Adaptive confidence thresholding for monocular depth estimation

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Abstract

Self-supervised monocular depth estimation has become an appealing solution to the lack of ground truth labels, but its reconstruction loss often produces over-smoothed results across object boundaries and is incapable of handling occlusion explicitly. In this paper, we propose a new approach to leverage pseudo ground truth depth maps of stereo images generated from self-supervised stereo matching methods. The confidence map of the pseudo ground truth depth map is estimated to mitigate performance degeneration by inaccurate pseudo depth maps. To cope with the prediction error of the confidence map itself, we also leverage the threshold network that learns the threshold dynamically conditioned on the pseudo depth maps. The pseudo depth labels filtered out by the thresholded confidence map are used to supervise the monocular depth network. Furthermore, we propose the probabilistic framework that refines the monocular depth map with the help of its uncertainty map through the pixel-adaptive convolution (PAC) layer. Experimental results demonstrate superior performance to state-of-the-art monocular depth estimation methods. Lastly, we exhibit that the proposed threshold learning can also be used to improve the performance of existing confidence estimation approaches.

1. Introduction

Monocular depth estimation, which predicts a dense depth map from a single image, plays an important role in various fields such as scene understanding and autonomous driving. Early works [7, 30, 3] are based on supervised learning in which the performance depends on a huge amount of training data with ground truth labels. Since establishing such a large-scale training data is very costly and labour-intensive, recent approaches rely on the self-supervised learning regime [10, 12, 31, 13, 35]. Instead of using ground truth labels for training the network, they attempt to leverage the self-supervision from a pair of stereo images or monocular video sequences, under the assumption that the geometric structure of a scene can be encoded with the reconstruction loss based on pixel-wise intensity similarities [10]. This loss function seems to be an appealing alternative to the lack of large-scale ground truth labels, but it often leads to blurry results around depth boundaries and does not consider occluded pixels [12].

Instead of relying on the self-supervised reconstruction loss across stereo images, Cho et al. [5] attempted to train the monocular depth estimation network through pseudo depth labels of the stereo images generated from pre-trained stereo matching network [33]. To mitigate performance degeneration by inaccurate pseudo depth labels, they leverage stereo confidence maps (∈ [0, 1]) indicating the reliability of the pseudo depth labels. The confidence map is truncated with a threshold [5, 45] so that depth values with low confidence are excluded. However, a fixed threshold for all training dataset still has the risk of inaccurate pseudo depth values being used in the network training [5]. The method of [45] attempted to address this issue by learning the threshold with an additional regularization term, but the performance gain is rather limited due to its hard thresholding and the implicit constraint by the regularization term.

To overcome this limitation, we propose a novel architecture that adaptively learns the threshold dynamically conditioned on the pseudo depth map. For a given inaccurate pseudo depth map, the stereo confidence map and its associated threshold are inferred in an end-to-end manner. The confidence map is then thresholded through a differential soft-thresholding operator controlled by the learned threshold. The proposed threshold learning is capable of dealing with the prediction errors of the confidence map more effectively. Note that we leverage the soft-thresholding operator to make the network differentiable. The thresholded confidence map is then used together with
the pseudo depth labels for training the monocular depth estimation network. Additionally, we propose to enhance the monocular depth map in a probabilistic inference framework. Unreliable parts of the monocular depth map are identified using the uncertainty map, and these are refined through the pixel-adaptive convolution (PAC) layer [44]. Experimental results validate that the monocular depth accuracy is significantly improved by leveraging the proposed threshold learning and probabilistic depth refinement modules.

Interestingly, the threshold learning can also be beneficial to improve the performance of existing stereo confidence estimation approaches [37, 24]. The confidence map obtained from the existing approaches [37, 24] is refined through the soft-thresholding function controlled by the learned threshold. As shown in Fig. 2, the soft-thresholding function attenuates low confidence values that are less than the learned threshold \( \tau \) to become as close as 0 while amplifying high confidence values to converge to 1. We validate through experiments that this process improves the prediction accuracy of the existing confidence estimation approaches. To sum up, our contributions are as follows.

• We propose a novel framework of monocular depth estimation using pseudo depth labels generated from self-supervised stereo matching methods.

• We introduce the threshold network that adaptively learns the threshold of the confidence map for better predicting the reliability of the inaccurate pseudo depth labels.

• The monocular depth map is further refined through the probabilistic refinement module based on the PAC layer.

• It is shown that the threshold network can also be used to enhance the prediction accuracy of existing confidence estimation approaches.

2. Related Work

Monocular depth estimation. Eigen et al. [7] initiated the monocular depth estimation through deep network that regresses a depth map with ground-truth depth information, inspiring numerous approaches based on multi-scale images [30], up-projection technique [28], motion parallax [49], ordinal regression [8], and semantic divide-and-conquer [50]. Despite remarkable performance over classical handcrafted approaches, they rely on abundant and high-quality ground-truth depth maps, which is costly to obtain.

To overcome this limitation, self-supervised learning has been introduced by leveraging other forms of supervision from stereo images and video sequences instead of ground truth depth maps. Garg et al. [10] used the stereo photometric reprojection. Godard et al. [12] further used the left-right consistency between stereo images. Zhou et al. [55] proposed to leverage multi-view synthesis procedure, and this idea was extended using the feature-based warping loss in [54]. To take advantages of both supervised and self-supervised learning methods, semi-supervised learning methods have also been presented. Kuznietsov et al. [27] directly combined supervised and unsupervised loss terms. Ji et al. [21] utilizes an image-depth pair discriminator with a small amount of labeled dataset, alleviating the reliance on supervision. Recently, Gonzalebello et al. [14] proposed mirrored exponential disparity (MED) probability volumes to handle occluded areas.

The most related to our work is the methods of Guo et al. [17], Cho et al. [5], and Tonioni et al. [45] in which a stereo matching knowledge is distilled to train a monocular depth network. Since the disparity map estimated by stereo matching inherently contain unreliable ones, they used stereo confidence to build a pseudo-ground-truth disparity map by thresholding the confidence. Guo et al. [17] used a handcrafted occlusion map sensitive to outliers. Cho et al. [5] used a fixed threshold empirically, but it is ineffective to use the same threshold for all images. Unlike this, Tonioni et al. [45] tried to learn the threshold by using an additional regularization term that allows it to be between 0 and 1, but it is also difficult to learn the appropriate threshold with the implicit constraint by the regularization term. In our method, effective threshold learning is the main contribution.

Stereo confidence estimation. In parallel with the development of predicting depth from images, stereo confidence estimation has also been actively studied. Machine learning approaches [34, 43, 25] relying on shallow classifier, e.g., random tree [1], enable one to classify correct and incorrect pixels. Recently, deep convolutional neural network (CNN)-based approaches have become a mainstream. Various methods have been proposed that use the single- or bi-modal input, e.g., disparity [37], left and right disparities [40], 3D matching cost [41], 3D matching cost and disparity [26], and disparity and color image [48, 9]. Kim et al. [24] proposed to make full use of the tri-modal input in conjunction with locally adaptive attention and scale networks, achieving state-of-the-art prediction accuracy. All of these techniques require ground truth depth maps and have been used to refine a depth (or disparity) map with a fixed threshold which is set empirically. Poggi et al. [36] introduced a method for learning self-supervised confidence measure with various criterions.

3. Proposed Method

Unlike recent self-supervised monocular depth estimation approaches [10, 12, 31, 13, 55], we leverage the pseudo
The proposed architecture consisting of ThresNet, DepthNet, and RefineNet. Given a pair of stereo images, the pseudo ground truth depth map $d^{pnt}$ is precomputed using a self-supervised stereo matching network. The proposed model training begins with $d^{pnt}$ by computing its confidence map $c$ and the threshold $\tau$ through the ThresNet. The thresholded confidence map $c^T$ is obtained using the soft-thresholding function. The DepthNet that infers the monocular depth map $d$ and uncertainty map $\sigma$ is trained by minimizing an objective defined using $d^{pnt}$ filtered out by $c^T$. The monocular depth map $d$ is finally refined through the probabilistic refinement module based on the pixel-adaptive convolution (PAC) layer in the RefineNet.

3.1. Network Architecture

3.1.1 ThresNet

The ThresNet predicts the confidence map of the inaccurate pseudo depth label and its threshold in an adaptive manner and then generates the thresholded confidence map via the soft-thresholding function. For the confidence estimation network $M_C$, we adopted the CCNN [37] thanks to its simplicity, but more sophisticated models [37, 24, 48] can also be utilized as a backbone. The threshold network $M_T$ consists of four convolutional layers, followed by global average pooling and $1 \times 1$ convolution.

The estimated confidence map $c$ is modulated by the threshold $\tau$, such that a depth value with a higher confidence value than a specific $\tau$ value assumes to be trustworthy. A key issue is how to set accordingly $\tau$ which needs to vary depending on images. This threshold $\tau$ should be set low in the image where depth inference is easy while being set high in the opposite case (see Fig. 3). We approximate the thresholding operation with a smooth, differentiable function. The thresholded confidence map $c^T$ is computed using the differentiable soft-thresholding function as follows:

$$c^T_p(\tau) = \frac{1}{1 + e^{-\varepsilon(c_p - \tau)}}$$

where $p$ represents a pixel. The slope of the thresholded confidence map $c^T$ is adjusted by a hyperparameter $\varepsilon$, which is a positive constant. Too large $\varepsilon$ changes the soft-thresholding function too rapidly (e.g., $\varepsilon = 90$), often making it non-differentiable. We set $\varepsilon = 10$ in experiments. The pixel-varying confidence map is transformed with the per-image threshold $\tau$. We also investigated a pixel-varying threshold map $\tau_p$, but its performance gain was negligible.

Fig. 2 compares the confidence thresholding functions. In Fig. 2 (a), the confidence threshold $\tau$ is fixed with a predefined value for all training images without considering image characteristics, often causing inaccurate pseudo depth values to be used during training. In Fig. 2 (b), it is learned using an additional regularization term [45], but its performance gain on the monocular depth estimation is rather limited, as reported in the original paper [45]. The proposed differential soft-thresholding function, controlled by the threshold $\tau$ dynamically conditioned on the pseudo depth map, leads to superior performance on the monocular depth estimation, when the threshold loss $L_T$ is used...
3.2. Loss Functions

3.2.1 Thresholding loss

The ThresNet with confidence and threshold networks can be trained in a supervised manner [37] or a self-supervised manner [36]. For the supervised training, we propose to use the sparse ground truth depth data provided by public benchmarks. For instance, we can leverage extremely sparse LiDAR depth maps of 3% density provided with a set of stereo image pairs in the KITTI dataset. The ground truth of the thresholded confidence map is generated using the sparse ground truth depth data like existing confidence estimation approaches [24] and this is used to train the ThresNet using a cross-entropy loss $L_T$. More details on the ground truth confidence map are provided in the supplementary material. Alternatively, the ThresNet can be trained in the self-supervised manner without using the LiDAR depth maps. Following [36], we generate the pseudo ground truth of the thresholded confidence map according to various criterions (e.g., reprojection error, disparity agreement). The loss $L_T$ for the self-supervised training is defined as a multi-modal binary cross entropy loss of [36]. In Table 1, we compare the monocular depth accuracy when using the supervised and self-supervised ThresNets, and found the accuracy is almost similar.

In [45], the threshold is also learned to exclude depth values with low confidences when training their network. It was reported that when using the depth regression loss only, the threshold $\tau$ would converge to 1 for masking out all pixels [45]. Thus, they propose to include an additional regularization loss, $-\log(1 - \tau)$, that prevents the threshold $\tau$ from approaching 1. Though this term allows $\tau$ to be between 0 and 1, it does not guarantee to yield accurate prediction results of the threshold $\tau$. Contrastingly, our method attempts to learn the threshold $\tau$ with the soft-thresholding function and the explicit supervision. We will verify the effectiveness of our threshold learning approach in the ablation study of Table 4.

3.2.2 Depth regression loss

A monocular depth map from the DepthNet is leveraged to compute a confidence-guided depth regression loss $L_D$.
assisted by the thresholded confidence map $c^T$ as follows:

$$L_D = \frac{1}{Z} \sum_{p \in \Omega} c^T_p(\tau) \cdot |d_p - d_{pgt}|,$$

(3)

where $d$ and $d_{pgt}$ indicate the predicted depth map and pseudo ground truth depth map, respectively. $\Omega$ represents a set of all pixels. The loss $L_D$ is normalized with $Z = \sum c^T_p(\tau)$.

Additionally, we leverage the negative log-likelihood minimization to infer the uncertainty of the network output. The predictive distribution of the network output $d$ can be modelled as the Laplacian likelihood [23, 20, 22] as follows:

$$L_U = \frac{1}{|\Omega|} \sum_{p \in \Omega} \left( \frac{|d_p - d_{pgt}|}{\sigma_p} + \log \sigma_p \right),$$

(4)

where the variance $\sigma$ represents the uncertainty map of the predicted depth map. The logarithmic term $\log \sigma$ prevents $\sigma$ from approaching to infinity [23]. We combine two losses $L_D$, taking into account the reliability of the pseudo ground truth depth map $d_{pgt}$, and $L_U$ predicting the uncertainty of the predicted depth map $d$, such that

$$L = L_D + \lambda L_U,$$

(5)

where $\lambda$ represents hyperparameter that balances two losses which is experimentally determined to $10^{-3}$. This enables for modeling the uncertainty of the monocular depth estimation network while considering the confidence of the pseudo depth label. As shown in Fig. 1, the DepthNet that infers both the monocular depth map and uncertainty map is trained with $L$ in (5), while the RefineNet leverages $L_D$ in (3) as it predicts the final monocular depth map only.

### 3.3. Training Details

In our work, the DepthNet and RefineNet are trained simultaneously by minimizing $L$ and $L_D$, while the ThresNet consisting of confidence and threshold networks is trained solely by minimizing $L_T$, similar to existing confidence estimation approaches [37, 34, 43, 24]. Though the whole networks can be trained end-to-end, we found through experiments that the performance gain over the separate training is relatively marginal.

It has been reported in literature [37, 48] that the confidence network trained with one dataset exhibits a good generalization capability for another dataset. In a similar context, our confidence and threshold networks trained with the KITTI dataset show satisfactory generalization capability for different datasets. Taking these into account, we transfer the knowledge learned from one dataset to another. To be specific, when only stereo image pairs are available for training (e.g. Cityscape dataset), the DepthNet and RefineNet are trained via the minimization of $L$ and $L_D$, with the ThresNet being frozen with the parameters trained with the KITTI dataset. As shown in Fig. 3, the ThresNet trained with the KITTI dataset produces appropriate thresholds for both the KITTI and Cityscape datasets.

### 4. Extension to Confidence Estimation

The soft-thresholding attenuates low confidence values that are less than $\tau$ to become as close as 0 while amplifying high confidence values to converge to 1. It reduces the number of ambiguous pixels to determine the reliability, for which a confidence value is far from 0 or 1. We discuss how the soft-thresholding based on the threshold network can improve the prediction accuracy of existing confidence estimation approaches [37, 24]. In the ThresNet of Fig. 1, the confidence network can be replaced with the existing confidence estimation approaches. One difference is that the loss $L_T$ (cross-entropy loss) is measured on the disparity domain, considering that the existing confidence estimation approaches are trained on the disparity domain. This formulation is model-agnostic, and any kind of existing confidence estimation approaches can be used in a plug-and-play fashion.

### 5. Experimental results

#### 5.1. Implementation details

The proposed method was implemented in PyTorch framework and run Titan RTX GPU. We trained the whole networks on the learning rate of $10^{-4}$ and batches of 32 images resized to $192 \times 480$ for 30 epochs. We trained the proposed monocular depth estimation network consisting of DepthNet and RefineNet on the standard 20k stereo images provided in the KITTI dataset. We evaluate our methods on following five metrics ‘RMSE’, ‘RMSE log’, ‘Abs Rel’, ‘Sq. Rel’, and ‘Accuracy’, proposed in Eigen et al. [7].

#### 5.2. Evaluation on monocular depth estimation

**5.2.1 KITTI**

In Table 1, we evaluated the monocular depth estimation performance quantitatively on the KITTI Eigen Split [7] dataset with setting maximum depth to 80 meters with Gargs crop [10]. A comprehensive evaluation was conducted with Monodepth [12], Uncertainty [35], MonoResMatch [47], Monodepth2 [13], DepthHint [51], PackNet-SMF [16], and Insta-DM [29]. For the training data, ‘S’ indicates using stereo images for self-supervised monocular depth estimation. ‘M’ represents a monocular video sequence. The evaluation of the proposed method is twofold; ‘Ours (D)’ trained with only the DepthNet using $L_D$ in (3) without refining the depth map, and ‘Ours (D+R)’ trained with the DepthNet and RefineNet.
Table 1. Quantitative evaluation for depth estimation with existing methods on KITTI Eigen Split [7] dataset. Numbers in bold and underlined represent 1st and 2nd ranking, respectively. ‘Ours†’ is obtained using the self-supervised ThresNet [36], while ‘Ours’ indicates the results obtained using the supervised ThresNet.

| Method                  | Data | #p  | time  | Abs Rel | Sqr Rel | RMSE  | RMSE log | \( \delta < 1.25 \) | \( \delta < 1.25^2 \) | \( \delta < 1.25^3 \) |
|------------------------|------|-----|-------|---------|---------|-------|----------|---------------------|---------------------|---------------------|
| Monodepth [12]         | S    | 56M | 9.4ms | 0.138   | 1.186   | 5.650 | 0.234    | 0.813               | 0.930               | 0.969               |
| Monodepth2 [13]        | S    | 14M | 2.9ms | 0.108   | 0.842   | 4.891 | 0.207    | 0.866               | 0.949               | 0.976               |
| Uncertainty [35]       | S    | 14M | 3.6ms | 0.107   | 0.811   | 4.796 | 0.200    | 0.866               | 0.952               | 0.978               |
| MonoResMatch [47]      | S    | 41M | 8.3ms | 0.111   | 0.867   | 4.714 | 0.199    | 0.864               | 0.954               | 0.979               |
| DepthHint [51]         | S    | 33M | 6.6ms | 0.102   | 0.762   | 4.602 | 0.189    | 0.880               | 0.960               | 0.981               |
| PackNet-SfM [16]       | M    | 122M| 9.5ms | 0.111   | 0.785   | 4.601 | 0.189    | 0.878               | 0.960               | **0.982**           |
| Insta-DM [29]          | M    | 14M | 3.0ms | 0.112   | 0.777   | 4.772 | 0.191    | 0.872               | 0.959               | **0.982**           |
| Ours (D)               | S    | 28M | 6.8ms | 0.099   | 0.652   | 4.266 | 0.187    | 0.883               | 0.960               | 0.981               |
| Ours (D+R)             | S    | 42M | 8.2ms | **0.096**| **0.627**| **4.201**| 0.186    | **0.885**           | **0.961**           | **0.982**           |
| Ours† (D)              | S    | 28M | 6.8ms | 0.100   | 0.644   | 4.251 | 0.187    | 0.882               | 0.960               | 0.981               |
| Ours† (D+R)            | S    | 42M | 8.2ms | 0.098   | 0.621   | 4.215 | 0.185    | **0.885**           | **0.961**           | **0.982**           |

As reported in Table 1, although ‘Ours (D)’ leverages a rather simple encoder-decoder architecture, it achieves the superior performance over existing methods, demonstrating the effectiveness of the proposed threshold learning approach. In ‘Ours (D+R)’, the monocular depth accuracy was further improved by making use of the probabilistic refinement module based on the uncertainty map and the PAC layer in the RefineNet. We also evaluated the number of parameters used and an inference time, noted as ‘#p’ and ‘time’, respectively. Our method uses relatively smaller or similar number of parameters compared to other methods. ‘Ours†’ is obtained using the self-supervised ThresNet [36], while ‘Ours’ indicates the results obtained using the supervised ThresNet. We found that their monocular depth accuracy is almost similar. The following results including ablation study were conducted with the supervised ThresNet. Fig. 4 shows the qualitative comparison with existing methods on the KITTI Eigen Split [7] dataset. It was shown that the proposed method recovers complete instances better while preserving fine object boundaries.

5.3. Cityscapes

We also evaluated the performance of the proposed method on the Cityscapes dataset. The Cityscapes dataset provides only stereo images without the ground truth, and thus the ThresNet trained with the KITTI dataset was used to infer the threshold. Table 2 shows the quantitative evaluation on Cityscapes dataset [6] with the DepthNet and RefineNet fine-tuned on the Cityscapes dataset, while the ThresNet is frozen. We compared our results with Monodepth2 [13], DepthHint [51] and PackNet-SfM [16]. We set maximum depth to 80 meters with the per-image median scaling approach [55]. We used the SGM depth [18] as ground truth for the evaluation. The outstanding performance of our method supports the claim that the ThresNet trained with the KITTI dataset shows a satisfactory generalization capability for different datasets.

5.4. Evaluation on uncertainty estimation

To evaluate the performance of the uncertainty measure, we use sparsification plots used in [20]. ‘AUSE’ denotes the Area Under the Sparsification Error which quantifies how...
Table 2. Quantitative evaluation for monocular depth estimation results on Cityscapes validation dataset with fine-tuning on Cityscapes training dataset. Numbers in bold and underlined represent 1st and 2nd ranking, respectively.

| Method         | Data | Abs Rel | Sq rel | RMSE | RMSE log | δ < 1.25 | δ < 1.25^2 | δ < 1.25^3 |
|----------------|------|---------|--------|------|----------|----------|------------|------------|
| Monodepth2 [13]| S    | 0.124   | 1.287  | 7.293| 0.223    | 0.785    | 0.947      | 0.981      |
| Struct2Depth [4]| M    | 0.145   | 1.737  | 7.280| 0.205    | 0.813    | 0.942      | 0.978      |
| DepthHint [51] | S    | 0.128   | 1.268  | 7.156| 0.218    | 0.812    | 0.949      | 0.982      |
| Gordon [15]    | M    | 0.127   | 1.330  | 6.960| 0.195    | 0.830    | 0.947      | 0.981      |
| Ours (D)       | S    | 0.123   | 1.141  | 6.735| 0.204    | 0.844    | 0.962      | 0.985      |
| Ours (D+R)     | S    | 0.115   | 1.125  | 6.584| 0.195    | 0.857    | 0.963      | 0.986      |

Figure 5. Qualitative evaluation for depth estimation with existing methods on Cityscapes validation dataset: (a) Input image, (b) Monodepth [12], (c) MonoResMatch [47], (d) DepthHint [51], (e) PackNet-SfM [16] (f) Ours (D+R).

5.5. Ablation study

Threshold learning In Table 4, we conducted the ablation study to validate the performance improvement by the proposed threshold learning over existing thresholding approaches [5, 45]. For a fair comparison, we obtained the results using the monocular depth network trained with only the DepthNet (without the uncertainty decoder), when varying thresholding functions. ‘Baseline’ represents the results obtained using the confidence map without thresholding. The results of [5] were obtained using the hard thresholding of Fig. 2 (a) with τ = 0.3, following the setup of [5]. The performance of [5, 45] was almost similar, though the method in [45] learned the threshold τ with the thresholding function of Fig. 2 (b). We found that the regularization loss $-\log(1 - \tau)$ [45], used to prevent the threshold τ from approaching 1, does not generate a meaningful variant for the learned threshold due to the lack of explicit supervision for the threshold learning. ‘Tonioni et al. [45] $+ L_T$’ were obtained using the thresholding function of Fig. 2 (b) and our loss $L_T$. The performance gain over ‘Tonioni et al. [45]’ demonstrates the effectiveness of $L_T$. ‘Ours (D)’ achieves a substantial performance gain, demonstrating the effectiveness of the proposed threshold learning with $L_T$.

Adaptability We also validated the effectiveness of our method when applied to different network architectures, e.g., PackNet [16]. Table 5 shows quantitative evaluation results when using our confidence threshold learning and probabilistic refinement on the PackNet architecture. ‘PackNet (D)’ represents the results obtained using the DepthNet only, whereas ‘PackNet (D+R)’ is the results using both DepthNet and RefineNet. We observed that our framework also improves the monocular depth accuracy for the PackNet architecture.

Uncertainty To evaluate the importance of using the estimated uncertainty in the RefineNet, we compared the results obtained using the proposed depth refinement of (2) and the simple depth refinement ($d' = d + d'$) without σ in Table 6, demonstrating the effectiveness of the depth refinement based on the uncertainty map.

Pseudo ground truth depth labels So far, all experiments were conducted with the self-supervised pseudo depth maps obtained using [52]. To validate the adaptability of our framework with respect to the pseudo depth labels, we performed additional experiments with the pseudo ground truth depth maps generated by [46], which are trained with synthetic data and fine-tuned with an self-supervised recon-

Table 3. Quantitative evaluation for uncertainty estimation with the state-of-the-art method on KITTI Eigen Split [7] dataset. Numbers in bold indicate the better performance.

| Method         | RMSE | δ ≥ 1.25 |
|----------------|------|----------|
| Uncertainty [35]| 0.022| 0.036    |
| Ours           | 0.021| 0.048    |

Table 4. Quantitative evaluation for uncertainty estimation with the state-of-the-art method on KITTI Eigen Split [7] dataset. Numbers in bold indicate the better performance.

| Method         | RMSE | δ ≥ 1.25 |
|----------------|------|----------|
| Uncertainty [35]| 0.022| 0.036    |
| Ours           | 0.021| 0.048    |
We validated the effectiveness of the proposed threshold learning in terms of confidence prediction accuracy by applying it to two confidence estimation approaches, CCNN [37] and LAFNet [24]. We trained the two confidence estimation methods with 20 out of 194 images provided in the KITTI 2012 training dataset [11]. Note that the confidence estimation approaches [37, 24] are evaluated by training them in a supervised manner. The area under the curve (AUC) [19], which is a common metric for confidence estimation approaches, was used for an objective evaluation. Refer to the supplementary material for details on measuring AUC and optimal AUC and more results. Following confidence estimation literatures, input disparity maps used for predicting the confidence maps were obtained using two popular stereo algorithms, ‘Census-SGM’ [18] and ‘MC-CNN’ [53].

Table 8 shows objective evaluation results for 200 images of KITTI 2015 dataset [32] and 15 images of Middlebury v3 dataset [39]. "w/τ" denotes our results using the soft-thresholding technique. LAFNet* denotes the LAFNet [24] in which 3D cost volume is not used as an input. Our approach consistently outperforms the original confidence estimation methods, demonstrating the effectiveness of the proposed threshold learning. Fig. 6 compares the confidence maps visually. While the original confidence maps contain ambiguous values for which it is difficult to determine whether the depth label is correct, our thresholded confidence map yields more distinct values that are close to 0 or 1. Such a binarization enables the estimated confidence to have similar distribution to ground truth confidence, thus improving a discriminative power.

6. Conclusion

In this work, we have proposed a novel framework for monocular depth estimation based on pseudo depth labels generated by self-supervised stereo matching methods. The confidence map is used to exclude erroneous depth values within the pseudo depth labels. The prediction errors in the confidence map are further suppressed by making use of the soft-thresholding based on threshold learning. Furthermore, the probabilistic refinement module enables improving the monocular depth accuracy with the help of the uncertainty map. The proposed framework has shown impressive performances over state-of-the-arts on several popular datasets. It was also shown that threshold learning can also boost the prediction accuracy of existing confidence approaches.
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Adaptive confidence thresholding for monocular depth estimation
- Supplementary material

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In this document, we provide more comprehensive results not provided in the original manuscript due to the page limit as below. The code to reproduce our results will be publicly available soon. Note that all experiments were conducted with the supervised ThresNet.

• Histogram of the learned threshold $\tau$ and qualitative evaluation of depth results computed using different thresholding methods (Section 1)
• Qualitative evaluation for monocular depth estimation with state-of-the-arts on KITTI and Cityscapes datasets (Section 2.2 and 2.3)
• Quantitative evaluation for monocular depth estimation on Cityscape dataset without fine-tuning (Section 2.4)
• Quantitative evaluation for monocular depth estimation using improved ground truth depth maps [22] on KITTI dataset (Section 2.5)
• Performance analysis according to a hyperparameter $\varepsilon$ used in the soft-thresholding function (Section 2.6)
• Quantitative evaluation of the proposed method according to the use of DepthNet and RefineNet (Section 2.7)
• Ground truth confidence map and evaluation metric used in the confidence estimation (Section 3.1 and 3.2)
• Qualitative result for confidence estimation with state-of-the-arts on KITTI dataset (Section 3.3)
• Evaluation metric used in the uncertainty estimation (Section 4.1)
• Qualitative result for uncertainty maps on KITTI dataset (Section 4.2)

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Figure 4. Qualitative evaluation with existing monocular depth estimation methods on the Eigen split [3] of KITTI dataset: (a) input image, (b) Kuznietsov et al. [13], (c) Monodepth [5], (d) Monodepth2 [5], (e) DepthHint [24], and (f) Ours (D+R) in the submitted manuscript. Compared to other results, our method predicts instances very well without holes or distortions while recovering fine object boundaries. Additionally, our method is capable of predicting thin instances precisely.

Cho et al. [1] fixed the threshold to 0.3 for all training images. Tonioni et al. [20] attempted to learn the threshold adaptively for each image by applying the regularization loss $-\log(1 - \tau)$, but it simply prevents $\tau$ values from converging to 0 or 1 and does not take into account image characteristics that enable $\tau$ to be learned adaptively. As shown in Fig. 2 (b), $\tau$ values predicted by [20] are concentrated around specific values (0.1) with very small variance, meaning that almost similar threshold $\tau$ is used for all training images. This is the reason why the performance gain of Tonioni et al. [20] over Cho et al. [1] is relatively marginal, as reported in Tab. 4 of the original manuscript. Contrarily, our method learns image-adaptive $\tau$ values as plotted in Fig. 2 (c). Fig. 3 of the original manuscript also reports that the proposed method learned the threshold $\tau$ accordingly. The threshold $\tau$ was set low in the images where depth inference is easy, while being set high in the opposite case including saturation, low-light, and textureless region.

Fig. 3 shows the examples of gradually improved depth results according to different thresholding methods. The proposed method yields qualitatively better results, where complete instances are recovered and fine object boundaries are well preserved, than other hard thresholding methods. Also, in Tab. 4 of the original manuscript, it can be seen that the proposed method outperforms the two methods quanti-
Figure 5. Qualitative evaluation for depth estimation with existing methods on Cityscapes validation dataset: (a) input image, (b) [5], (c) [21], (d) [24] and (e) Ours (D+R) of the original manuscript. Similar to KITTI results, our method is remarkable at predicting fine details with no distortions at all instances and recovering thin objects that appear frequently in the Cityscapes dataset, whereas other methods often fail to predict accurate depth values at these regions.

2. Monocular depth estimation results

This section provides more results for comparative study with state-of-the-art methods in terms of monocular depth accuracy.

2.1. Evaluation metrics

In order to evaluate the depth estimation performance, same as the original manuscript, five commonly-used evaluation metrics proposed in [3] were adopted as follows:

- \( \text{Abs Rel} = \frac{1}{|\Omega|} \sum_{p \in \Omega} \frac{|d_p - d_{gt}^p|}{d_{gt}^p} \)
- \( \text{Sq Rel} = \frac{1}{|\Omega|} \sum_{p \in \Omega} \frac{(d_p - d_{gt}^p)^2}{d_{gt}^p} \)
- \( \text{RMSE} = \sqrt{\frac{1}{|\Omega|} \sum_{p \in \Omega} (d_p - d_{gt}^p)^2} \)
- \( \text{RMSE log} = \sqrt{\frac{1}{|\Omega|} \sum_{p \in \Omega} (\log(d_p) - \log(d_{gt}^p))^2} \)
- \( \delta < 1.25^n = \% \text{ of } d_p \text{ s.t. } \delta = \max\left(\frac{d_p}{d_{gt}^p}, \frac{d_{gt}^p}{d_p}\right) < 1.25^n \text{ for } n = 1, 2, 3, \)

where \( d_p \) and \( d_{gt}^p \) indicate the estimated depth map and ground truth depth map at a pixel \( p \), respectively. \( \Omega \) represents a set of valid pixels.

2.2. Qualitative evaluation on KITTI

Fig. 4 shows more results on the Eigen Split [3] of KITTI dataset. We compared our results with (b) Kuznietsov et
Table 1. Quantitative evaluation for depth estimation with existing methods on Cityscapes validation dataset without fine-tuning on Cityscapes training dataset. Numbers in bold and underlined represent 1st and 2nd ranking, respectively.

| Method                  | Data | Abs Rel | Sqr Rel | RMSE | RMSE log | δ < 1.25 | δ < 1.25² | δ < 1.25³ |
|-------------------------|------|---------|---------|------|----------|----------|-----------|----------|
| Monodepth [5]           | S    | 0.631   | 10.257  | 13.424 | 0.525    | 0.281    | 0.546     | 0.749    |
| MonoResMatch [21]       | S    | 0.241   | 2.149   | 9.064  | 0.296    | 0.570    | 0.891     | 0.966    |
| PackNet-SfM [7]         | M    | 0.245   | 2.240   | 8.920  | 0.298    | 0.557    | 0.892     | 0.967    |
| Monodepth2 [6]          | S    | 0.242   | 2.308   | 8.563  | 0.290    | 0.591    | 0.904     | 0.971    |
| DepthHint [24]          | S    | 0.220   | 2.008   | 8.363  | 0.273    | 0.613    | 0.922     | 0.975    |
| Ours (D)                | S    | 0.238   | 1.983   | 8.176  | 0.282    | 0.629    | 0.923     | 0.976    |
| Ours (D+R)              | S    | 0.225   | 1.962   | 8.010  | 0.276    | 0.631    | 0.924     | 0.976    |

Table 2. Quantitative evaluation for monocular depth estimation with existing methods on KITTI Eigen split dataset [3] with improved ground truth depth maps [22]. Numbers in bold and underlined represent 1st and 2nd ranking, respectively.

| Method                  | Data | Abs Rel | Sqr Rel | RMSE | RMSE log | δ < 1.25 | δ < 1.25² | δ < 1.25³ |
|-------------------------|------|---------|---------|------|----------|----------|-----------|----------|
| SfMLearner [25]         | M    | 0.176   | 1.532   | 6.129 | 0.244    | 0.758    | 0.921     | 0.971    |
| Vid2Depth [15]          | M    | 0.134   | 0.983   | 5.501 | 0.203    | 0.827    | 0.944     | 0.981    |
| DDVO [23]               | M    | 0.126   | 0.866   | 4.932 | 0.185    | 0.851    | 0.958     | 0.986    |
| EPC++ [14]              | M    | 0.120   | 0.789   | 4.755 | 0.177    | 0.856    | 0.961     | 0.987    |
| Monodepth2 [6]          | S    | 0.090   | 0.545   | 3.942 | 0.137    | 0.914    | 0.983     | 0.995    |
| Uncertainty (Boot+Log)  | S    | 0.085   | 0.511   | 3.777 | 0.137    | 0.913    | 0.980     | 0.994    |
| Uncertainty (Boot+Self) | S    | 0.085   | 0.510   | 3.792 | 0.135    | 0.914    | 0.981     | 0.994    |
| Uncertainty (Snap+Log)  | S    | 0.084   | 0.529   | 3.833 | 0.138    | 0.914    | 0.980     | 0.994    |
| Uncertainty (Snap+Self) | S    | 0.086   | 0.532   | 3.858 | 0.138    | 0.912    | 0.980     | 0.994    |
| UnRectDepthNet [12]     | M    | 0.081   | 0.414   | 3.412 | 0.117    | 0.926    | 0.987     | 0.996    |
| PackNet-SfM [7]         | M    | 0.078   | 0.361   | 3.223 | 0.120    | 0.930    | 0.987     | 0.996    |
| Ours (D)                | S    | 0.076   | 0.340   | 3.171 | 0.119    | 0.931    | 0.987     | 0.996    |
| Ours (D+R)              | S    | 0.076   | 0.340   | 3.171 | 0.119    | 0.931    | 0.987     | 0.996    |

2.3. Qualitative evaluation on Cityscapes dataset

Fig. 5 shows more qualitative results on Cityscapes dataset [2] of Fig. 5 in original manuscript. Note that it is fine-tuned on Cityscapes dataset. We compared our results with three existing methods: (b) [5], (c) [21], (d) [24] and (e) Ours (D+R) in the original manuscript. Similar to KITTI results, our method is remarkable at predicting fine details with no distortions while recovering fine object boundaries. Additionally, our method is capable of predicting thin objects precisely.

2.4. Quantitative evaluation on Cityscapes dataset without fine-tuning

We also evaluated the performance of the proposed method on the Cityscapes dataset without fine-tuning. Table 1 provides the quantitative evaluation on the Cityscapes validation dataset [2], setting maximum depth to 80 meters. The performance evaluation includes Monodepth [5], MonoResMatch [21], Monodepth2 [6], DepthHint [24], PackNet-SfM [7]. Even without fine-tuning on the Cityscapes dataset, our method still outperforms state-of-the-arts approaches, and it shows that our model trained on KITTI dataset generalizes well on other dataset without bias.

2.5. Quantitative evaluation on KITTI improved ground truth depth maps

To strengthen credibility to quantitative evaluation, we also measured the monocular depth accuracy by using test frames with the improved ground truth depth maps made available in [22] for KITTI Eigen split dataset [3]. The improved ground truth maps are high quality depth maps gen-
Table 3. Quantitative depth estimation results according to $\varepsilon$ value evaluated on KITTI Eigen Split [3] raw dataset.

| $\varepsilon$ | Abs Rel | Sqr Rel | RMSE  | RMSE log | $\delta < 1.25$ | $\delta < 1.25^2$ | $\delta < 1.25^3$ |
|---------------|---------|---------|-------|----------|-----------------|-----------------|-----------------|
| 10            | 0.099   | 0.652   | 4.266 | 0.187    | 0.883           | 0.960           | 0.981           |
| 30            | 0.102   | 0.657   | 4.290 | 0.189    | 0.881           | 0.959           | 0.980           |
| 50            | 0.100   | 0.649   | 4.272 | 0.188    | 0.881           | 0.959           | 0.979           |

Table 4. Quantitative depth estimation results for three cases of the proposed method on KITTI Eigen Split [3] raw dataset.

| Method      | Abs Rel | Sqr Rel | RMSE  | RMSE log | $\delta < 1.25$ | $\delta < 1.25^2$ | $\delta < 1.25^3$ |
|-------------|---------|---------|-------|----------|-----------------|-----------------|-----------------|
| Ours (D)    | 0.099   | 0.652   | 4.266 | 0.187    | 0.883           | 0.960           | 0.981           |
| Ours (R)    | 0.096   | 0.646   | 4.280 | 0.189    | 0.882           | 0.959           | 0.980           |
| Ours (D+R)  | 0.096   | 0.629   | 4.187 | 0.185    | 0.887           | 0.963           | 0.983           |

2.6. Choice of $\varepsilon$ value

We set $\varepsilon = 10$ for the differentiable soft-thresholding function in (1) of the original manuscript. Table 3 shows the quantitative results according to $\varepsilon$ on the KITTI Eigen split [3] raw dataset. Though the best accuracy was achieved with $\varepsilon = 10$, no significant change was observed depending on varying $\varepsilon$.

2.7. Ablation study of DepthNet and RefineNet

The evaluation of the proposed method was conducted for three cases; ‘Ours (D)’ trained with only the DepthNet using $L_D$ without refining the depth map, ‘Ours (R)’ trained with the DepthNet and RefineNet using $L_D$ only, and ‘Ours (D+R)’ trained with the DepthNet and RefineNet using all losses. Table 4 shows the quantitative results of the above three cases on KITTI Eigen Split [3] dataset. The performance gain of ‘Ours (D+R)’ over ‘Ours (R)’ supports the effectiveness of the proposed confidence learning.

3. Confidence estimation results

3.1. Generating ground-truth confidence map

To train the confidence network, the ground truth confidence map is required as supervision. Following existing confidence estimation approaches [18, 11], the ground truth confidence map $c^{gt}$ was computed by using an absolute difference between the ground truth disparity map and the input disparity map (the pseudo ground truth disparity map in our work).

$$c^{gt}_p = \begin{cases} 
1, & \text{if } |d_p - d^{gt}_p| \leq \rho, \\
0, & \text{otherwise}.
\end{cases}$$ (1)

The threshold value $\rho$ is set to 3 for KITTI [16] and 1 for Middlebury [19].

3.2. Evaluation metric

The area under the curve (AUC) [9] was used for evaluating the performance of estimated confidence maps. The receiver operating characteristic (ROC) curve is first computed by sorting disparity pixels in a decreasing order of confidence and sequentially sampling high confidence disparity pixels. It computes the error rate indicating the percentage of pixels with a difference larger than $\rho$ from ground truth disparity. Then, AUC is computed by integral of the ROC curve. The optimal AUC is computed according to the fact that the error rate $\zeta$ is ideally 0 when sampling the first $(1 - \zeta)$ pixels [9], which is equal to

$$AUC_{opt} = \int_{1-\zeta}^{1} \frac{x - (1 - \zeta)}{x} dx = \zeta + (1 - \zeta) \ln 1 - \zeta.$$ (2)

3.3. Qualitative evaluation on KITTI 2015 dataset

Fig. 6 shows more qualitative results of confidence map evaluated on KITTI 2015 dataset [16]. Input disparity maps used for confidence estimation were obtained by Census-SGM [8]. The estimated confidence maps for each input disparity map are displayed every two rows. The top and bottom of two rows indicate: (a) color image and input disparity image, (b) CCNN [18] and CCNN w/r, (c) LAFNet* [11] and LAFNet* w/r and (d) LAFNet and LAFNet w/r. ‘w/r’ denotes the thresholded confidence map obtained using the soft-thresholding. LAFNet* denotes the LAFNet [11] in which 3D cost volume is not used as an input. As shown in Fig. 6, the proposed thresholded confidence maps contain fewer ambiguous values than the original confidence maps.
Figure 6. Qualitative evaluation for confidence estimation on KITTI 2015 dataset [16]: Input disparity maps used for confidence estimation were obtained by Census-SGM [8]. The estimated confidence maps for each input disparity map are displayed every two rows. The top and bottom of two rows indicate: (a) color image and input disparity image, (b) CCNN [18] and CCNN w/τ, (c) LAFNet* [11] and LAFNet* w/τ and (d) LAFNet and LAFNet w/τ. ‘w/τ’ denotes the proposed network using the soft-thresholding. LAFNet* denotes the LAFNet [11] in which 3D cost volume is not used as an input.
4. Uncertainty Estimation Details

4.1. Evaluation metric

We evaluated the performance of the uncertainty estimation used in the proposed model using the sparsification error [10]. Similar to the confidence evaluation, we first sorted disparity pixels following decreasing order of uncertainty, and iteratively extracted high uncertain disparities and provided them as inputs for computing error metrics. The ideal error ranked by the true error to the ground truth is referred to as oracle. With a sparsicification error, we computed the Area Under the Sparsification Error curve (AUSE) and the Area Under the Random Gain (AURG) to evaluate the quality of the uncertainty map. While the AUSE is measured as the difference between the sparsification and its oracle, the AURG is obtained as subtracting the estimated sparsification curve from flat curve with a random uncertainty which is modeled as a constant.

4.2. Qualitative evaluation on KITTI dataset

Fig. 7 shows the qualitative results of uncertainty map evaluated on KITTI Eigen Split [3] test dataset. The qualitative result indicates that uncertain areas of the estimated depth map are usually located around object boundaries and sky.

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