Second-Order Occlusion-Aware Volumetric Radiance Caching

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We present a second-order gradient analysis of light transport in participating media and use this to develop an improved radiance caching algorithm for volumetric light transport. We adaptively sample and interpolate radiance from sparse points in the medium using a second-order Hessian-based error metric to determine when interpolation is appropriate. We derive our metric from each point’s incoming light field, computed by using a proxy triangulation-based representation of the radiance reflected by the surrounding medium and geometry. We use this representation to efficiently compute the first- and second-order derivatives of the radiance at the cache points while accounting for occlusion changes. We also propose a self-contained two-dimensional model for light transport in media and use it to validate and analyze our approach, demonstrating that our method outperforms previous radiance caching algorithms both in terms of accurate derivative estimates and final radiance extrapolation. We generalize these findings to practical three-dimensional scenarios, where we show improved results while reducing computation time by up to 30% compared to previous work.

CCS Concepts: • Computing methodologies → Ray tracing;

Additional Key Words and Phrases: global illumination, rendering, irradiance caching, participating media, radiance derivatives

ACM Reference format:

1 INTRODUCTION

Accurately simulating the complex lighting effects produced by participating media in the presence of arbitrary geometry remains a challenging task. Monte Carlo-based methods like path tracing numerically approximate the radiative transfer equation (RTE) [Chandrasekhar 1960] by stochastically sampling radiance in the medium. These approaches can handle complex geometry and general scattering properties, but since they lack memory and are largely blind to the radiance signal, they perform many redundant computations leading to high cost. A common strategy to increase efficiency is to adaptively sample radiance based on its frequency content, limiting the sampling density in regions where radiance barely changes, and placing more samples in regions with higher frequency variation [Zwicker et al. 2015].

Based on this principle, volumetric radiance caching [Jarosz et al. 2008] computes and stores radiance at sparse cache points in the medium, and uses these samples to reconstruct radiance at nearby locations whenever possible. The method is based on first-order translational derivatives of the radiance, which are used to i) determine how far away a cache point can be reused while controlling error, and ii) improve reconstruction quality by extrapolating the cached radiance values along their gradients. Unfortunately, since the gradient derivations ignore occlusion/visibility changes, the method fails in scenes containing occluders where changes in visibility are the dominant factor in local radiance behavior. Moreover, the reconstruction and error metric both rely on the same gradient estimates and ignore variations caused by higher-order derivatives. These factors lead to suboptimal cache point distributions, which fail to properly sample high-frequency features such as occlusions, while simultaneously oversampling other regions of the scene. This results in reduced efficiency and visible rendering artifacts.

Second-order illumination derivatives have proven to be a powerful and principled tool for sparsely sampling and interpolating surface irradiance [Jarosz et al. 2012; Schwarzhaupt et al. 2012], as well as controlling error in density estimation techniques [Belcour et al. 2014; Hachisuka et al. 2010; Kaplanyan and Dachsbacher 2013]. Inspired by these recent developments, we propose a new second-order, occlusion-aware radiance caching method for participating media which overcomes the limitations of current state-of-the-art methods.

To this end, we introduce a novel approach to compute first- and second-order occlusion-aware derivatives of both single and multiple scattering, and generalize the Hessian-based metric of Schwarzhaupt et al. [2012] for controlling the error introduced by first-order extrapolation of media radiance. In addition, we extend recent work on 2D radiometry, currently limited to surfaces [Jarosz et al. 2012], and derive a 2D theory of light transport in participating media. We use this framework to illustrate and analyze the limitations of the state of the art, as well as the benefits of our proposed method. We demonstrate the generality of our approach by deriving occlusion-aware derivatives of 3D media radiance and applying our Hessian-based metric to 3D cache distributions, showing that the benefits predicted by our 2D analysis hold equally in 3D. Our approach improves volumetric cache point distributions in isotropic homogeneous media, providing a significantly more accurate reconstruction of difficult high-frequency features, as Figure 1 shows.

2 RELATED WORK

We summarize here existing work on radiance caching methods as well as other techniques that leverage illumination derivatives to improve Monte Carlo rendering. For a general overview of scattering and existing adaptive sampling and reconstruction techniques, we refer the reader to other recent sources of information [Gutierrez et al. 2008; Zwicker et al. 2015].

Radiance caching: Irradiance caching was originally proposed by Ward et al. [1988] to accelerate indirect illumination in Lambertian scenes. The method computes and caches indirect irradiance
Ours

Jarosz et al. [2008] proposed volumetric radiance caching, which accelerates single and multiple scattering in participating media. They proposed an error metric based on the first-order derivative of the radiance, but their formulation ignored volumetric occlusion changes. In follow-up work, Jarosz et al. [2008] derived occlusion-aware gradients, but only of surface illumination in the presence of absorbing and scattering media, ignoring gradients of the media radiance itself. Both approaches are prone to suboptimal cache point distributions and visible artifacts since they ignore higher order derivatives or occlusion changes in media. Our work addresses both of these issues. Ribardièr et al. [2011] proposed using anisotropic cache points and a second-order expansion for radiance reconstruction. Their approach, however, did not consider visibility changes due to their point-to-point computation of derivatives.

Recently, Jarosz et al. [2012] and follow-up work [Schwarzhaupt et al. 2012] made significant progress in heuristics-free error control for surface irradiance caching by formulating error in terms of second-order derivatives. In particular, Schwarzhaupt et al. [2012] proposed a novel radiometrically equivalent formulation of irradiance gradients and Hessians, which properly accounted for occlusions. The authors used these for extrapolation and principled error control, respectively. We extend these ideas and apply them to light transport in participating media, deriving first- and second-order occlusion-aware derivatives for improved reconstruction and principled error control in volumetric radiance caching.

Fig. 1. Statues scene rendered with both single and multiple scattering. Radiance at surfaces is excluded for illustration purposes (please refer to the digital version for accurate visualization). (a) PT1: Path tracing, 2k samples/pixel, 2h. PT2: Path tracing, 500k samples/pixel, 500h. [Jarosz et al. 2008]: Occlusion-unaware, gradient-based error metric, ∼19k cache points, 16k samples/cache, 155 minutes. Ours: Occlusion-aware, Hessian-based metric, ∼19k cache points, 16k samples/cache, 154 minutes. (b) Cached point distribution as seen from above for both single and multiple scattering. Ignoring visibility derivatives fails at representing high-frequency shadows from the windows (a, blue and yellow) due to poor cache distribution, as well as other rapid radiance changes (a, red) in areas with good cache distribution, due to imprecise extrapolation during reconstruction. In contrast, our occlusion-aware Hessian-based method correctly handles these higher-frequency features by improving the sample distribution, as well as the reconstruction. The occlusion-unaware approach (b, top-left) concentrates the samples excessively near the surfaces, usually reaching the cache minimum radius (see top-right histograms), but ignoring occlusion changes throughout the scene. Using occlusion-aware first- and second-order derivatives, our method predicts the error introduced by gradient extrapolation more robustly, increasing cache density in regions where gradients change rapidly (b, bottom).
Table 1. Notation for the optical properties of participating media, and their differences in 3D and 2D.

<table>
<thead>
<tr>
<th>Quantity</th>
<th>Symbol</th>
<th>Expression</th>
<th>Units</th>
<th>2D</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Particle density</td>
<td>( \rho )</td>
<td>Particles per unit volume</td>
<td>m(^{-3})</td>
<td>Particles per unit area</td>
<td>m(^{-2})</td>
</tr>
<tr>
<td>Cross-section</td>
<td>( \sigma )</td>
<td>Area</td>
<td>m(^2)</td>
<td>Length</td>
<td>m</td>
</tr>
<tr>
<td>Scattering coefficient</td>
<td>( \mu_s )</td>
<td>Probability density per differential length</td>
<td>m(^{-1})</td>
<td>Probability density per differential length</td>
<td>m(^{-1})</td>
</tr>
<tr>
<td>Absorption coefficient</td>
<td>( \mu_a )</td>
<td>Probability density per differential length</td>
<td>m(^{-1})</td>
<td>Probability density per differential length</td>
<td>m(^{-1})</td>
</tr>
<tr>
<td>Extinction coefficient</td>
<td>( \mu_t )</td>
<td>( \mu_t = \mu_a + \mu_s )</td>
<td>m(^{-1})</td>
<td>( \mu_t = \mu_a + \mu_s )</td>
<td>m(^{-1})</td>
</tr>
<tr>
<td>Transmittance</td>
<td>( T_r )</td>
<td>( T_r(x_t, x_s) = \exp(-\int_{x_t}^{x_s} \mu_t(x) dx) )</td>
<td>unitless</td>
<td>( T_r(x_t, x_s) = \exp(-\int_{x_t}^{x_s} \mu_t(x) dx) )</td>
<td>unitless</td>
</tr>
<tr>
<td>Phase Function</td>
<td>( f(x, \omega_i, \omega_o) )</td>
<td>Angular scattering of light at a point</td>
<td>sr(^{-1})</td>
<td>Angular scattering of light at a point</td>
<td>rad(^{-1})</td>
</tr>
</tbody>
</table>

**Differential domain:** Arvo [1994] derived closed form expressions for irradiance derivatives in polygonal environments, and Holzschuch and Sillion [1998, 1999] derived second-order illumination derivatives for error control in the radiosity algorithm. Local differentials have also proven useful for texture filtering [Igehy 1999; Suykens and Willems 2001], photon density estimation [Jarosz et al. 2011a; Schjøth et al. 2007], and spectral rendering [Elek et al. 2014]. Ramamoorthi et al. [2007] analyzed gradients of various surface lighting effects, including occlusions, and showed how these can be used for adaptive sampling and interpolation in image space. Lehtinen et al. [2013] and follow-up work [Manzi et al. 2014], proposed to compute image gradients instead of actual luminance values in Metropolis light transport (MLT), and feed a Poisson solver with these gradients to reconstruct the final image. Later work [Kettunen et al. 2015; Manzi et al. 2015] extended the applicability of this gradient domain idea to simpler Monte Carlo path tracing methods, and demonstrated how solving light transport in the gradient domain improves over primal space, while remaining unbiased. Rousseau et al. [2016] showed how such Poisson-based reconstruction approaches can be directly formulated as control-variate estimators. Kaplanyan and Dachsbacher [2013] leveraged second-order derivatives of irradiance to estimate optimal kernel bandwidth in progressive photon mapping, focusing on surface light transport only.

Closely related to our work, Belcour et al. [2014] performed a frequency analysis of light fields within participating media. They summarize the local light field using covariance matrices, which provides Hessians of fluence (up to sign) due to scattering and absorption. Their approach explicitly accounts for radiance changes only in the plane perpendicular to ray propagation, needing to average the per-light-path information from many rays to compute the 3D fluence spectrum. To account for visibility changes, they also require precomputing the covariance matrices in a finite neighborhood, sacrificing locality and incurring the cost of scene voxelization. In contrast, we provide a fully local method for computing first- and second-order derivatives of media radiance, without requiring voxelization, all while accounting for changes due to visibility, scattering, and transmittance.

**2D spaces:** Simplification to lower-dimensional spaces is a recurring tool used in problem analysis. In image synthesis, reduction to hypothetical 2D worlds has been used to obtain insights and illustrate the benefits of more complex 3D approaches [Heckbert 1992; Orti et al. 1996]. More recent analyses of derivative and frequency domains [Durand et al. 2005; Mehta et al. 2013; Ramamoorthi et al. 2007], as well as recent work on complex reflectance filtering [Yan et al. 2014, 2016] reduce the complexity of their derivations by performing them in 2D, before showing how the gained insights generalize to 3D. Jarosz et al. [2012] introduced a 2D surface radiometry and global illumination framework, and showed how this allows for a more practical analysis of 2D versions of standard rendering algorithms due to faster computation and simpler visualization. Other fields such as acoustic rendering have recently benefited from 2D reduction to provide interactive simulations [Allen and Raghuvanshi 2015]. Two-dimensional simulations have also been proved useful to synthesize higher-dimensional light transport, as in transient rendering [Bitterli 2016b; Jarabo et al. 2014]. In this paper we follow a similar methodology as Jarosz et al. [2012], providing a novel 2D radiometry framework for participating media.

3 **2D AND 3D LIGHT TRANSPORT IN PARTICIPATING MEDIA**

We describe here the main radiometric aspects of working in a two-dimensional domain, compared to 3D. Similar to Jarosz et al. [2012], we assume an *intrinsic model* where light is generated, scattered, and absorbed within a plane, thus ensuring energy conservation.

The outgoing radiance at a point \( x \) in a medium is defined as the angular integral of the incident radiance \( L_i(x, \omega_i) \), modulated by the scattering phase function \( f_s(x, \omega_i, \omega_o) \):

\[
L(x, \omega_o) = \int_{\Omega} f_s(x, \omega_i, \omega_o) L_i(x, \omega_i) \, d\omega_i,
\]

where \( \omega_i \) and \( \omega_o \) are directions over the spherical domain \( \Omega \) pointing into and out of the point \( x \) respectively. The incident radiance \( L_i = L_m + L_s \) is the sum of radiance arriving from the surrounding medium \( (L_m) \) and from surfaces \( (L_s) \):

\[
L_m(x, \omega_i) = \int_0^s \mu_s(y(t)) T_r(x, y(t)) L(y(t), \omega_i) \, dt,
\]

\[
L_s(x, \omega_i) = T_r(x, y_s) L_o(y_s, \omega_i),
\]

where \( y(t) = x - t \overrightarrow{0i} \) is a point in the medium, and \( y_s \) is a point on a surface at distance \( s \) with outgoing radiance \( L_o \) modeled by the rendering equation [Kajiya 1986]. The transmittance \( T_r \) models the attenuation due to scattering and absorption between two points, and \( \mu_s(x) = \rho \sigma_s \) is the scattering coefficient at \( x \), with \( \rho \) and \( \sigma_s \) the density and scattering cross-section in the medium, respectively. We detail our notation in Table 1, and highlight the main radiometric...
Differences in 2D: When moving to a 2D world, the intrinsic radiometric model implies that all radiance travels within a planar medium, scattering therefore over angle instead of solid angle. This means that radiance falls off with the inverse distance instead of inverse squared distance [Jarosz et al. 2012]; this will become important in our analysis of first- and second-order derivatives.

The main changes when applying Equations (1–3) in 2D are:

- The integration domain $\Omega$ of Equation (3) becomes circular instead of spherical.
- The phase functions in 2D must be normalized over the circle, not the sphere, of incident directions.
- $L_\omega(y_s)$ now indicates radiance from the closest curve (the 2D equivalent of a 3D surface).

In the next sections, we use this self-contained 2D world to better depict and reason about the improvements of our new occlusion-aware gradients (Section 4), and our second-order error metric (Section 5), before extending them to a more practical three-dimensional world. Working in 2D also allows us to avoid collapsing a 3D scene into a 2D image for visualization, where information from many media points would contribute to a practical three-dimensional world. Working in 2D also allows us to depict radiometric model implies that all radiance travels within a planar medium, scattering therefore over angle instead of solid angle.
independently on each radiance sample—it is not able to capture global effects such as visibility gradients. As a consequence, changes in radiance that becomes occluded/unoccluded as the shaded point is translated are not taken into account (see Figures 2a and 2b, red). As an illustrative example, Figure 3 shows how ignoring occlusions (purple line) leads to incorrect single- and multiple-scattering gradients in the penumbra region beneath the occluder.

In the remainder of this paper we describe our novel Hessian-based radiance caching method for participating media that overcomes the aforementioned limitations. In Section 4 we introduce our approach for computing occlusion-aware first- and second-order derivatives of media radiance. Then, in Section 5 we introduce our Hessian-based error metric and extrapolation method for volumetric radiance caching.

4 RADIOMETRIC DERIVATIVES IN MEDIA

Following the work of Schwarzhaupt et al. [2012] on global illumination on surfaces, we formulate the radiance at x as a piecewise linear representation of the incoming radiance. Conceptually, we build an approximated coarse representation of the scene as seen from the media point x by triangulating adjacent stochastic angular samples y_i (see Figures 2c and 2d). The interesting property of this triangulation is that the geometry term for each triangle (segments in 2D) models the attenuation due to the solid angle; as a consequence, changes in the geometry term (due to translation of x) model changes in the observed radiance.

We extend Schwarzhaupt et al.’s [2012] formulation to handle not only light transport from surfaces, but also from media. In the case of surfaces, the sample points y_i are located at the first surface point as seen from x in direction y_ix (Figure 2d). For points in a participating medium, however, radiance arrives from multiple distances along each direction. We therefore consider a set of concentric triangulations at increasing distances r_i, each representing the outgoing radiance at that particular distance in the medium. If occluding geometry exists closer than the distance r_i, we place a zero-radiance sample at the surface intersection (points marked with ⋄ in Figure 2e).

Handling Occlusions and Transmittance: In essence, we are approximating the integration along Ω by transforming the scene into a discrete set of virtual piecewise linear representations of the geometry and media around x. As noted by Schwarzhaupt et al., this representation implicitly encodes changes in visibility by means of the geometry term. Our approach for media, however, requires taking transmittance into account and using different geometry terms (see Figure 2c), since surface-medium light transport only has a cosine term at the source y_i. We illustrate this with a 2D example in Figure 4, left and center: Assuming a constant angle γ between vectors y_0 and y_1, occlusions generate segments ℓ = y_1 − y_0 at grazing angles, with derivatives proportional to the steepness of the segment. When moving within the medium, the projected angle of ℓ towards x is proportional to cos θ_y, and therefore the radiance from ℓ increases with cos θ_y. This allows modeling the visibility changes as a change on the 2D geometry term G = cos θ_y/||y||. This principle holds also for 3D, as Figure 4, right, shows: Occlusions are represented by slanted triangular faces, and visibility changes are modeled as changes in the 3D geometry term between the triangle points y ∈ Ω and x.

Using the formulation presented before, we approximate L(x, d_0) by discretizing the space into a set of concentric rings R as:

\[ L(x, d_0) \approx \sum_{\ell_i \in R} \frac{1}{\text{pdf}(r_i)} \sum_{\ell_j \in L_i} L_j(x, d_0), \]

where the last ring r_i ∈ R has all its vertices on surfaces, L_i is the set of segments for ring r_i, and pdf(r_i) is the probability of sampling a particular distance when building the ring (for the surface ring, we have pdf(r_i) = 1). L_j is the radiance contributed by each segment ℓ_j ∈ L_i, defined by the integral:

\[ L_j(x, d_0) = \int_{\ell_j} f(x, d_0, G(x, y) T_v(x, y) L(y, d_0) \parallel y \parallel). \]

By construction, the visibility between x and y is V(x, y) = 1, and y is a point on a virtual surface; we thus need to account for the foreshortening at y. This allows for a unified formulation of both surface-to-medium and medium-to-medium radiance derivatives, using the same geometry term in both cases. Note that we have

\[ \text{For convenience, we formulate all the equations in terms of 2D media and geometry subdivisions in segments } \ell, \text{ but all formulae are equally applicable in 3D by substituting segments } \ell \text{ by triangles } \Delta. \]
merged together the phase function \( f_r(x, \bar{\omega}_r, \bar{\omega}_o) \) and scattering coefficient \( \mu_s(x) \) as a directional scattering function \( f(x, \bar{\omega}_r, \bar{\omega}_o) \approx \mu_s(x)f_r(x, \bar{\omega}_r, \bar{\omega}_o) \), to make the following derivations simpler.

Differentiating Equation (6) with respect to \( x \) provides approximations for the first and second order derivatives:

\[
\nabla L(x, \bar{\omega}_o) \approx \sum_{r \in \mathbb{R}} \sum_{l_j \in L_r} \frac{\nabla L_j(x, \bar{\omega}_o)}{p(d(r))},
\]

\[
H_L(x, \bar{\omega}_o) \approx \sum_{r \in \mathbb{R}} \sum_{l_j \in L_r} \frac{\nabla \nabla L_j(x, \bar{\omega}_o)}{p(d(r))},
\]

which in turn require differentiating the radiance from each segment.

Unfortunately, we cannot compute Equation (7) and its derivatives analytically in closed-form, while computing it numerically would be prohibitively expensive. We instead introduce a set of assumptions to build a closed-form approximation:

- For a sufficiently fine subdivision the angle \( \gamma \) tends to 0, so \( \bar{\omega}_o \) can be regarded as constant for the whole segment, and \( f(x, \bar{\omega}_r, \bar{\omega}_o) \approx f(x, \bar{\omega}_r, \bar{\omega}_o) \), with \( \bar{\omega}_r \) a fixed direction from \( x \) to a point in segment \( l \).
- For all \( y \in l \), we assume constant \( T_r(x, y) = T_r(x, y_f) \), and \( L(y, \bar{\omega}_o) = L(y_f, \bar{\omega}_o) \). Following existing approaches for surface irradiance, we choose \( y_f \) as the furthest point in the segment \( l \), which will be the first to be occluded/unoccluded.

These assumptions allow us to significantly simplify the integral in Equation (7) to:

\[
\nabla L_j(x, \bar{\omega}_o) \approx f(x, \bar{\omega}_r, \bar{\omega}_o) T_r(x, y_f) L(y_f, \bar{\omega}_o) \int_{l_f} G(x, y) \, dy
\]

\[
\approx f(x, \bar{\omega}_r, \bar{\omega}_o) T_r(x, y_f) L(y_f, \bar{\omega}_o) F_{l_f}(x),
\]

which now admits a closed-form solution in both 2D and 3D (see Appendices B and C). More importantly, this allows us to approximate the derivatives of \( L_j \) in closed form as:

\[
\nabla L_j \approx L_j F_f + \nabla L F_f,
\]

\[
H_L \approx L F_H f + \nabla L F_T f + \nabla \nabla L F_T f + H_L F_f,
\]

where

\[
\nabla L_f = L_f \nabla F_f + \nabla L \nabla F_f,
\]

\[
H_L = L_f H_{f} + \nabla L \nabla H_{f} + \nabla \nabla L \nabla H_{f} + H_L F_f,
\]

\[
\nabla \nabla L = L \nabla T_r + \nabla L \nabla T_r + \nabla \nabla L \nabla T_r + \nabla \nabla L \nabla H_L + \nabla \nabla L \nabla T_r + H_L F_f.
\]

For brevity we have omitted function parameters, and we express gradients and Hessians in terms of the standard radiance \( L_f = F_f L_r \), and the reduced radiance \( L_r = L T_r \). While Equations (10–16) are general, we restrict our work to Lambertian surfaces and isotropic, homogeneous media (in Section 7 we discuss how to extend it to anisotropic and heterogeneous media). This means that both \( L \) and \( f \) are constant, and therefore their derivatives cancel out as \( \nabla L = H_L = \nabla f = H_f = 0 \), removing directional dependences; this allows us to simplify Equations (11) and (12) to:

\[
\nabla L_j \approx L_j (T_r \nabla f_{l_f} + \nabla T_r F_{l_f}),
\]

\[
H_L \approx L_j (T_r H_{f} + \nabla T_r \nabla f_{l_f} + \nabla F_{l_f} \nabla T_r + H_{T_r} F_{l_f}).
\]

We refer to Appendices A, B and C for all the terms.

By construction, our formulation in Equation (6) and its derivatives (Equations (8) and (9)) are biased but consistent estimators of \( L(x, \bar{\omega}_o) \), \( \nabla L(x, \bar{\omega}_o) \), and \( H_L(x, \bar{\omega}_o) \), respectively. In addition the assumptions imposed in Equation (10) introduce some additional bias due to the piecewise assumption in the scattering \( f \), transmittance \( T_r \), and radiance terms \( L \). However, as shown in Figure 3 our formulation converges accurately to the actual derivatives. Note that we use this biased but consistent approximation only to compute first- and second-order derivatives of media radiance (Equations (8) and (9)), while computing actual radiance values (Equation (1)) using the standard unbiased Monte Carlo estimator. In the following, we describe how to use the derivatives in Equations (8) and (9) for interpolating radiance from a set of cache points, and define an error metric for such interpolation.

5 SECOND-ORDER ERROR CONTROL FOR MEDIA RADIANCE EXTRAPOLATION

The error in radiance caching is controlled by a tolerance value \( \varepsilon \), and depends both on how radiance is extrapolated, and on the radiance moments at cache point \( x \). These moments define a valid bounding region \( \mathcal{N} \) where a point \( x' \) can be used for extrapolation. We provide here the key ideas and resulting equations for the valid regions in the context of 2D and 3D participating media and provide detailed derivations in the supplementary material.

Existing work on radiance caching for participating media estimates the relative error using radiance gradients at \( x \). However, ignoring higher-order derivatives creates suboptimal cache distributions that often oversample regions near surfaces and light sources. Given the radiance and the first \( n \) derivatives at a media point \( x \), we can approximate radiance at point \( x' \in \mathcal{N} \) using an \( n \)th-order Taylor expansion. Following previous work [Schwarzhaup et al. 2012] we truncate to order one, approximating \( L(x', \bar{\omega}_o) \) as:

\[
L(x', \bar{\omega}_o) \approx L(x, \bar{\omega}_o) + \nabla L(x, \bar{\omega}_o) (x' - x).
\]

Since we focus on isotropic media, we remove the directional dependence in the following derivations to simplify notation. By using a second order expansion of \( L(x) \) as our oracle, we can approximate the relative error \( \tilde{\varepsilon}'(x') \) of the extrapolation as:

\[
\tilde{\varepsilon}'(x') \approx \frac{1}{2} \left( \frac{H_L(x) \Delta x}{L(x)} \right)^{1/2},
\]

with \( H_L(x) \) the Hessian matrix of \( L(x) \). This expression is similar to the second-order error metric proposed by Jarosz et al. [2012] and follow-up work by Schwarzhaup et al. [2012], although these works dealt with surfaces only.

By integrating Equation (20) in the neighborhood of \( x \) for a given error tolerance \( \varepsilon \), we can express the valid region in two-dimensional media as an ellipse with principal radii \( R_{x}^{2D} \) (see Equations (S.9)-(S.12) in the supplemental for the complete derivation):

\[
R_{x}^{2D} = \sqrt{\frac{4\varepsilon^2}{\pi \lambda_1}},
\]

where \( \lambda_1 \) is the \( i \)-th eigenvalue of the radiance Hessian \( H_L(x) \). This formula is analogous to the relative error metric presented by Schwarzhaup and colleagues [2012] for surfaces, but here the
radii are computed by taking the principal components of the volumetric radiance Hessian. Adding the third dimension, the valid region for a cache point becomes a 3D ellipsoid, whose principal radii are:

$$R_{3D}^\epsilon = \sqrt[3]{\frac{15L(x)^k}{4\pi|\lambda_j|}}$$

(22)

Our second-order error metric and its derived radius assume knowledge of the radiance and its derivatives at $x$. In practice, these are usually computed by Monte Carlo techniques, which lead to other sources of error such as variance (inherent to Monte Carlo sampling), or bias (due to inaccuracies computing the derivatives).

The presented metric describes the error introduced by extrapolation from a single cache point in participating media. However, at render time, we compute radiance at each shaded point by interpolating from multiple cached points, as:

$$L(x') = \frac{\sum_{k \in C} \{L(x_k) + \nabla L(x_k) \cdot \Delta x' w(x_k, x') \}}{\sum_{k \in C} w(x_k, x')}$$

(23)

with $C$ the set of cache points whose radii include $x'$, and $w(x_k, x')$ the interpolation kernel. Following Jarosz et al. [2008], we use a cubic interpolation kernel $w(x_k, x') = 3d^2 - 2d^3$ with $d = 1 - \frac{\|x' - x_k\|^2}{R_{k}^2}$. Since Equation (23) only interpolates from cache points which predict a maximum error $\epsilon'$ $< \epsilon$ at $x'$, the error of the weighted sum is equally upper-bounded by $\epsilon$. Note that, as opposed to Jarosz et al. [2008] (4), we interpolate in linear space, where the error is more accurately predicted by our Hessian-based metric described in Equation (20).

6 RESULTS

In the following we illustrate the accuracy and benefits of our method. We start showing our results in a two-dimensional world, and compare it against a 2D version of the current state-of-the-art method [Jarosz et al. 2008]. We refer the reader to the supplementary material for the additional expressions to compute two-dimensional occlusion-unaware gradients. Then, we move to 3D, to demonstrate that our results are also consistent in a more practical three-dimensional scenario. For comparison purposes, all 3D insets show only single and multiple scattering in media, discarding surface radiance. Unless it is explicitly mentioned, we use isotropic points with the smallest principal axis of the Hessian. This is the most costly scenario for our method in comparison to previous work, since we cannot adapt to the signal as faithfully as with anisotropic points, and therefore require more points.

Implementation: We compute both radiance and derivatives at point $x$ by stratified sampling uniformly in the sphere, with equal solid angle strata (in the case of 2D, this stratification is in the circle, using equal angle stratification). This reduces variance compared to pure uniform sampling. More importantly, it allows to very simply build the subdivision using the angular samples, by just connecting samples from adjacent strata [Schwarzhaupt et al. 2012]. This stratification is used for both media and surfaces, including area light sources, while other direct light sources (such as directional or point lights) must be handled separately. The accuracy of the subdivision for computing the derivatives relies on a dense sampling of the angular domain, and, as in any sampling problem, our sampling rate limits the amount of radiance changes that we can recover. This is especially important when capturing fine details such as small light sources, which are not computed using next event estimation (NEE), but could also be important in high-frequency fluctuations of radiance in media. However, in practice our method presents much better convergence than previous work [Jarosz et al. 2008] with increasing number of angular samples, as shown in Figure 3. Introducing a NEE-aware subdivision combined with the standard angular one via multiple importance sampling could significantly improve the performance of the derivative computation, although we leave this to future work. We perform the subdivision within the medium by uniformly ray-marching the medium at discrete distances around $x$, and joining adjacent angular samples within each marching step (see Figure 2e).

Unless stated otherwise, single scattering in all compared methods refers to radiance emitted or reflected (first bounce) by surfaces. We limit multiple scattering to the second bounce for all methods. We did this mainly to reduce excessive variance when computing reference derivatives with finite differences. Note that both occlusion-unaware and occlusion-aware methods are equally applicable to
higher number of media bounces, although they usually require a high number of samples to obtain noiseless solutions.

Following previous methods [Jarosz et al. 2008], we first pre-populate the cache by uniformly sampling a ray from the camera, and ray-marching along the media, placing cache points in case they do not fulfill our error metric (Section 5). At render time, we evaluate Equation (23) at ray-marched points $x'$ in the medium, extrapolating radiance from the surrounding valid cache points. If no valid cache points are found for $x'$ then we compute its radiance and derivatives, and add it to the cache. As in previous methods [Jarosz et al. 2008], we separate single and multiple scattering caches, each in a different octree for efficient cache query.

All results were computed on a desktop PC with an Intel Core i7 3.4 GHz CPU and 16GB RAM. Note that all methods used for rendering comparisons of the complex 3D scenes Whiteroom and Staircase were accelerated with Embree ray-tracing kernels [Wald et al. 2014], and therefore the performance with respect to the other 3D scenes is higher.

6.1 Results in 2D

To evaluate the error introduced by our occlusion-aware computations of derivatives in a clear, intuitive way, we rely on their two-dimensional versions. In Figure 3 we showed the convergence of gradient computation with the number of angular samples. Previous approaches not taking into account visibility changes fail to estimate the gradient. In contrast, our derivative formulation converges to the actual gradient, even in areas of penumbra for both single and multiple scattering. The quality of our estimated derivatives increases with the number of angular samples, since the approximations introduced by our assumptions vanish as the strata size diminishes.

In Figure 5 we compare the evolution of single and multiple scattering gradients across a penumbra region, computed with our method and previous work. We illustrate them in polar coordinates (magnitude and orientation) in a simple scene with a medium illuminated by an area light on top, and a line acting as an occluder within the medium. We compute reference gradients with path traced finite differences. Our approach manages to correctly compute both gradients magnitude and orientation in the penumbra region. The right graphs show a progression of gradients along the dotted line. The graphs show that our method is able to match the ground-truth, while the occlusion-unaware method both underestimates the magnitude of the gradient and computes an incorrect direction.

Figure 6 shows a comparison of gradients (shown as a vector field) with the occlusion-unaware method, our technique, and a ground-truth solution computed with finite differences. Our method correctly captures complex radiance changes, including strong changes near occluder boundaries, closely matching the ground-truth reference.

Our error metric takes into account second-order derivatives to drive sample-point density in the scene. Since we use the estimated occlusion-aware Hessians as an oracle of the error, this allows us to place more cache points in areas with higher frequencies. Additionally, our improved gradients allow for a more accurate extrapolation within the valid region of the cache points. Figure 7 (top) shows a scene with overlapping shadows, created by four lights and four
occluders (top-left diagram indicates the shaded region in green). Previous work (second column) drives point density based on the log-space gradient of radiance; in practice this tends to drastically increase point density near light-reflecting geometry, failing to efficiently sample shadowed regions. This can only be mitigated by radius-clamping heuristics (in this case based on the pixel size), thus breaking the principled properties of the approach. In contrast, our method (last two columns) does not rely on heuristics and manages to correctly capture shadows by placing more points near shadow boundaries.

By computing principal components of radiance Hessians, we can use the radiance eccentricity (i.e. the eccentricity of the ellipse defined by the Hessian of the radiance) to stretch media cache points along the components with lower radiance variation, obtaining elliptic (2D) or ellipsoidal (3D) cache points. In Figure 7 (bottom) we compare previous work with our isotropic and anisotropic cache distributions. Even with a similar number of isotropic points (~13k), our improved derivatives manage to capture the overlapping shadows much better; using our anisotropic technique, we manage to reduce cache size by 32%, while keeping the same error threshold. Figure 8 illustrates eccentricity across a 2D scene with a square light emitter in the center. By keeping the same error threshold, our anisotropic cache reduces the number of cache points by up to 20%.

6.2 Results in 3D

Here we further analyze occlusion-unaware gradients and our occlusion-aware Hessians on four 3D scenes: Strips, Statues, Patio and Cornell holes. Unless stated otherwise, all renders are taken using 16 samples per pixel, and performing uniform ray marching with a step size of 0.1.

The Statues scene shown in Figure 1 combines both surface-to-media single scattering, and media-to-media (two-bounce) multiple scattering. The scene includes distant and local light sources (side windows and ceiling, respectively). Occlusion-unaware single and multiple scattering gradients lead to big splotches on the boundaries of light beams coming through the windows. In the case of light coming through the ceiling, while the point distribution captures shadow contours fairly well, extrapolation fails since occlusion-unaware gradients ignore light effects produced in the penumbra region. Moreover, occlusion-unaware techniques concentrate most cache points near light sources and reflecting surfaces (Figure 1, middle), as seen previously in 2D. Since the gradients are large in these areas, this results in very small valid radii for the cache points. Histograms (Figure 1, right) show how for previous work nearly 8000 points (leftmost bin, top blue histogram) on single scattering reach the minimum radius, which is close to a 40% of the total number of points. This implies that the performance of this approach is highly dependent on the value of such minimum radius, which undermines the principled basis of its error metric. In contrast our method generates better point distributions, which correctly capture light gradients while avoiding additional heuristics to control oversampling in certain regions.

The Strips scene (Figure 9) shows surface-to-medium single scattering, for an increasing number of cache sizes. Surface radiance is excluded for illustration purposes. The occlusion-unaware method needs an order of magnitude more cache points to get comparable results to ours (see progression insets). This implies that we have to significantly drop the tolerance parameter to create sufficiently fine point distributions in occluded regions. As we can observe in Figure 9, top row, our method yields better sampling density and extrapolation from the sampled points, achieving similar results with an order of magnitude less points.

Computing derivatives of surface-to-medium form factor involves operating with $3 \times 3$ matrices (see Appendix C). Including the cost of scene subdivision, this introduces an overhead per cache point of just 9%, compared to computing only point-to-point first derivatives (see Table 2 for the Patio scene). Nevertheless, as we can see in

![Image](ImageURL)
Fig. 10. *Patio* scene with single scattering. Our method outperforms existing occlusion-unaware techniques on an equal-time comparison. Moreover, our anisotropic cache manages to significantly reduce total time under the same error tolerance $\varepsilon = 1.5 \times 10^{-4}$ than our isotropic cache, while still retaining shadow details on window boundaries and near thin handrails as shown in the insets.

Table 2. Computation data for the *Patio* scene. For the isotropic case, our method yields better results in equal time. Using anisotropic points provides a further 30% computation time reduction at the same low error threshold due to the improved point distributions and larger valid regions.

<table>
<thead>
<tr>
<th>Method</th>
<th>Error tol.</th>
<th>Cache gen.</th>
<th>Time / point</th>
<th>Total time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jarosz et al. 2008</td>
<td>0.3</td>
<td>124 min / 36k pts</td>
<td>206 ms</td>
<td>136 min</td>
</tr>
<tr>
<td>Ours (isotropic)</td>
<td>$\varepsilon = 1.5 \times 10^{-4}$</td>
<td>122 min / 32k pts</td>
<td>225 ms</td>
<td>135 min</td>
</tr>
<tr>
<td>Ours (anisotropic)</td>
<td>$\varepsilon = 1.5 \times 10^{-4}$</td>
<td>81 min / 21k pts</td>
<td>225 ms</td>
<td>94 min</td>
</tr>
</tbody>
</table>

Figure 10, our method yields better equal-time results with isotropic points. Moreover, our anisotropic approach stretching spherical cache points along the principal components of radiance, allows to reduce both the number of points and the total computation time by 30% for the same error tolerance.

The *Cornell Holes* scene (Figure 11) shows how our method successfully resolves difficult, high-frequency occlusions due to light coming out of the box. Our method provides a built-in mechanism to significantly reduce error in two ways: additional samples reduce variance but also create finer subdivisions, thus improving accuracy when detecting occlusions.

We also demonstrate the benefits our method in scenes of higher complexity. In the *Staircase* scene (Figure 12) we show an equal-time comparison with a render time of 90 minutes. Path tracing has not fully converged to the reference solution in that time, and while the point distributions of occlusion-unaware methods manage to capture the main shadow boundaries, occlusion-unaware gradients still create visible artifacts on the shadow patterns created by light coming from different windows. Progressive photon beams [Jarosz et al. 2011b] manages to capture high frequency changes, but fails to densely sample the medium due to distant lighting. In equal time, our method manages to get the closest match to the reference by correctly capturing complex shadow configurations. In Figure 13 we also illustrate convergence of our occlusion-aware gradients in the same scene by analyzing the changes on a XZ-aligned slice of the media crossing through the light shafts. We compare our gradients against finite differences gradients on two orthogonal scanlines that cross through the shadows, and demonstrate how our method converges to the reference gradients by creating finer subdivisions with higher number of angular samples.

Finally we perform comparisons up to equal-quality in the *White-room* scene, which presents high scattering due to bright white walls and furniture. In a sequence of insets with increasing render time, we show how our method manages to recover high-frequency shadows in much less time than other methods, which also fail to capture thin shadows near window boundaries.

7 CONCLUSIONS
We have presented a new occlusion-aware method for efficiently computing light transport in homogeneous isotropic media, including both single and multiple scattering. At the core of our method lies an efficient computation of radiance derivatives for both surface-to-medium and medium-to-medium light transport. Our radiance derivatives, including visibility changes for single and multiple scattering, improve both the placement of cache points, as well as their interpolation using a Taylor expansion.

We have additionally formalized light transport in participating media in a self-contained 2D world; we hope that this framework becomes a valuable contribution for the graphics community as a
Fig. 12. Staircase scene showing equal-time comparisons of path tracing, progressive photon beams (PPB), occlusion-unaware gradients [Jarosz et al. 2008], and our second-order occlusion-aware solution. We include a fully converged solution for path tracing. Each cache in both our method and Jarosz et al. is computed using 16k stratified angular samples, and rendered using 16 samples per pixel. The progressive photon beams solution was obtained using the publicly available Tungsten rendering engine [Bitterli 2016a]. Note how the occlusion unaware method creates visible artifacts in the patterns created by the shadows crossing from different windows, while our method correctly captures those details in equal time. Due to distant lighting, progressive photon beams fail to densely sample the light shafts coming through the windows, resulting in visible variance after 400 iterations of 1M beams/iteration.

Fig. 13. We demonstrate the convergence of our occlusion aware derivatives in complex 3D scenarios like Staircase. We illustrate this using an XZ-aligned slice of the media that captures the occlusion changes produced by the light shafts through the windows. Right graphs show our computed gradients across two orthogonal scan lines of the slice, where we can observe how our method matches the reference derivatives computed with finite differences. In the bottom graph we also illustrate convergence at the white dot respect to the number of angular samples. Higher number of angular samples create finer scene subdivisions and increase the precision of our derivatives, which provide a very good estimation of the actual derivatives.

Our error metric assumes that the error is due to extrapolation only, with perfect radiance samples and derivatives. However, both are computed stochastically, which introduces variance (in the case of radiance), and bias (on the derivatives). Developing new metrics taking into account these additional sources of error, as well as accurately characterizing them, are interesting avenues of future work. In this regard, analyzing other consistent approaches to compute derivatives (e.g. using photon mapping [Kaplanyan and Dachschafer 2013]) might be helpful. Evaluating whether using our biased estimator of radiance (Equation (6)) instead of our Monte Carlo estimate of Equation (1) would be interesting too, making our cache points more robust by reducing variance (at the price of additional bias). Finally, it may be possible to use our first- and second-order derivatives to accurately estimate the optimal kernel in density estimation algorithms for participating media [Hachisuka et al. 2013], as well as to guide sampling in media or to improve quadrature-based ray-marching methods [Muñoz 2014].

testbed for novel algorithms. Our results (2D and 3D) demonstrate a significant improvement over the current state of the art, both in equal-time and equal-error comparisons.

Limitations & Future Work. Our work shares some of the limitations of traditional radiance caching algorithms, namely the assumption of relatively low frequency transport with finite derivatives. High-frequency illumination due to e.g. small light sources would require a very fine-grained subdivision to accurately find shadow boundaries. Other high-frequency effects such as caustics would additionally require departing from the assumption of constant angular radiance $L_\alpha$ in Equation (10), which would in turn require computing its translational derivatives.

In our implementation we have assumed isotropic media, which helps reduce the complexity and storage requirements of the cache points. By using an angularly-resolved caching of radiance and its derivatives (by using e.g. spherical harmonics [Jarosz et al. 2008; Křivánek et al. 2005]) anisotropic phase functions could be added. Incorporating heterogeneous media would break the assumption of constant scattering term (i.e. $\nabla f \neq H f \neq 0$) given the variability of $\mu_s$ and $f_s$ within the media. This would require us to use the full radiance derivatives (Equations (11) and (12)), instead of the simplified Equations (17) and (18). Moreover, it would require changing our derivatives of transmittance $T_r$; given our marching procedure for subdividing the media, a similar approach to Jarosz et al.’s [2008] for single scattering could be used. Finally, high-frequency heterogeneity in the medium would require a very fine subdivision, which would potentially make our approach impractical.

Fig. 14. We illustrate convergence to an equal-quality reference solution with our algorithm, Jarosz et al. method, and path tracing for the Whiteroom scene. In 3D scenes of higher complexity, our method presents much better convergence properties than previous ones, being able to reconstruct the shadow boundaries near the window frames in much less time.

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**REFERENCES**


APPENDICES

In the following we summarize 2D and 3D expressions of translational derivatives of transmittance and form factors needed for our method. We box all relevant final expressions that to the best of our knowledge are new to the literature. We define column vectors as \( \mathbf{v} \) and row vectors as \( \mathbf{v}^T \). Expressions such as \( \mathbf{r}_1 \cdot \mathbf{r}_2 \) denote dot (inner) products, while expressions such as \( \mathbf{r}_1 \times \mathbf{r}_2 \), \( \nabla \ldots \nabla^T \ldots \) denote vector outer products.

A HOMOGENEOUS TRANSMITTANCE DERIVATIVES

Homogeneous transmittance is modeled by the exponential decay due to extinction,

\[
T_r = e^{-\mu_l |\mathbf{y} - \mathbf{x}|}
\]

(24)

where \( |\mathbf{y} - \mathbf{x}| \) denotes distance between source \( y \) and shaded point \( x \). Its gradient and Hessian with respect to a translation \( \mathbf{y} \) are

\[
\nabla T_r = -\mu_l \frac{\mathbf{y} - \mathbf{x}}{|\mathbf{y} - \mathbf{x}|} T_r,
\]

\[
\nabla^2 T_r = -\mu_l \left( \frac{\mathbf{y} - \mathbf{x}}{|\mathbf{y} - \mathbf{x}|} \mathbf{y} \mathbf{x}^T - \mu_l \mathbf{I} \right) T_r,
\]

(25)

(26)

B 2D SEGMENT-MEDIA FORM FACTOR DERIVATIVES

The form factor between a 2D segment \( \ell \) and a media point \( \mathbf{x} \) (Figure 15, left) is defined as the integrated curve-media geometry term along all segment points. This is equivalent to the angular ratio covered by \( \ell \) as seen from such a term:

\[
F_\ell(x) = \frac{1}{2\pi} \int_{y_0}^{y_1} \frac{\cos \theta_y}{|x - y|} \, dy = \frac{1}{2\pi} \arccos \left( \frac{\mathbf{x} \cdot \mathbf{y}_0 \times \mathbf{y}_1}{r} \right)
\]

(27)

where \( r_i = |\mathbf{y}_i| \). The form factor gradient and Hessian become

\[
\nabla F_\ell(x) = -\frac{1}{2\pi} \left( \frac{J(\nabla \cos \theta')}{\sqrt{1 - \cos^2 \theta'}} \times \nabla \cos \theta' \nabla \cos \theta' \right)^T
\]

\[
\nabla^2 F_\ell(x) = \frac{1}{2\pi} \left( \frac{J(\nabla \cos \theta')}{\sqrt{1 - \cos^2 \theta'}} \times \nabla \cos \theta' \nabla \cos \theta' \right)^T
\]

(28)

where \( J \) is the Jacobian operator, and:

\[
\nabla \cos \theta' = \frac{\cos \theta'}{r_1^2} \mathbf{x}_0^T + \frac{\cos \theta'}{r_1^2} \mathbf{y}_1^T
\]

\[
= \left( \mathbf{x}_0^T + \mathbf{y}_1^T \right) / r_1^2
\]

\[
J(\nabla \cos \theta') = -J(\nabla \cos \theta') = -J \left( \frac{\mathbf{x}_0^T}{r_0 r_1} + J \left( \frac{\mathbf{y}_1^T}{r_0 r_1} \right) \right) + J \left( \frac{\mathbf{x}_0^T}{r_0} \right) + J \left( \frac{\mathbf{y}_1^T}{r_1} \right)
\]

\[
J \left( \frac{\mathbf{x}_0^T}{r_0} \right) = J \left( \frac{\mathbf{x}_0^T}{r_0} \right) + \frac{\mathbf{x}_0 \mathbf{y}_0^T}{r_0^3} + \frac{\mathbf{x}_0 \mathbf{y}_1^T}{r_0^3}
\]

\[
J \left( \frac{\mathbf{y}_1^T}{r_1} \right) = J \left( \frac{\mathbf{y}_1^T}{r_1} \right) + \frac{\mathbf{x}_0 \mathbf{y}_1^T}{r_0^3} + \frac{\mathbf{x}_1 \mathbf{y}_1^T}{r_0^3}
\]

(30)

(31)

(32)

C 3D TRIANGLE-MEDIA FORM FACTOR DERIVATIVES

The form factor between a 3D triangular face \( \triangle \) and a media point \( \mathbf{x} \) (see Figure 15, right) is defined as the integrated surface-media geometry term along all points in the triangle. Analogous to 2D,
The gradient of \(A\) becomes
\[
\nabla A = J (\vec{r}_2 \times \vec{r}_3) \vec{r}_1 + J (\vec{r}_1) (\vec{r}_2 \times \vec{r}_3) .
\]
(43)

By the Jacobi identity we have that
\[
J (\vec{r}_2 \times \vec{r}_3) = \vec{r}_2 \times J (\vec{r}_3) - \vec{r}_3 \times J (\vec{r}_2)
\]
(44)

where any vector-matrix cross product \(\vec{v} \times J (\bullet)\) can be expressed by means of the matrix multiplication form
\[
\vec{v} \times J (\bullet) = \begin{pmatrix} v(1) \\ v(2) \\ v(3) \end{pmatrix} \begin{pmatrix} 0 & -v(3) & v(2) \\ v(3) & 0 & -v(1) \\ -v(2) & v(1) & 0 \end{pmatrix}
\]
(45)

Since \(J (\vec{r}_1) = J (\vec{r}_2) = J (\vec{r}_3) = -I_3\), we have that
\[
\nabla A = (J (\vec{r}_1) (\vec{r}_3 - \vec{r}_2) \vec{r}_1 - (\vec{r}_2 \times \vec{r}_3)
\]
\[
=(\vec{r}_3 - \vec{r}_2) \vec{r}_1 - (\vec{r}_2 \times \vec{r}_3).
\]
(47)

Note that \((\vec{r}_3 - \vec{r}_2) = (y_3 - y_2)\) and therefore does not depend on \(x\), and \((\vec{v})^T = -\vec{v}\) (see Equation (46)). As a result, the Jacobian of \(\nabla A\) becomes a zero matrix.

The gradient of \(B\) becomes
\[
\nabla B = \nabla ((r_1 r_2 r_3) + \sum_j (\vec{r}_j \times \vec{r}_1 + \vec{r}_2 \times \vec{r}_j))
\]
(49)

where
\[
\nabla (\vec{r}_j \times \vec{r}_k) = (\vec{r}_j \times \vec{r}_k) - r_k (\vec{r}_j \times \vec{r}_k)
\]
(50)
\[
\nabla r_j = - \vec{r}_j
\]
(52)

Jacobian of \(\nabla B\) yields
\[
J (\nabla B) = J (\nabla (r_1 r_2 r_3)) + J (\nabla ((\vec{r}_2 \times \vec{r}_3) (r_1))
\]
\[
+ J (\nabla ((\vec{r}_2 \times \vec{r}_3) (r_1))) + J (\nabla ((\vec{r}_2 \times \vec{r}_3) (r_2)))
\]
(53)

where
\[
J (\nabla (r_1 r_2 r_3)) = \sum_j r_j \nabla r_j + (\vec{r}_j \times \vec{r}_2) \nabla r_1 + (\vec{r}_j \times \vec{r}_3) \nabla r_2 + (\vec{r}_1 \times \vec{r}_j) \nabla r_3
\]
(54)
\[
J (\nabla ((\vec{r}_1 \times \vec{r}_j) (r_k))) = (\vec{r}_1 \times \vec{r}_j) \nabla r_k + 2 r_k \vec{I}
\]
\[
- (\vec{r}_1 \times \vec{r}_j) (\vec{r}_k \times \vec{r}_j) \nabla r_k
\]
(55)
\[
J (\nabla r_j) = \frac{r_j}{r} - \vec{r}_j \vec{r}_k r_k
\]
(56)