pixels were used, supporting the validity of the quadratic function.

Then the performance of our automatic estimation method under the presence of objects, where a high number of outliers existed, was compared with the calibrated ground-truth backscatter. Figure 7b shows the RMSE for our method, and the one of Mortazavi and Oakley [9] (Section 4). Our method outperformed [9] for all the imaged objects. Regarding the Sphere and Head objects, whose images include a significantly large number of white pixels, backscatter was still estimated effectively, while the error for [9] increased significantly, overestimating the backscatter due to the unrealistic assumption that this is proportional to a low-pass filtered version of the image. For these objects our method rejected all the outliers on the white object, approximating the backscatter from a small number of scene points on the background. As we described earlier, an advantage of our method is that due to backscatter saturation with scene depth, the selected backscatter pixels do not have to be dark patches on the object; they can also be dark or infinity points on the background 7. In the case where white objects covered the whole image would lead to erroneous backscatter estimation. However, such a case would be rare in deep-sea scenarios where infinite depth usually surrounds the imaged objects 12, and even then additional frames could be employed by moving the camera to target surrounding dark or infinity pixels.

**Shape Recovery:** The recovered normal vectors were quantitatively assessed using the Sphere object whose normals are a priori known. Figure 6a shows the RMSE value between the estimated and the ground-truth maps for each scattering level considering: our 3-source proposed method for both calibrated and uncalibrated backscatter estimation, traditional PS method where backscatter is neglected, the 4-source linear approach of Narasimhan et al. [12] described in Section 3, and PS method after estimating and subtracting backscatter using [9]. Our approach yields effective normals estimation similar to those in totally clean water, for a very wide range of scattering levels. The performance is decreased beyond 1.5L of milk, in a similar manner that other methods are decreased within the lowest murkiness levels. This effect is reasonable, since beyond 1.5L the degrading effects are so severe that the backscatter component takes up almost all of the dynamic range of the sensor (Figure 9).

The shape reconstruction results using the man-made objects of Figure 6 were next evaluated. The outputs of the PS method are the normals and the scaled albedo \( g_{sc} \) of...
Figure 8: Shape reconstruction results using different methods: (1) neglecting backscatter, (2) our proposed method, (3) Mortazavi and Oakley [9], and (4) Narasimhan et al [12].

Figure 10: Murky and restored port-water images.

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References


Full contrast was rescaled after backscatter compensation.
Figure 9: Top row: captured images indicating the respective level of water murkiness. Rows 2 – 4: our reconstruction result.


