Deep Multi-view Depth Estimation with Predicted Uncertainty

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Abstract—In this paper, we address the problem of estimating dense depth from a sequence of images using deep neural networks. Specifically, we employ a dense-optical-flow network to compute correspondences and then triangulate the point cloud to obtain an initial depth map. Parts of the point cloud, however, may be less accurate than others due to lack of common observations or small baseline-to-depth ratio. To further increase the triangulation accuracy, we introduce a depth-refinement network (DRN) that optimizes the initial depth map based on the image’s contextual cues. In particular, the DRN contains an iterative refinement module (IRM) that improves the depth accuracy over iterations by refining the deep features. Lastly, the DRN also predicts the uncertainty in the refined depths, which is desirable in applications such as measurement selection for scene reconstruction. We show experimentally that our algorithm outperforms state-of-the-art approaches in terms of depth accuracy, and verify that our predicted uncertainty is highly correlated to the actual depth error.

I. INTRODUCTION

Estimating dense depth from a sequence of images is an important problem for applications such as 3D scene reconstruction and augmented reality. Classical methods address this problem by first computing point correspondences based on hand-crafted matching criteria, and then constructing a 3D point cloud, given the camera pose estimates from structure-from-motion (SFM) [1] or visual-inertial simultaneous localization and mapping (SLAM) [2], [3]. They typically fail, however, to obtain reliable correspondences at low-textured or reflective regions. As a result, parts of the scene are missing from the point cloud, leading to an incomplete reconstruction.

Recently, deep learning-based methods have shown the potential to compensate for the aforementioned limitation of the classical methods. Specifically, approaches such as [4], [5] predict dense depth from a single image by taking advantage of images’ contextual cues learned from large datasets; hence, they rely less on texture, as compared to classical methods. Moreover, to overcome the scale issue of single-view methods, depth-completion networks (e.g., [6], [7], [8], [9], [10]) leverage sparse point clouds from classical methods and complete the dense depth map using single-view cues. In order to further exploit multi-view information, depth-estimation networks taking multiple images as input have also been considered. In particular, [11], [12] employ cost volumes in their networks to embed geometric information, while [13], [14] explicitly leverage multi-view geometry by estimating dense optical flow.

In this work, we follow the latter paradigm. Specifically, we employ an optical flow network to compute dense correspondences between a keyframe image and its immediate neighbors, and then triangulate the dense matches to compute the 3D point cloud given the cameras’ poses. Challenging conditions, however, such as lack of common observations or small baseline-to-depth ratios cause some points to have low-accuracy depth estimates. To represent these errors, we employ the Hessian and the residual of the triangulation least squares and define the confidence scores for the initially triangulated depths, which we then use in the depth-refinement network (DRN).

Although some of the aforementioned issues can be partially alleviated by applying an adaptive frame selection policy† we primarily focus on improving the accuracy by taking advantage of single-image depth estimation networks. Specifically, in order to leverage the image’s contextual information as well as the confidence scores, we introduce a DRN that takes as input the initial triangulated depths, their confidence scores, and the keyframe image and produces a refined depth map. In particular, we propose an iterative refinement module (IRM) in its decoder that iteratively refines deep feature extracted by the encoder using a least-squares layer, which significantly improves the depths’ accuracy compared to the initial ones. Additionally, the DRN predicts the uncertainty for each point in the refined depth map. As shown by our experiments, these are highly correlated with the actual depth errors and thus provide valuable information for selecting and fusing measurements in 3D scene reconstruction. To summarize, our main contributions are:

- We introduce an algorithm for estimating depth from multiple images, which outperforms state-of-the-art methods (~20% lower RMSE on ScanNet [15] dataset).
- We propose a depth refinement network (DRN) with an iterative refinement module (IRM) that greatly improves the depths’ accuracy and estimates their uncertainty.
- We further improve the depth estimation from multi-view by applying an adaptive frame selection policy.

II. RELATED WORK

Multi-view depth-estimation methods can be classified as:

Depth completion: One approach towards dense depth estimation from multiple views is to: (i) Create a sparse point cloud (by tracking distinct 2D points across images and triangulating their 3D positions) and then (ii) Employ a depth-completion neural network that takes the sparse depth image along with the RGB image as inputs and exploits the scene’s context to create a dense-depth estimate (e.g., [6], [7], [8], [9], [10]). Although these approaches have relatively low processing requirements, they are typically sensitive to the inaccuracies and sparsity level of their depth input; thus, they often fail to produce accurate depth estimates in

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†The impact of this is accessed in our experiments (Sec. IV).


**Text:**

Textureless regions that lack sparse depth information. To overcome this limitation, we obtain a **dense initial depth map** by triangulating a dense set of correspondences estimated by an optical flow method such as [16]. By doing so, we show experimentally that we can significantly improve accuracy as compared to sparse-to-dense depth completion approaches.

**Depth cost volume:** Another way to obtain dense information from multiple frames is to estimate a depth probability volume from depth cost volumes [17], [12], [18], [19], [11], [20]. Specifically, by employing information across multiple frames, depth-cost-volume approaches yield higher accuracy compared to sparse-to-dense methods. Their precision, however, is bounded by the range of their depth sweeping planes predefined in the cost volumes. In contrast, our algorithm relies on optical flow and triangulation and thus, it is not restricted by the limited range and discretization effects of cost volumes. In our experiments, we show that our method outperforms [11], a state-of-the-art depth cost volume approach, by a significant margin (~20% lower RMSE).

**Flow-to-depth:** Lastly and closely related to our work is the approach of estimating dense depth from dense optical flow [21], [13]. Specifically, an initial depth map along with its confidence scores are first obtained through least-squares triangulation of the dense optical-flow correspondences. Subsequently, the initial depth map is further improved by a depth-refinement network, often realized as a deep autoencoder, using its confidence scores and the RGB image. This depth refinement network, however, may inaccurately modify the initial depth map, even for pixels with high confidence scores (see Sect. [III-B] for more details). Previous works [22], [23] address this issue, in the context of depth completion when a *sparse ground truth depth map* is given, by (i) replacing the refined depths with the ground truth ones where these are available, and (ii) propagating this information to the neighboring pixels via a convolution spatial propagation operator. Our initial depth map, however, may contain significant noise and outliers, hence it cannot be employed as ground truth for depth propagation.

To address this issue, we propose to improve the DRN by introducing an IRM that seeks to minimize the difference between the initial and final depth estimates of pixels with high confidence scores. We do so by iteratively refining the joint deep feature representation of the RGB image, initial depth, and its confidence scores using a least-squares layer, analogous to the one in [24], [25]. As shown in our experiments, the proposed IRM leads to a significant improvement in accuracy as compared to simply passing the confidence score as input to a neural network. Furthermore, our approach estimates the refined depths’ uncertainty (aleatoric uncertainty model [26], [27], [28]), which is employed to fuse dense-depth estimates across a scene [12], [7] (see 3D reconstruction experiment in Sect. [IV-C]).

**III. TECHNICAL APPROACH**

We hereafter present our method for estimating the dense depth map of an image $I_1$ given $N-1$ adjacent images $I_2, I_3, \ldots, I_N$ and their corresponding relative camera poses (these need not to be precise, e.g., estimated from online visual-inertial SLAM systems). Fig. 1 depicts an overview of our pipeline. Specifically, we first employ a dense optical flow network between images $I_1$ and $I_k$, for every pixel $(*2, \ldots, N)$, and then use the resulting correspondences and the relative poses for triangulation. As a result, we obtain an initial depth map for $I_1$, as well as the triangulation’s confidence scores. To further improve the initial depth map, we employ a DRN that takes the initial depth map, the confidences scores, and image $I_1$ as input to compute the refined depth map. As mentioned earlier, in the DRN, we include an IRM which significantly increases the accuracy over iterations. Additionally, the DRN predicts the uncertainties of the refined depths. As evident in the experimental results, these are highly correlated with the actual errors and thus they can be used for measurement selection or fusion. Next, we describe each module in detail.

**A. Optical Flow and Triangulation**

For estimating optical flow, we employ the network of RAFT [16] that takes as input a source image $I_1$ and a target image $I_k$ and estimates a displacement $\Delta u_k$ for every pixel position $u_k = [x_k, y_k, 1]^T$ of $I_1$, so that $u_k = u_k + \Delta u_k$ is its corresponding pixel in $I_k$. Given a keyframe image $I_1$, for which we estimate the depth, and $N-1$ adjacent frames $I_2, \ldots, I_N$, we run the optical-flow network pairwise between

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**Fig. 1. Overview of the system. For a keyframe $I_1$, Step 1: We compute the dense optical flow between image $I_1$ and $I_k$, $k = 2, \ldots, N$. Step 2: We triangulate the initial depth map of $I_1$ and compute its confidence scores (see Sec. III-A). Step 3: The DRN (Sec. III-B) takes image $I_1$, the initial depth map, and confidence scores as input and iteratively outputs the refined depth map and its uncertainties, which features an iterative refinement module (Sec. III-B.2) in its decoder.
From these correspondences and the relative poses of frames $I_1$ and $I_k$, $k = 2, \ldots, N$, so as to find the corresponding pixel in $I_k$ for every pixel of $I_1$.

From these correspondences and the relative poses of frames $I_1$ and $I_k$, we compute the initial depth $d_i$ of each pixel in $I_1$ via triangulation. Specifically, we solve the following linear least-squares problem:

$$
\tilde{d} = \min_{d_i} \sum_k N \left\langle \left\langle k \mathbf{R}_i \mathbf{u}_i, d_i + k \mathbf{p}_1 \right\rangle \right\rangle \right\rangle^2
$$

where $k \mathbf{R}_i$, $k \mathbf{p}_1$ are the orientation and position of frame $I_1$ with respect to frame $I_k$. As mentioned earlier, this initial depth map will be further improved by the DRN using as confidence scores the square root of the Hessian (which is a scalar here) and the norm of the residual from the least squares. The former reflects the quality of triangulation, i.e., the baseline-to-depth ratio, while the latter represents the reprojection error. Optionally, we select frames $I_2 \ldots I_N$ through an adaptive policy based on minimal rotation and translation thresholds, instead of using a fixed, time based, step size; thus helps to further improve the initial depth map’s accuracy.

For training this optical flow and triangulation module, a naive way is applying an $I_1$ or $I_2$ loss on the depth computed from $I_1$. This loss, however, only imposes constraints for the optical flow along the direction affecting the depth, i.e., the epipolar line, but not the direction perpendicular to it, where the magnitude of the triangulation residual is determined. To capture the errors in all directions, we propose the following loss by substituting the ground truth depth $d_i$ of pixel $i$ to the least squares’ cost function of a function $a$ triangulation:

$$
l_o = \sum_i \left\langle \left\langle \left( k \mathbf{R}_i \mathbf{u}_i, d_i + k \mathbf{p}_1 \right) \right\rangle \right\rangle \right\rangle^2
$$

B. Depth Refinement Network (DRN)

The initial depth map and confidence scores (see Sect.III-A) are used by the DRN for further accuracy improvement. In particular, the DRN seeks to preserve the initial triangulated depths in the final estimates for pixels with high confidence scores, while inpainting the rest of the depth map using the prior learned from the training data. Previous works [21], [13] propose simply passing the initial depth map, its confidence scores, and the RGB image to an autoencoder to refine depth. As shown in Fig. 2, however, although the refined depths from an autoencoder network are overall more accurate than the triangulated depths, they are often incorrectly modified in the low-error regions. We overcome this limitation by employing the IRM described in Sect.III-B.2 (see Fig. 2). Finally, the DRN approximates each output depth pixel as an independent Laplacian random variable and the training of depth and uncertainty is performed with the aleatoric uncertainty model [27], [26]. The structure of DRN (Fig.1) comprises: (i) An Encoder Module, and (ii) An IRM. In what follows, we describe each module in details.

1) Encoder Module: The Encoder Module is an extension of the one in [6]. It computes a deep feature representation of the RGB image, the surface normal as well as the dense depth and concatenates them to generate a joint feature tensor

2) Iterative Refinement Module (IRM): The output of the depth decoder $\hat{d}$ from the initial step of DRN may contain erroneous estimates. The IRM aims to update the deep feature $h$ such that the difference between the estimated depth $d$ and the initial depth estimate $\hat{d}$ becomes smaller for pixels with high confident values $\hat{c}$. This can be formulated as a weighted least-squares problem, in which the weights $\hat{w}$ are computed from the deep feature $h$ via a weight decoder $\hat{w}$ with the learned parameters $\gamma$:

$$
\hat{C}(h) = \sum_i \hat{w}_i(d_i - \hat{d}_i)^2 = \sum_i \hat{w}_i(h; \gamma)(h; \theta) - \hat{d}_i)^2
$$

where $i$ indicates pixel position. Note that $\hat{w}_i$ contains the joint information of the confidence scores and other inputs to the DRN. We solve for $h^*$ as a minimizer of $C(h)$ using an iterative process that incrementally updates $h$:

$$
h^{(k+1)} = h^{(k)} - \nabla_h C(h^{(k)})
$$

where $\nabla_h C(h)$ is constructed using a gated recurrent unit (GRU) [29] (see also [30]). Lastly, the refined depth and its uncertainty are updated as:

$$
\hat{d}^{(k+1)} = \hat{D}(h^{(k+1)}; \theta), \hat{\sigma}^{(k+1)} = \Sigma(h^{(k+1)}; \phi)
$$

3) Note that only $h$ is updated, while $\theta$ and $\gamma$ are fixed during this process.
Fig. 3. An update block inside the IRM of Fig. 1. It takes as input \(x^{(k)}\) comprising the feature \(h^{(k)}\), estimated depth \(\hat{d}^{(k)}\) at iteration \(k\), and the optical-flow-based depth \(\hat{d}^{\star}\) along with its confidence \(\bar{c}\), and outputs the updated feature \(h^{(k+1)}\) and the updated estimated depth \(\hat{d}^{(k+1)}\) and its confidence \(\bar{c}^{(k+1)}\).

Table I summarizes the quantitative evaluation results of our proposed method and other state-of-the-art algorithms on the ScanNet test set. As evident, \(Ours\) (fixed) outperforms all alternative approaches with a clear margin in all evaluation metrics. Moreover, we further improve the performance by employing the adaptive frame selection policy [\(Ours\) (adaptive)], featuring an overall \(\approx20\%\) decrease in RMSE as compared to DeepV2D and Flow2Depth.

During training, we execute the above optimization with a fixed number of \(K\) iterations. We employ the negative log-likelihood loss on the estimated depths with Laplacian damping factor. In our experiments, \(K = 5\) and \(\lambda = 0.83\).
third) image, while Our (adaptive) employs five images with adaptive policy. Table II shows that Our (fixed) outperforms DeepV2D [11] in all metrics and DDE-VISLAM [6] in RMSE, 1.05, and 1.10. Moreover, the adaptive frame selection policy employed by Our (adaptive) further improves the results and achieves the best accuracy in all metrics. Fig. 4 (bottom two rows) depicts the qualitative results of our method on Azure Kinect dataset.

Table II

| Method       | RMSE ↓ | 1.05  | 1.10  | 1.25  |
|--------------|--------|-------|-------|-------|
| DDE-VISLAM [6] | 0.299  | 28.75 | 50.46 | 86.67 |
| DeepV2D [11]  | 0.321  | 33.62 | 54.65 | 83.46 |
| Ours (fixed)   | 0.287  | 33.72 | 56.68 | 85.49 |
| Ours (adaptive)| 0.265  | 35.97 | 58.86 | 87.35 |

C. Uncertainty Estimation

To verify the correlation between the predicted uncertainty estimates and the actual errors, we compare the depth error statistics when excluding points whose uncertainty estimates are larger than certain thresholds as shown in Table III [using results of Our (adaptive)]. Decreasing the value of the acceptable predicted uncertainty \( \delta \) results in more accurate depth estimates at a small loss of image coverage. For example, we retain 90% of the depth values and reduce the RMSE by \( \sim 20\% \) when excluding points with uncertainty above 0.1. Additionally, the impact of the uncertainty-based masking of the predicted depth images on scene reconstruction (from ScanNet dataset) is depicted in Fig. 5, where the depth RMSE was reduced by more than x1.4 (x3.1) for the scenes in the top (bottom) row, while only removing 20% of the total depth estimates. Hence, we demonstrated quantitatively and qualitatively that the uncertainty-based depth masking improves reconstruction accuracy.

D. Ablation Study

In this section, we analyze each component of our pipeline that contributes to the overall performance gain (19% in RMSE as compared to other state-of-the-art methods).

Sparse vs. Dense: In the proposed method, a dense initial depth map is provided to the DRN, instead of a sparse one as in depth-completion approaches. In order to study the effect of the initial depth map’s density, we compare our DRN, without the IRM in its decoder [Ours (w/o IRM)] (see Sect. III-B), to the DDE-VISLAM [6], a depth completion network that takes sparse depth as input. Specifically, we randomly sample a fixed number of sparse points (e.g., 10, 100, 200 in Table IV) from the initial triangulated depth map that have high confidence scores (see Sect. III-A). These sampled depths are added to the sparse depth input of the DDE-VISLAM. In Table IV, we show that providing the dense depth estimates together with confidence scores contributes \( \sim 14.5\% \) in RMSE improvement as compared to the depth completion (DDE-VISLAM+200) and state-of-the-art approaches. These results confirm our hypothesis that employing a dense initial depth map results in improved accuracy as compared to a sparse one.

Note that DDE-VISLAM+200 performs comparable to the state-of-the-art methods DeepV2D and Flow2Depth in RMSE.
Fig. 5. 3D scene reconstructions using the ground-truth, predicted, and masked depths.

TABLE IV
DEPTH ACCURACY WITH SPARSE AND DENSE INPUT

| Method                  | Dense | RMSE $\downarrow$ | $E(d, \delta)$ $\downarrow$ |
|-------------------------|-------|-------------------|-----------------------------|
|                         |       | 1.05  | 1.10  | 1.25  |
| DDE-VISLAM              | $\times$ | 0.300 | 30.92 | 52.82 | 80.22 |
| DDE-VISLAM + 10         | $\times$ | 0.218 | 45.92 | 70.92 | 92.21 |
| DDE-VISLAM + 100        | $\times$ | 0.201 | 51.23 | 75.72 | 93.76 |
| DDE-VISLAM + 200        | $\times$ | 0.200 | 51.43 | 75.91 | 93.79 |
| Ours (w/o IRM)          | $\checkmark$ | 0.171 | 59.25 | 82.32 | 96.16 |

Iterative vs. Non-iterative: To demonstrate the effectiveness of the proposed IRM (Sect. III-B.2), we compare our DRN with and without it, denoted as Ours (w/ IRM), and Ours (w/o IRM), respectively. During training, we use five iterations, while at inference time, we use seven iterations. Table V shows that the IRM contributes an additional 4.5% improvement in RMSE. Furthermore, we observe that there is little improvement after seven iterations, hence we limit the refinement steps during inference accordingly.

TABLE V
DEPTH ACCURACY WITH IRM

| Method                  | Iterations | RMSE $\downarrow$ | $E(d, \delta)$ $\downarrow$ |
|-------------------------|------------|-------------------|-----------------------------|
|                         |            | 1.05  | 1.10  | 1.25  |
| Ours (w/o IRM)          | 0          | 0.171 | 59.25 | 82.32 | 96.16 |
|                         | 1          | 0.166 | 61.60 | 83.60 | 96.35 |
|                         | 3          | 0.163 | 62.47 | 84.20 | 96.72 |
|                         | 5          | 0.162 | 62.59 | 84.33 | 96.76 |
|                         | 7          | 0.162 | 62.63 | 84.34 | 96.77 |
|                         | 9          | 0.162 | 62.64 | 84.35 | 96.78 |

Importance of the triangulation confidence scores: To assess the significance of the initial depths’ confidence scores (Sec. III-A), we train our proposed DRN with the IRM as previously described, with four different input options: (i) The triangulated depth map ($d$); (ii) The triangulated depth map and the residual as confidence score ($d, \tilde{c}_r$); (iii) The triangulated depth map and the square root of the Hessian as confidence score ($d, \tilde{c}_h$); (iv) The triangulated depth map and both confidence scores ($d, \tilde{c}$), $\tilde{c} = \{\tilde{c}_r, \tilde{c}_h\}$. From Table VI, we observe that using both confidence scores yields the best result with less than 0.02% increase in parameters [see Param.s column in (M) millions].

V. CONCLUSIONS AND FUTURE WORK

In this paper, we introduced a multi-view depth estimation approach that computes the dense depths as well as their uncertainty for an image. Specifically, pixels tracked by dense optical flow are triangulated and provided to our proposed depth refinement network (DRN) to further improve depth accuracy. To do so, the DRN first extracts deep features from the inputs and then performs a neural least-squares optimization within its iterative refinement module. In addition to the depth estimates, their corresponding uncertainty is predicted which is shown experimentally to be highly correlated to the actual errors. In our future work, we will employ the uncertainty for measurement selection on global 3D scene reconstruction.
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