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Multi-View Reconstruction using Signed Ray Distance Functions (SRDF)

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Abstract

In this paper, we investigate a new optimization framework for multi-view 3D shape reconstructions. Recent differentiable rendering approaches have provided breakthrough performances with implicit shape representations though they can still lack precision in the estimated geometries. On the other hand multi-view stereo methods can yield pixel wise geometric accuracy with local depth predictions along viewing rays. Our approach bridges the gap between the two strategies with a novel volumetric shape representation that is implicit but parameterized with pixel depths to better materialize the shape surface with consistent signed distances along viewing rays. The approach retains pixel-accuracy while benefiting from volumetric integration in the optimization. To this aim, depths are optimized by evaluating, at each 3D location within the volumetric discretization, the agreement between the depth prediction consistency and the photometric consistency for the corresponding pixels. The optimization is agnostic to the associated photo-consistency term which can vary from a median-based baseline to more elaborate criteria e.g. learned functions. Our experiments demonstrate the benefit of the volumetric integration with depth predictions. They also show that our approach outperforms existing approaches over standard 3D benchmarks with better geometry estimations.

1. Introduction

Reconstructing 3D shape geometries from 2D image observations has been a core issue in computer vision for decades. Applications are numerous and range from robotics to augmented reality and human digitization, among others. When images are available in sufficient numbers, multi-view stereo (MVS) is a powerful strategy that has emerged in the late 90s (see [57]). In this strategy, 3D geometric models are built by searching for surface

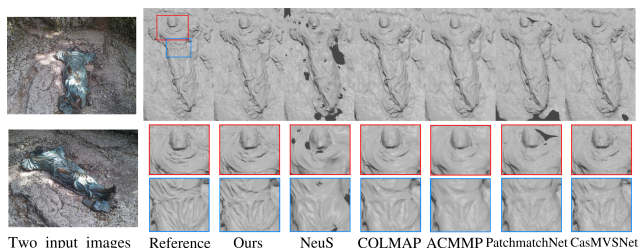


Figure 1. Reconstructions with various methods using 14 images of a model from BlendedMVS [69].

locations in 3D where 2D image observations concur, a property called photo-consistency. This observation consistency strategy has been later challenged by approaches in the field that seek instead for observation fidelity using differentiable rendering. Given a shape model that includes appearance information, rendered images can be compared to observed images and the model can thus be optimized. Differentiable rendering adapts to several shape representations including point clouds, meshes and, more recently, implicit shape representations. The latter can account for occupancy, distance functions or densities, which are estimated either directly over discrete grids or through continuous MLP network functions. Associated to differentiable rendering these implicit representations have provided state-of-the-art approaches to recover both the geometry and the appearance of 3D shapes from 2D images.

With the objective to improve the precision of the reconstructed geometric models and their computational costs, we investigate an approach that takes inspiration from differentiable rendering methods while retaining beneficial aspects of MVS strategies. Following volumetric methods we use a volumetric signed ray distance representation which we parameterize with depths along viewing rays, a representation we call the Signed Ray Distance Function or SRDF. This representation makes the shape surface explicit with depths while keeping the benefit of better distributed gradients with a volumetric discretization. To optimize this shape representation we introduce an unsupervised differ-

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entiable volumetric criterion that, in contrast to differentiable rendering approaches, does not require color estimation. Instead, the criterion considers volumetric 3D samples and evaluates whether the signed distances along rays agree at a sample when it is photo-consistent and disagree otherwise. While being volumetric our proposed approach shares the following MVS benefits:

- i) No expensive ray tracing in addition to color decisions is required;
- ii) The proposed approach is pixel-wise accurate by construction;
- iii) The optimization can be performed over groups of cameras defined with visibility considerations. The latter enables parallelism between groups while still enforcing consistency over depth maps.

In addition, the volumetric scheme provides a testbed to compare different photo-consistency priors in a consistent way with space discretizations that do not depend on the estimated surface.

To evaluate the approach, we conducted experiments on real data from DTU Robot Image Data Sets [22], Blended-MVS [69] and on synthetic data from Renderpeople [2] as well as on real human capture data. Ablation tests demonstrate the respective contributions of the SRDF parametrization and the volumetric integration in the shape reconstruction process. Comparisons with both MVS and Differential Rendering methods also show that our method consistently outperforms state of the art both quantitatively and qualitatively with better geometric details.

2. Related Work

2.1. Multi-view Stereo

Reconstructing 3D shapes from multiple images is a long-standing problem in computer vision. Traditional MVS approaches can be split into two categories. Seminal methods [5, 9, 29, 58] use a voxel grid representation and try to estimate occupancies and colors. While efficient their reconstruction precision is inherently limited by the memory requirement of the 3D grid when increasing resolution. On the other hand depth-based methods [3, 6, 12, 14, 56, 65] have been proposed that usually try to match image features from several views to estimate depths. Additional post-processing fusion and meshing steps [7, 26, 27, 35] are required to recover a surface from the multi-view depth maps. Despite the usually complex pipeline, multi-view depth map estimation offers the advantage to give access to pixel-accuracy, a strong feature for the reconstruction quality which has made this strategy common in MVS approaches. We also consider multi-view depth maps that are however included into a volumetric framework, with signed distances, with the aim to improve global consistency. With the advances in deep learning, several methods propose to

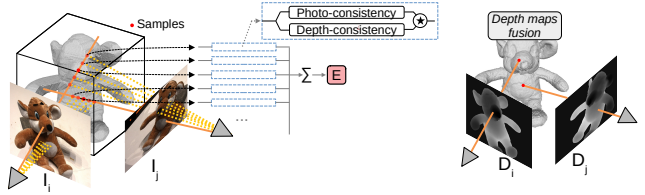


Figure 2. Our method overview. Left: Given multiple RGB images and an initial coarse reconstruction, our method optimizes depth maps using a volumetric shape energy E that is evaluated at samples along viewing lines. Right: The optimized depth maps are further fused into a surface model.

learn some parts of the MVS pipeline such as the image feature matching [17, 30, 75] or the depth map fusion [11, 53]. Others even propose to learn the full pipeline in an end-to-end manner [16, 19, 40, 52, 60, 63, 67, 68, 75]. These learning based methods offer fast inference and exhibit interesting generalization abilities. Optimization based methods can be seen as alternative or complementary solutions with better precision and generalization abilities, as shown in our experiment in sec. 5.6.

2.2. Differentiable Rendering

Another line of works has explored differentiable rendering approaches. Many of these works are used for novel view rendering applications however several also consider 3D shape geometry reconstruction, often as part of the new image generation process. They build on a rendering that is differentiable and henceforth enable shape model optimization by differentiating the discrepancy between generated and observed images. These methods were originally applied to various shape representations including meshes [18, 25, 32, 47], volumetric grids [13, 24, 42, 62, 76] or even point clouds [20, 23, 41]. In association with deep learning, new neural implicit representations have also emerged. Their continuous nature and light memory requirements are attractive and they have been successfully applied to different tasks: 3D reconstruction [36, 46, 49, 54, 55, 66] or geometry and appearance representations [15, 37, 44, 59, 61]. Most of these methods solve for 3D shape inference and require 3D supervision, however recent works combine implicit representations with differentiable rendering and solve therefore for shape optimization with 2D image supervision. They roughly belong to two categories depending on the shape representation they consider.

Volume-based methods use a volumetric renderer with 3D samples and estimate for each sample a density as well as a color conditioned on a viewing direction. Colors and densities of the samples are integrated along viewing rays to obtain image colors that can be compared with the observed pixel colors. The pioneer work of Mildenhall *et al.* [38] opened up this research area with impressive results on novel view synthesis. The quality of the associated ge-

ometry as encoded with densities is however not perfect and often noisy. Several works have followed that target generalization to new data [21, 74], dynamic scenes [31, 50] or propose new formulations based on Signed Distance Functions to improve the estimated geometry [64, 70]. [8] also proposes a finetuning strategy based on image warpings to take advantage of high-frequency texture. A main limitation of methods based on neural volumetric rendering lies in the optimization time complexity which often plagues the shape modeling process. To address this limitation various strategies have been investigated: a divide-and-conquer strategy [51], more efficient sampling [4], traditional volumetric representations to directly optimize densities and colors inside octrees [73], or voxel grids [72] and efficient multi-resolution hash tables [39]. See [10] for more details. These strategies dramatically decrease the optimization time while maintaining very good results for novel view rendering. However the estimated geometry can still lack precision as the methods are not primarily intended to perform surface reconstruction.

Surface-based methods [28, 33, 43, 71] address this issue with a surface renderer that estimate 3D locations where viewing rays enter the surface and their colors. By making the shape surface explicit, these approaches obtain usually better geometries. Nevertheless, they are more prone to local minima during the optimization since gradients are only computed near the estimated surface as opposed to volumetric strategies. An interesting hybrid approach [45], proposes to combine the advantages of both volumetric and surface rendering and shows good surface reconstructions.

3. Method

Our method takes as input N calibrated color images $\mathcal{I} = I_{j \in [1, N]}$ and assumes N initial associated depth maps $\mathcal{D} = D_{j \in [1, N]}$ that can be obtained using an initial coarse reconstruction, with for instance pre-segmented image silhouettes as in Fig. 2. It optimizes depth values along pixel viewing lines by considering a photo-consistency criterion that is evaluated in 3D over an implicit volumetric shape representation. Final shape surfaces are thus obtained by fusing depth maps, as in e.g. [7, 14]. The main features of the method are:

- Shape representation (Sec 3.1): depth maps determine the signed distances, along pixel viewing rays, that define our volumetric shape representation with the SRDF. Parameterizing with depths offers several advantages: it better accounts for the geometric context by materializing the shape surface; it enables pixel accuracy regardless of the image resolution; it allows for coarse to fine strategies as well as parallelization with groups of views.
- Energy function (Sec 3.2): our shape energy function is evaluated at sample locations along viewing

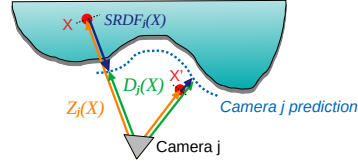


Figure 3. For any 3D point X , its ray signed distance $SRDF_j(X) = D_j(X) - Z_j(X)$ with respect to camera j is the signed shortest distance from X to the surface, as predicted by camera j along the corresponding viewing line.

lines and involves multiple depth maps simultaneously, therefore enforcing spatial consistency. It focuses on the geometry and avoids potential ambiguous estimation of the appearance.

- Photometric prior (Sec 3.3): The photo-consistency hypothesis evaluated by the energy function along a viewing line can be diverse. We propose a criterion that is learned over ground truth 3D data such as DTU [22]. We also experiment a baseline unsupervised criterion that builds on the median color.

3.1. Signed Ray Distance Function

Our shape representation is a volumetric signed distance function parameterized by depths along viewing rays. This is inspired by signed distance functions (SDF) and shares some similarities with more recent works on signed directional distance functions (SDDF) [77]. Unlike traditional surface-based representations such a function is differentiable at any point in the 3D observation volume.

Instead of considering the shortest distances along any direction as in standard SDF, or in a fixed direction as in SDDF [77], we define, for a given 3D point X , its N signed distances with respect to cameras $j \in [1, N]$ as the signed distances of X to its nearest neighbor on the surface as predicted by camera j along the viewing ray passing through X . We denote the distance for X and camera j by the *Signed Ray Distance Function (SRDF)*, as shown in Fig. 3:

$$SRDF(X, D_j) = SRDF_j(X) = D_j(X) - Z_j(X), \quad (1)$$

where $D_j(X)$ is the depth in depth map D_j at the the projection of X and $Z_j(X)$ the distance from X to camera j .

3.2. Volumetric Shape Energy

The intuition behind our volumetric energy function is that photometric observations across different views should be consistent on the surface and not elsewhere. Importantly such a behavior should be shared by the SRDF predictions across views that should also consistently identify zero distances for points on the surface and non consistent distances elsewhere. Given this principle, illustrated in Fig. 4, a computational strategy is to look at the correlation between these 2 signals, the observed photo-consistency and the predicted SRDF consistencies, and to try to maximise it at 3D sample locations $\{X\}$ in the observation space (see Fig. 5).

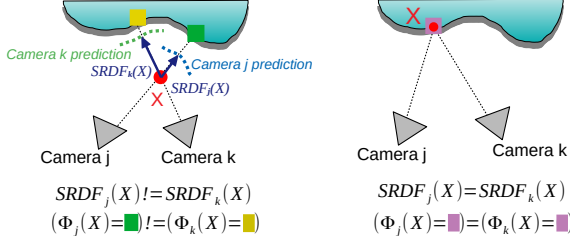


Figure 4. Inconsistency (left) and consistency (right) of the ray signed distances $SRDF_{j,k}(X)$ and of the photometric information $\Phi_{j,k}(X)$ at X with respect to cameras j and k .

To this purpose we introduce the following consistency energy function:

$$E(\{X\}, \mathcal{D}, \mathcal{I}) = \sum_X C_{SRDF}(X, \mathcal{D}) C_{\Phi}(X, \mathcal{I}), \quad (2)$$

where $\{X\}$ are the 3D sample locations, $C_{SRDF}(X, \mathcal{D})$ and $C_{\Phi}(X, \mathcal{I})$ represent measurements of consistency among the predicted SRDFs values $SRDF_{j \in [1, N]}(X)$ and among the observed photometric observations $\Phi_{j \in [1, N]}(X)$, respectively, at location X . Both are functions that return values between 0 and 1 that characterize consistency at X . We detail below the SRDF consistency measure $C_{SRDF}(X)$. The photo-consistency measure $C_{\Phi}(X)$ is discussed in Section 3.3. The above energy E is differentiable with respect to the predicted depths values \mathcal{D} and computed in practice at several sample locations along each viewing ray of each camera, which enforces SRDFs to consistently predict surface points over all cameras.

SRDF consistency From the observation that SRDF consistency is only achieved when X is on the surface, *i.e.* when $SRDF_j(X) = 0$ for all non occluded cameras j , we define:

$$C_{SRDF}(X) = \prod_{j=1}^N \left(\exp\left(-\frac{SRDF_j(X)^2}{\sigma_d}\right) + \Gamma_{SRDF} \right), \quad (3)$$

where the ray signed distances are transformed into probabilities using an exponential which is maximal when $SRDF_j(X) = 0$. Γ_{SRDF} is a constant that prevents the product over all cameras to cancel out in case of inconsistencies caused by camera occlusions. It can be interpreted as the probability of the $SRDF_j$ value at X knowing camera j is occluded, which can be set as constant for all values. σ_d is a hyper parameter that controls how fast probabilities decrease with distances to the surface. It should be noted here that the above energy term C_{SDRF} is a product over views at a 3D point X and not a sum, hence gradients w.r.t. depth values are not independent at X , which forces distances to become consistent across views, as shown in the ablation test provided in the supplemental.

3.3. Photometric Consistency

Our model is agnostic to the photo-consistency measure $C_{\Phi}(X)$ that is chosen. In practice we have considered 2 in-

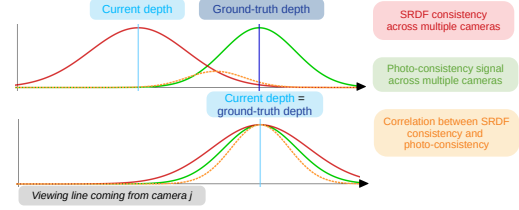


Figure 5. The SRDF consistency (red) and photo-consistency signals (green) along a viewing line. Their cross correlation will be maximal when the current predicted depth aligns with the ground truth depth.

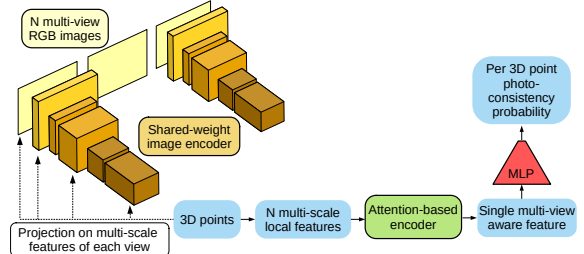


Figure 6. Proposed architecture to learn photo-consistency.

stances of $C_{\Phi}(X)$: A baseline version that relies on the traditional Lambertian prior assumption for the observed surface and a learned version that can be trained with ground truth 3D data.

Baseline Prior assumes a Lambertian surface and therefore similar photometric observations for points on the observed surface for all non-occluded viewpoints. While ignoring non diffuse surface reflections the assumption has been widely used in image based 3D modelling, especially by MVS strategies. The associated consistency measure we propose accounts for the distance to the median observed value. Under the Lambertian assumption all observed appearances from non-occluded viewpoints should be equal. Assuming further that occluded viewpoints are fewer we define the photo-consistency as:

$$C_{\Phi}(X) = \prod_{j=1}^N \left(\exp\left(-\frac{\|\Phi_j(X) - \tilde{\Phi}(X, \mathcal{I})\|^2}{\sigma_c}\right) + \Gamma_{\Phi} \right), \quad (4)$$

where $\Phi_j(X)$ is photometric observation of X in image j , typically a RGB color, and $\tilde{\Phi}(X, \mathcal{I})$ is the median value of the observations at X over all images. Similarly to equation 3, Γ_{Φ} is a constant that prevents the product over all cameras to cancel out in case of occlusion and σ_c is a hyper-parameter. As shown in Section 5 this baseline photometric prior yields state-of-the-art results on synthetic 3D data for which the Lambertian assumption holds but is less successful on real data.

Learned Prior. In order to better handle real images that are noisy and for which the Lambertian assumption is partially or not satisfied, we have experimented a more elaborated photo-consistency measure with a data driven approach. Inspired by previous works [17, 30], we cast

the problem as a classification task between points that are photo-consistent across multiple views and points that are not and train a network for that purpose.

As described in Fig. 6, the network architecture tries to match the local appearance of a 3D point in different views and outputs a photo-consistency score between 0 and 1. This module is independent of the number of cameras and provides very good results on real data and generalization abilities as demonstrated in Section 5. Please refer to the supplementary materials for more details about the architecture.

4. Implementation

4.1. Optimization Pipeline

To allow for efficient processing, we define G groups of cameras, which can be optimized in parallel. Since our approach optimizes geometry based on appearance matching, it is preferable to minimize occlusions. For this reason, we heuristically choose to gather cameras that are close to each other. More specifically, for DTU and Renderpeople in which the cameras follow a relatively standard placement and observe the front part of the objects, we use the euclidean distance between camera positions to calculate distances between pairs of cameras and form distinct camera groups. For DTU, each group contains 7 cameras and for Renderpeople, we form one group with 10 cameras and one with 9. For the real captured data with an irregular camera placement and wider baselines, we follow the more elaborated strategy of MVSNet [67] that computes a score based on sparse 3D points obtained with COLMAP [56] and a piece-wise Gaussian function. We create one group for each camera by considering the 6 closest cameras based on the computed scores.

For the depth maps associated to a camera group, at each epoch, we iterate over all rays r_j^i corresponding to foreground pixels i of cameras j , as defined by pre-segmented silhouettes, and sample points along r_j^i around the current depth estimation d_j^i . This sampling is parameterized by two parameters: an offset o that defines an interval for the sampling around the current depth $[d_j^i - o; d_j^i + o]$, and the density of the sampling which represents the number of points that we sample uniformly in that interval. Ideally, the real depth \hat{d}_j^i should be contained inside the interval $[d_j^i - o; d_j^i + o]$, otherwise it is difficult for the appearance to guide the geometry optimization. From that observation, we define a coarse-to-fine strategy for the sampling. With the aim to capture the ground truth depth in the interval, we start with a large interval that is gradually reduced. The sampling density can be adjusted in the same way but decreasing the size of the sampling interval already indirectly increases its density, so in practice we keep the sampling density constant.

Our shape energy, described in subsection 3.2, is computed over all the samples from all the rays of each camera. The gradients are computed using Pytorch autograd [48] and back-propagated to update depth maps.

4.2. Photo-consistency Network

To train the photo-consistency network, we use the DTU Robot Image Data Sets [22] composed of 124 scans of objects. For each scan, there are 49 or 64 images under 8 different illuminations settings, camera calibration and ground truth point cloud obtained from structured light. We select 15 test objects and remove all the scans that contain these objects from the training set which results in 79 training scans. Next, we reconstruct a surface from the ground truth point cloud using the Screened Poisson algorithm [27] and surface trimming of 9.5. From the reconstructed meshes we render ground truth depth maps and use them to sample points on the surface (positive samples) and points that are either in front or behind the surface (negative samples). We make sure to keep a balanced sampling strategy with an equal number of positive and negative samples.

To encourage the network to remain invariant to the number of cameras, at each training iteration, we randomly select a subset of K cameras from the total N cameras. Matching appearances between cameras too far from each other leads to inconsistencies as a result of the potentially high number of occlusions. To remedy this, we create the camera groups using a soft nearest neighbour approach. We randomly select a first camera, compute its K' nearest neighbours cameras with $K < K' < N$, and randomly select $K - 1$ cameras from them. In practice, $N = 49$ or 64 and we choose $K \in [4, 10]$ and $K' = \min(2K, 15)'$.

5. Experimental Results

To assess our method we conduct an evaluation on multi-view 3D shape reconstruction. First, we introduce the existing methods that we consider as our baseline. Then, we present the datasets as well as the evaluation metrics. We provide quantitative and qualitative comparisons against the current state of the art on real images using our learned prior for photo-consistency. Then, we also show that our method combined with a baseline prior for photo-consistency provides good reconstruction results under the Lambertian surface assumption. Finally, we demonstrate better generalization abilities of our method compared to deep MVS inference-based methods and that the latter can serve as an initialization. The values of our hyper parameters for each experiment are available in the supplementary.

5.1. Datasets and Metrics

To evaluate our method on real multi-view images with complex lighting, we use the 15 test objects from the DTU Data Sets [22] and BlendedMVS [69]. Note again

that BlendedMVS is not used to train our learned photo-consistency prior. For DTU, the corresponding background masks are provided by [71]. To test our method with the baseline prior for photo-consistency, we render multi-view images from Renderpeople [2] meshes. This dataset provides highly detailed meshes obtained from 3D scans of dressed humans and corrected by artists. We render 19 high-resolution images (2048x2048) that mostly show the frontal part of the human. For the quantitative evaluation with DTU we use a Python implementation [1] of the official evaluation procedure of DTU. The accuracy and completeness metrics, with the chamfer distances in *mm*, are computed w.r.t. ground truth point clouds obtained from structured light. Finally, to evaluate generalization to novel data, we also experiment with images from a large scale hemispherical multi-view setup with 65 cameras of various focal lengths.

5.2. Baseline Methods

To assess our approach, we evaluate the geometry against state-of-the-art methods among 3 categories: classic MVS, deep MVS and differential rendering based methods. First, COLMAP [56] and ACMMP [65] are classic MVS methods that have been widely used and demonstrate strong performances for MVS reconstruction. Among all the deep MVS methods, we consider two of the most efficient methods PatchmatchNet [63] and CasMVSNet [16] for which the code is available and easy to use. Finally, for the differentiable rendering based methods we consider IDR [71] which was one of the first works that combines a differentiable surface renderer with a neural implicit representation. It requires accurate masks but handles specular surfaces and has shown impressive reconstruction results. We also compare with two more recent works that use volumetric rendering and provide impressive reconstruction results: NeuS [64] and NeuralWarp [8].

For the evaluation on DTU using all the available views (49 or 64 depending on the scan) we retrain PatchmatchNet and CasMVSNet as their pre-trained models use a different train/test split. We use the pre-trained models for IDR, NeuS (with the mask loss) and NeuralWarp.

To recover meshes with our method, we use a post-processing step with a bilateral filter on the optimized depth maps, a TSDF Fusion [7] method and a mesh cleaning based on the input masks. For COLMAP, ACMMP, PatchmatchNet and CasMVSNet we try to use the same TSDF Fusion method [7] as much as possible. For differentiable rendering based methods (IDR, NeuS and NeuralWarp), the implicit representation is simply evaluated in a 3D grid of size 512^3 and then Marching Cubes [34] is applied.

5.3. Multi-view Reconstruction from Real Data

Qualitative results. In Fig. 7, we show comparisons between our method and the considered baselines. While IDR, NeuS and NeuralWarp produce high quality details, they show some artifacts on some misleading parts: some regions of the fruits (1st row), near the right arm of the figurine (2nd row) or at the separation between the belly and the legs of the statue (3rd row). In contrast, our method provides high level of details without failing on these difficult parts. For IDR and NeuS, the appearance prediction probably compensates for the wrong geometry during the optimization, however our approach exhibits more robustness by focusing on the geometry. Our method produces visual results comparable to COLMAP, ACMMP, PatchmatchNet and CasMVSNet with high fidelity and reduced noise. As shown in Fig. 1 and 8 our method provides similar results with high quality details on BlendedMVS, using the same photoconsistency prior trained on DTU. Note that in Fig. 1, we use a coarse initial reconstruction obtained with [63].

Quantitative results. In our quantitative evaluation, all the results are computed on the meshes obtained with the differentiable rendering based methods and directly on the point clouds fused from the depthmaps for COLMAP, ACMMP, PatchmatchNet, CasMVSNet and our method. On average, our method clearly outperforms methods based on differentiable rendering (IDR, NeuS and NeuralWarp) in terms of accuracy and completeness. Our method also demonstrates an improvement over classic MVS methods COLMAP and ACMMP. Compared to deep MVS methods that are trained end-to-end on DTU, the approach is on par, though better on combined accuracy and completeness, while training only a small neural network for photo-consistency that is used as a prior in the optimization. Note that quantitative results for PatchmatchNet and CasMVSNet are not as high as in their paper since the training set is not the same and in contrast to their train/test split, we remove all the scans from the training set in which a test object is seen.

Runtime analysis. As shown in Table 1, our method is competitive with the MVS methods COLMAP and ACMMP in terms of runtime. We note that it could also benefit from an easy parallelization by optimizing different groups of depthmaps on different GPUs or even machines which can significantly reduce the computation time. COLMAP, ACMMP and our method have a strong computation time advantage compared to methods based on differentiable rendering and neural implicit representations that require several hours before converging to an accurate 3D reconstruction. Of course, deep MVS methods like PatchmatchNet and CasMVSNet that perform only inference are inherently much faster than optimization based methods.

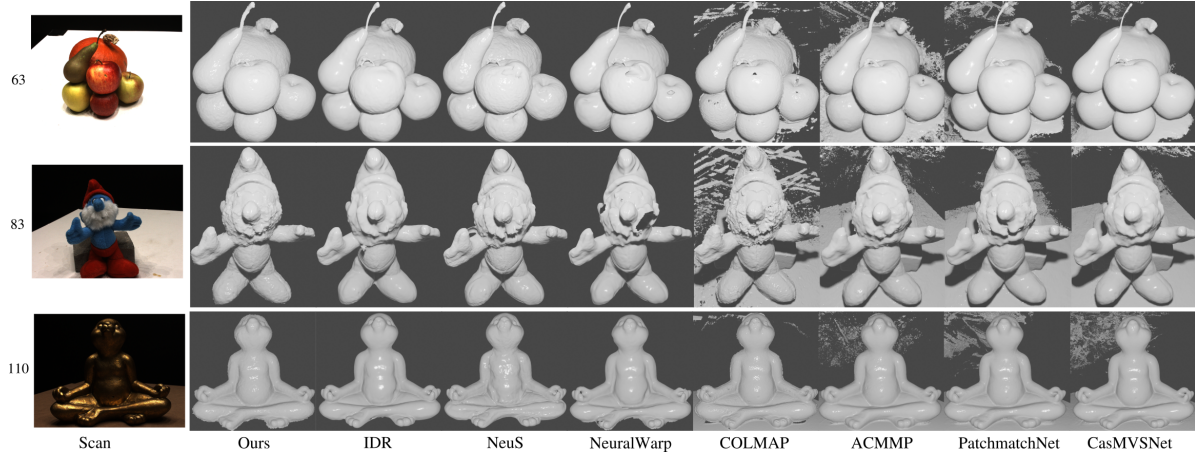


Figure 7. Qualitative comparisons with state-of-the-art methods.

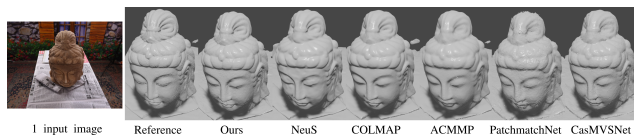


Figure 8. Qualitative comparison using 36 images of a model from BlendedMVS [69].

Methods	Use masks	Chamfer Distance ↓	Accuracy ↓	Completeness ↓	Time
IDR [71]	✓	0.89	1.02	0.79	8 h
NeuS [64]	✓	0.77	0.85	0.68	14 h
NeuralWarp [8]	✗	0.69	0.68	0.69	17 h
COLMAP [56]	✗	0.49	0.40	0.58	38 min
ACMMP [65]	✗	0.42	0.46	0.39	32 min
PatchmatchNet [63]	✗	0.40	0.44	0.35	1 min
CasMVSNet [16]	✗	<u>0.38</u>	0.34	0.43	3 min
Ours	✓	0.36	<u>0.37</u>	<u>0.36</u>	48 min

Table 1. Quantitative evaluation on DTU [22] (49 or 64 images per model). Best scores are in **bold** and second best are underlined. Last column: runtime comparison (single GPU, scan 83).

5.4. Reconstruction from Synthetic Data

To reinforce the validity of our volumetric shape energy, we experiment with the proposed baseline photo-consistency prior defined in Section 3.3. We use 19 synthetic images from Renderpeople [2] and compare qualitatively with classic MVS methods (COLMAP, ACMMP), differentiable rendering based methods (IDR, NeuS) and deep MVS methods (PatchmatchNet, CasMVSNet).

As shown in Fig. 9, our method is able to reconstruct very accurate and detailed meshes. COLMAP and ACMMP’s are less detailed and more noisy (e.g. COLMAP’s bottom row). IDR and NeuS also lack details and even fail to reconstruct correctly the geometry of the jacket on the first row because of the checkered texture. In that case, optimizing both the geometry and the color clearly leads to the wrong geometry. PatchmatchNet and CasMVSNet also work well with very little noise (e.g. feet on the first row) and slightly less pronounced details compared to our method (e.g. wrinkles on the scarf and sweater on the first row and on the upper part of the dress on the

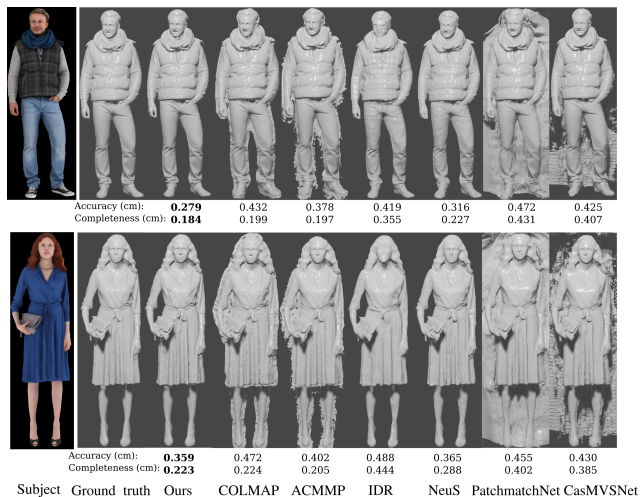


Figure 9. Qualitative and quantitative results with 19 images (Renderpeople [2]) and using the baseline photo-consistency prior defined in 3.3.

bottom row). The qualitative results are confirmed by the accuracy and completeness metrics computed between each reconstruction and the ground truth mesh.

5.5. Reconstruction from Real Captured Data

To further evaluate the generalization ability of our method, we apply it on human capture data. We use images from a hemispherical multi-camera platform composed of 65 cameras of various focal lengths. This setup is designed to capture humans moving in a large scene so the setting is significantly different from DTU with more distant cameras and significantly wider baselines.

Similarly to the previous experiments we compare with different methods: COLMAP, ACMMP, PatchmatchNet and CasMVSNet. For time reason, we only compare with one optimization method based on differentiable rendering. We choose NeuS as it performs better than IDR on DTU

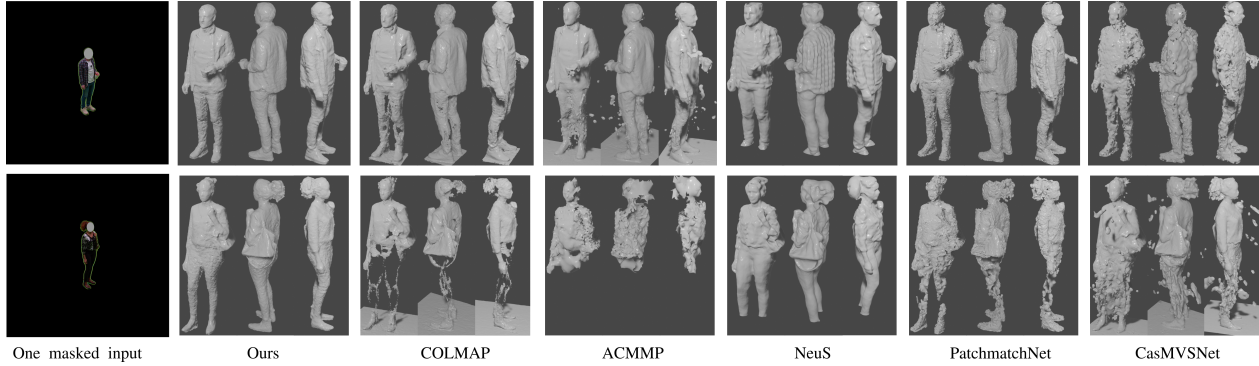


Figure 10. Left: One example image. Right: Qualitative comparison using 65 images from a multi-camera platform.

and is much faster than NeuralWarp which requires an expensive two stage optimization. Note that PatchmatchNet, CasMVSNet and our learned photo-consistency prior are all trained on the same training set of DTU.

Qualitatively, COLMAP performs well with the top row model, despite some holes in the legs. However it has difficulties with the black pants and the hair with the bottom row model. ACMMP is less precise but we mention that a single optimization iteration was used due to RAM’s limitation, even with 64Gb. NeuS reconstructs a nice watertight surface but lacks high-frequency details (*e.g.* faces on both rows) and exhibits poor geometries at different locations due to appearance ambiguities. The deep MVS methods PatchmatchNet and CasMVSNet partially succeed with the top example but fail with the bottom one. This illustrates the generalization issue with the full end-to-end learning based methods when the inference scenario is substantially different from the training one (*i.e.* DTU). On the other hand, our method shows detailed surfaces with limited noise even on some difficult parts as the black pants on the bottom row. It demonstrates the benefit of a weaker prior with local photo-consistency, that is anyway embedded in a global optimization framework.

5.6. Finetuning inference-based results

Deep MVS methods like PatchmatchNet and CasMVSNet present the advantage of very fast inference but, as shown in the previous experiment 5.5, tend to poorly generalize. From this observation, we experiment in this section the combination of an inference-based method with our optimization-based method. As shown in Fig. 11, the result of PatchmatchNet can be used as the initialization for the optimization rather than a coarse Visual Hull. Finetuning the results from PatchmatchNet exhibits more details and less noise but it fails to recover from large errors as with the top of the head, the top of the back and the left hip.

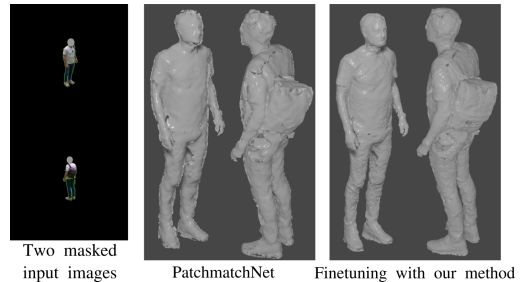


Figure 11. Finetuning the reconstruction result of PatchmatchNet with our optimization method.

6. Conclusion

We have presented a strategy that combines depth optimization, as performed in the latest MVS strategies, with volumetric representations as used in more recent methods based on differentiable rendering. Building on signed distances our SRDF representation allows to optimize multi-view depthmaps in a consistent way by correlating depth prediction with photometric observations along viewing rays. Experiments on real and synthetic data demonstrate the efficiency of our method compared to classic MVS, deep MVS and differentiable rendering based methods. We also demonstrate the good applicability of our method with a learned photo-consistency prior that generalize well on data completely different from the training set. As future work, we believe that photo-consistency priors can still be explored to improve generalization even further (data augmentation for example) or efficiency (specific architecture for very fast inference).

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