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

Pierre Zins<sup>1,2</sup> Yuanlu Xu<sup>2</sup> Edmond Boyer<sup>1</sup> Stefanie Wuhrer<sup>1</sup> Tony Tung<sup>2</sup>

<sup>1</sup>Univ. Grenoble Alpes, Inria, CNRS, Grenoble INP \*LJK, 38000 Grenoble, France

<sup>2</sup>Meta Reality Labs, Sausalito, USA

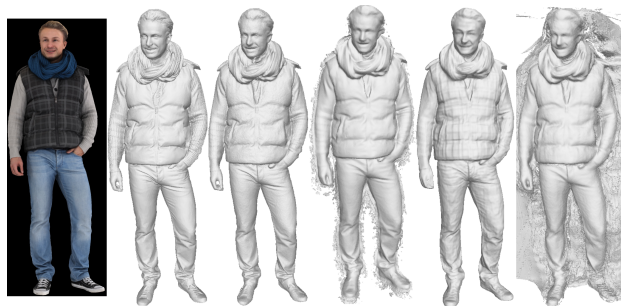
name.surname@inria.fr, merayxu@gmail.com, tony.tung@fb.com

## Abstract

*In this paper, we address the problem of multi-view 3D shape reconstruction. While recent differentiable rendering approaches associated to implicit shape representations have provided breakthrough performance, they are still computationally heavy and often lack precision on the estimated geometries. To overcome these limitations we investigate a new computational approach that builds on a novel shape representation that is volumetric, as in recent differentiable rendering approaches, but parameterized with depth maps to better materialize the shape surface. The shape energy associated to this representation evaluates 3D geometry given color images and does not need appearance prediction but still benefits from volumetric integration when optimized. In practice we propose an implicit shape representation, the SRDF, based on signed distances which we parameterize by depths along camera rays. The associated shape energy considers the agreement between depth prediction consistency and photometric consistency, this at 3D locations within the volumetric representation. Various photo-consistency priors can be accounted for such as a median based baseline, or a more elaborated criterion as with a learned function. The approach retains pixel-accuracy with depth maps and is parallelizable. Our experiments over standard datasets shows that it provides state-of-the-art results with respect to recent approaches with implicit shape representations as well as with respect to traditional multi-view stereo methods.*

## 1. Introduction

Reconstructing 3D shapes from their 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. The problem can be decomposed into two parts, the 3D shape



Subject Ground truth Ours ACMMP NeuS PatchmatchNet  
Figure 1. Reconstructions from 19 images (Renderpeople [2]).

geometry and the shape appearance estimations. While the second part is necessary to generate images from novel viewpoints, the first appears more crucial in most applications and is often a preliminary step to the appearance estimation. We focus on the shape geometry estimation in this paper.

When images are available in sufficient numbers, multi-view stereo (MVS) is a powerful strategy that has emerged in the late 90s (see [59]). In this strategy, 3D geometric models are built by searching for surface 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 shape models from images.

With the objective to improve the precision of the recon-

\*Institute of Engineering Univ. Grenoble Alpes

structured 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 state-of-the-art approaches we also consider an implicit shape representation with a signed distance function and its integration along viewing rays. However, instead of estimating color information we consider photo-consistency and its correlation with signed distances along viewing rays, i.e. photo-consistency should increase when approaching the surface. Such distances are by construction constrained by the observation process and we exploit this fact by parameterizing them with depths along rays, a representation we call the Signed Ray Distance Function or SRDF. We therefore formulate the problem of 3D shape reconstruction as an optimization of depths along viewing rays such that the associated signed distances along rays reach consensus with photo-consistency. Benefits of our proposed approach include: i) no expensive ray tracing in addition to color decisions is required; ii) the proposed approach is pixel-wise accurate by construction; iii) different priors for the photo-consistency can be considered, from baseline median tests to more elaborated learned functions. Furthermore, the optimization can be performed in a coarse-to-fine manner and over groups of cameras defined with visibility considerations. The latter enforces consistency over depth maps while still enabling parallelism between groups.

To summarize, we propose a new multi-view shape optimization approach that builds on a novel shape representation that allows to correlate depth prediction with photometric observations. We introduce for that purpose a data driven photo-consistency function. The evaluation on real data from the DTU Robot Image Data Sets [23], synthetic data from Renderpeople [2] as well as real human capture data demonstrate that this strategy compares favorably to state-of-the-art methods.

## 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 [10, 6, 60, 30] 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 [5, 13, 3, 7, 15, 58, 67] have been proposed that usually try to match image features from several views in order to estimate depths. Additional post-processing fusion and meshing steps [8, 37, 28, 27] 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 learn some parts of the MVS pipeline such as the image feature matching [18, 76, 32] or the depth map fusion [12, 55]. Others even propose to learn the full pipeline in an end-to-end manner [20, 69, 70, 76, 62, 42, 54, 65, 17]. 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 [34, 26, 19, 49], volumetric grids [64, 14, 14, 25, 77, 44] or even point clouds [24, 21, 43]. 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 [56, 57, 68, 38, 51, 48] or geometry and appearance representations [16, 63, 39, 46, 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.* [40] opened up this research area with impressive results on novel view synthesis. The quality of the associated geometry as encoded with densities is however not perfect and often noisy. Several works have followed that target generalization to new data [75, 22], dynamic scenes [52, 33] or propose new formulations based on Signed Distance Func-

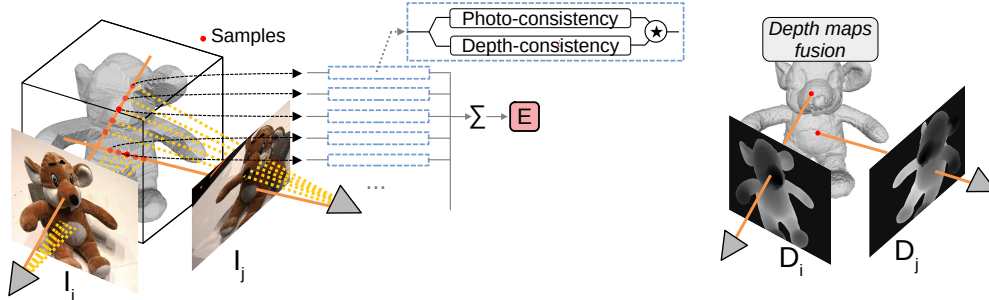


Figure 2. Our method overview. Left: Given multiple RGB images and an initial coarse reconstruction, our method optimizes depth maps using a volumetric shape energy  $E$  that is evaluated at samples along viewing lines. Right: The optimized depth maps are further fused into a surface model.

tions to improve the estimated geometry [66, 71]. [9] also proposes a finetuning strategy based on image warping to take advantage of high-frequency texture. A main limitation of methods based on neural volumetric rendering lies in the optimization time complexity which plagues the shape modeling process. To address this limitation various strategies have been investigated: a divide-and-conquer strategy [53], more efficient sampling [4], traditional volumetric representations to directly optimize densities and colors inside octrees [74], or voxel grids [73] and efficient multi-resolution hash tables [41]. See [11] for more details. These strategies dramatically decrease the optimization time while maintaining very good results for novel view rendering. However the geometry is still imprecise as a result of the non-explicit encoding with densities.

**Surface-based methods** [35, 72, 45, 29] 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 [47], proposes to combine the advantages of both volumetric and surface rendering and shows good surface reconstructions.

Following volumetric methods we use a volumetric signed ray distance representation which we parameterize with depths along viewing rays, hence making the surface explicit while keeping the benefit of better distributed gradients with a volumetric representation. To optimize this shape representation we introduce an unsupervised differentiable volumetric criterion that, in contrast to differentiable rendering approaches, does not require color estimation.

### 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 a coarse recon-

struction from pre-segmented image silhouettes [31] (see Figure 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.* [8, 15]. 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 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 [23]. 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) [78]. 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

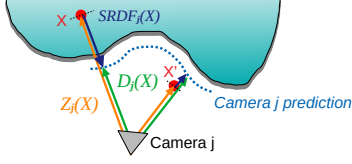


Figure 3. For any 3D point  $X$ , its ray signed distance  $SRDF_j(X) = D_j(X) - Z_j(X)$  with respect to camera  $j$  is the signed shortest distance from  $X$  to the surface, as predicted by camera  $j$  along the corresponding viewing line.

SDDF [78], 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 illustrated in Figure 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 Figure 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 Figure 5). 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.

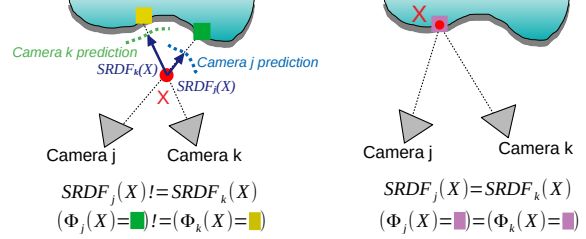


Figure 4. Inconsistency (left) and consistency (right) of the ray signed distances  $SRDF_{j,k}(X)$  and of the photometric information  $\Phi_{j,k}(X)$  at  $X$  with respect to cameras  $j$  and  $k$ .

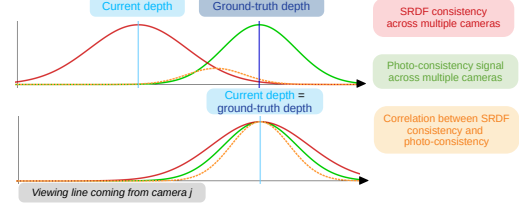


Figure 5. The SRDF consistency (red) and photo-consistency signals (green) along a viewing line. Their cross correlation will be maximal when the current predicted depth aligns with the ground truth depth.

**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  $SRDF_j(X) = 0$ .  $\Gamma_{SRDF}$  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.  $\sigma_d$  is a hyper parameter that controls how fast probabilities decrease with distances to the surface.

### 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 instances 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

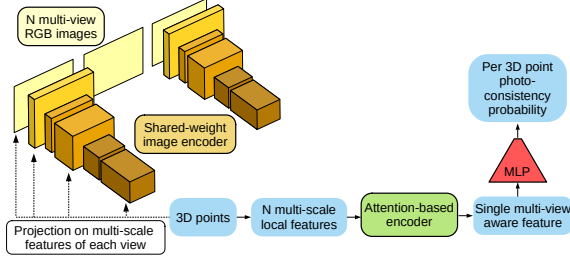


Figure 6. Proposed architecture to learn photo-consistency.

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,  $\Gamma_{\Phi}$  is a constant that prevents the product over all cameras to cancel out in case of occlusion and  $\sigma_c$  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 [32, 18], 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 Figure 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.

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 [50] 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 [23] 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 [28] 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  $K' = \min(2 * K, 15)'$ .

## 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 DTU Data Sets [23] that provide 124 ground truth point clouds from structured light. As explained in Section 4.2, we remove 15 objects from the training set when learning the photo-consistency prior. We use the scans of these 15 objects as test data for reconstruction. The corresponding background masks are provided by [72]. 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 [58] and ACMMP [67] 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 [65] and CasMVSNet [17] for which the code is available and easy to use. Finally, for the differentiable rendering based methods we consider IDR [72] 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 [66] and NeuralWarp [9].

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 [8] 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 [8] 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 [36] is applied.

### 5.3. Multi-view Reconstruction from Real Data

**Qualitative results.** In Figure 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 (4th 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 very good reconstruction of details and reduced noise.

**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 outperforms methods based on differentiable rendering (IDR, NeuS and NeuralWarp) in terms of accuracy and completeness. Our method also demonstrates a slight improvement over classic MVS methods COLMAP and ACMMP. Compared to deep MVS methods that are trained end-to-end on DTU, we obtain almost comparable quantitative results by training only our small neural network for photo-consistency and use it 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. A detailed table showing the metrics

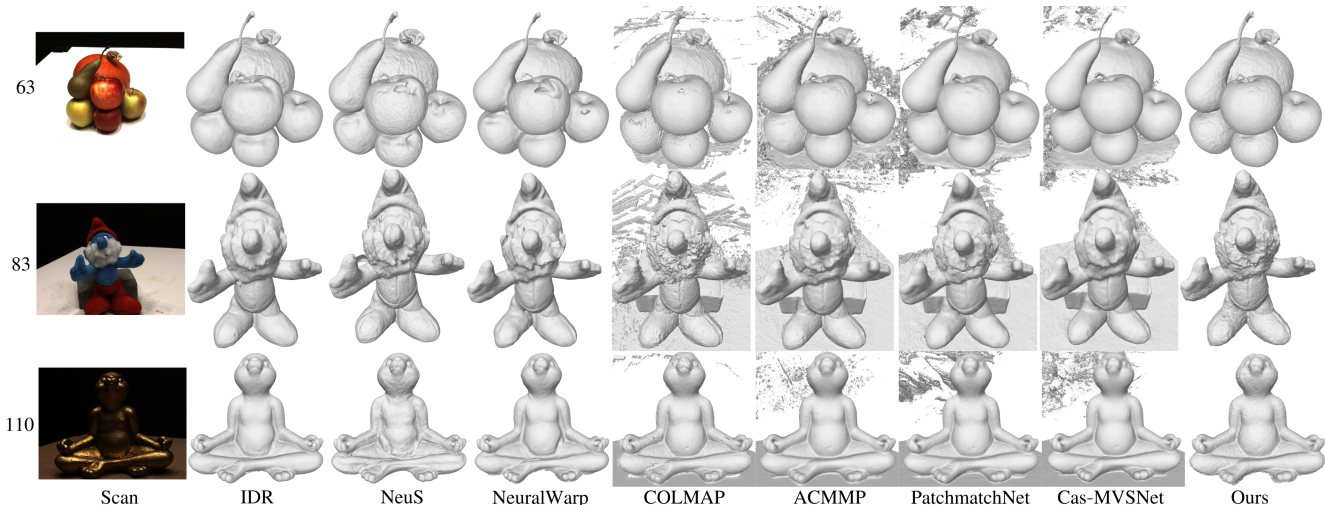


Figure 7. Qualitative comparisons with 5 state-of-the-art methods.

Methods	Accuracy	Completeness	Average
IDR [72]	1.02	0.79	0.89
NeuS [66]	0.85	0.68	0.77
NeuralWarp [9]	0.68	0.69	0.69
COLMAP [58]	0.40	0.58	0.49
ACMMP [67]	0.46	<u>0.39</u>	0.42
PatchmatchNet [65]	0.44	<b>0.35</b>	<u>0.40</u>
CasMVSNet [17]	<b>0.34</b>	0.43	<b>0.38</b>
Ours	<u>0.39</u>	0.41	<u>0.40</u>

Table 1. Quantitative evaluation on DTU [23] (49 or 64 images per model). Best scores are in **bold** and second best are underlined.

computed for each scan is available in the supplementary.

**Runtime analysis.** In terms of runtime, our method (single machine and GPU) is competitive with classic MVS methods COLMAP and ACMMP that take around 45 minutes to optimize with 49 images from DTU. It can 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 (IDR, NeuS and NeuralWarp) that require several hours (between 10h and 25h) before converging to an accurate 3D reconstruction. Of course, deep MVS methods like PatchmatchNet and CasMVSNet that perform only inference are inherently much faster (a few seconds or minutes) than optimization based methods.

#### 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 Figure 8, our method is able to re-

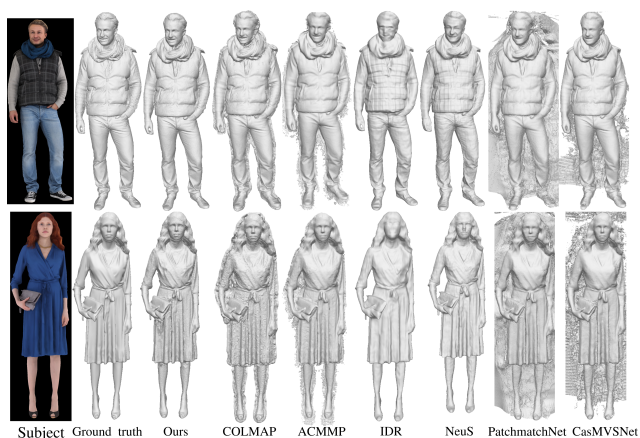


Figure 8. Qualitative results with 19 images (Renderpeople [2]) and using the baseline photo-consistency prior defined in 3.3.

construct 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 bottom row).

#### 5.5. Reconstruction from Real Capture 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



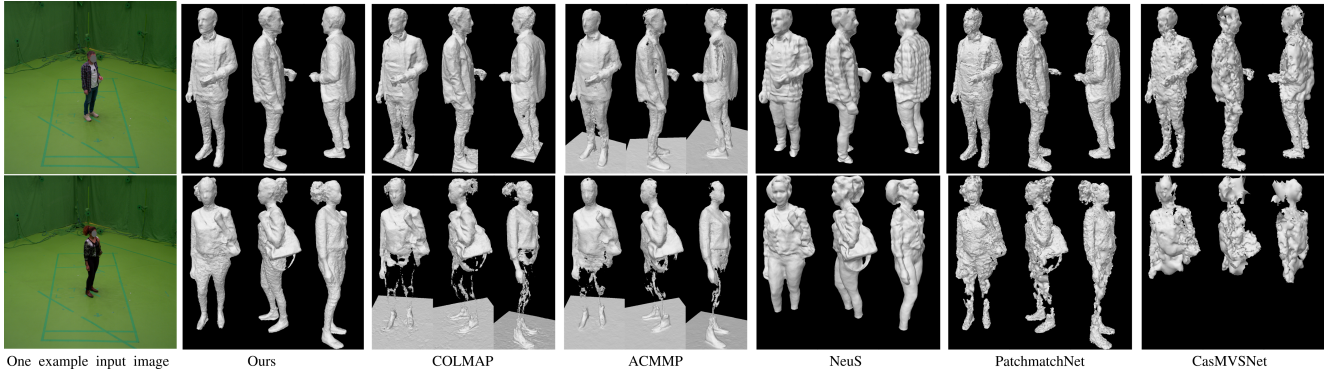


Figure 9. Left: One example image. Right: Qualitative comparison using 65 images from a multi-camera platform.

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 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. 10, 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.

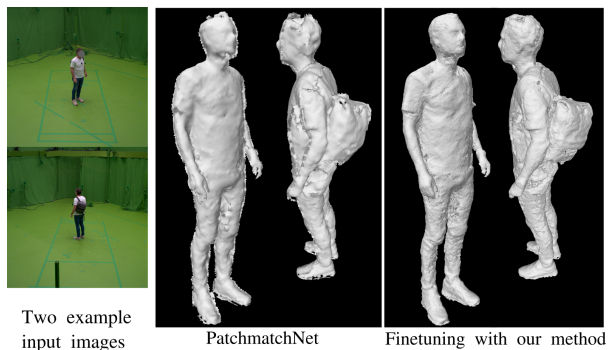


Figure 10. Finetuning the reconstruction result of PatchmatchNet with our optimization method.

## 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). We do not see any immediate negative societal impact of our method, but we still need to be very cautious as accurate 3D models of humans could be

used maliciously (deep fakes, identity theft, ...).

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