Practical Deep Stereo (PDS): Toward applications-friendly deep stereo matching.

Abstract

End-to-end deep-learning networks recently demonstrated extremely good performance for stereo matching. However, existing networks are difficult to use for practical applications since (1) they are memory-hungry and unable to process even modest-size images, (2) they have to be trained for a given disparity range.

The Practical Deep Stereo (PDS) network that we propose addresses both issues: First, its architecture relies on novel bottleneck modules that drastically reduce the memory footprint in inference, and additional design choices allow to handle greater image size during training. This results in a model that leverages large image context to resolve matching ambiguities. Second, a novel sub-pixel cross-entropy loss combined with a MAP estimator make this network less sensitive to ambiguous matches, and applicable to any disparity range without re-training.

We compare PDS to state-of-the-art methods published over the recent months, and demonstrate its superior performance on FlyingThings3D and KITTI sets.

1 Introduction

Stereo matching consists in matching every point from an image taken from one viewpoint to its physically corresponding one in the image taken from another viewpoint. The problem has applications in robotics [Menze and Geiger 2015], medical imaging [Nam et al. 2012], remote sensing [Shean et al. 2016], virtual reality and 3D graphics and computational photography [Wang et al. 2016], [Barron et al. 2015].

Recent developments in the field have been focused on stereo for hard / uncontrolled environments (wide-baseline, low-lighting, complex lighting, blurry, foggy, non-lambertian) [Verleysen and De Vleeschouwer 2016], [Jeon et al. 2016], [Chen et al. 2015], [Galun et al. 2015], [Queau et al. 2017], usage of high-order priors and cues [Hadfield and Bowden 2015], [Guney and Geiger 2015], [Kim and Kim 2016], [Li et al. 2016], [Ulusoy et al. 2017], and data-driven, and in particular, deep neural network based, methods [Park and Yoon 2015], [Chen et al. 2015], [Zbontar and LeCun 2015], [Zbontar and LeCun 2016], [Luo et al. 2016], [Tulyakov et al. 2017], [Seki and Pollefeys 2017], [Knobelreiter et al. 2017], [Shaked and Wolf 2017], [Gidaris and Komodakis 2017], [Kendall et al. 2017], [Mayer et al. 2016], [Pang et al. 2017], [Chang and Chen 2018], [Liang et al. 2018], [Zhong et al. 2017]. This work improves on this latter line of research.
Table 1: Number of parameters, inference memory footprint, 3-pixels-error (3PE) and mean-absolute-error on FlyingThings3D (960 × 540 with 192 disparities). DispNetCorr1D Mayer et al. [2016], CRL Pang et al. [2017], iResNet-i2 Liang et al. [2018] and LRCR Jie et al. [2018] predict disparities as classes and are consequently over-parameterized. GC Kendall et al. [2017] omits an explicit correlation step, which results in a large memory usage during inference. Our PDS has a small number of parameters and memory footprint, the smallest 3PE and second smallest MAE, and it is the only method able to handle different disparity ranges without re-training. Note that we follow the protocol of PSM Chang and Chen [2018], and calculate the errors only for ground truth pixel with disparity < 192. Inference memory footprints are our theoretical estimates based on network structures and do not include memory required for storing networks’ parameters (real memory footprint will depend on implementation). Error rates and numbers of parameters are taken from the respective publications.

| Method                        | Params [M] | Memory [GB] | 3EP [%] | MAE [px] | Modify. | Disp. |
|-------------------------------|------------|-------------|---------|----------|---------|-------|
| PDS (proposed)                | 2.2        | 0.4         | 3.38    | 1.12     | ✓       |       |
| PSM Chang and Chen [2018]     | 5.2        | 0.6         | n/a     | 1.09     | ✗       |       |
| CRL Pang et al. [2017]         | 78         | 0.2         | 6.20    | 1.32     | ✗       |       |
| iResNet-i2 Liang et al. [2018]| 43         | 0.2         | 4.57    | 1.40     | ✗       |       |
| DispNetCorr1D Mayer et al. [2016] | 42      | 0.1         | n/a     | 1.68     | ✗       |       |
| LRCR Jie et al. [2018]         | 30         | 9.0         | 8.67    | 2.02     | ✗       |       |
| GC Kendall et al. [2017]       | 3.5        | 4.5         | 9.34    | 2.02     | ✗       |       |

The first successes of neural networks for stereo matching were achieved by substitution of hand-crafted similarity measures with deep metrics Chen et al. [2015], Žbontar and LeCun [2015], Žbontar and LeCun [2016], Luo et al. [2016], Tulyakov et al. [2017] inside a legacy stereo pipeline for the post-processing (often Mei et al. [2011]). Besides deep metrics, neural networks were also used in other subtasks such as predicting a smoothness penalty in a CRF model from a local intensity pattern Seki and Pollefeys [2017], Knöbelreiter et al. [2017]. In Shaked and Wolf [2017] a “global disparity” network smooth the matching cost volume and predicts matching confidences, and in Gidaris and Komodakis [2017] a network detects and fixes incorrect disparities.

**End-to-end deep stereo.** Recent works attempt at solving stereo matching using neural network trained end-to-end without post-processing Dosovitskiy et al. [2015], Mayer et al. [2016], Kendall et al. [2017], Zhong et al. [2017], Pang et al. [2017], Jie et al. [2018], Liang et al. [2018], Chang and Chen [2018]. Such a network is typically a pipeline composed of **embedding**, **matching**, **regularization** and **refinement** modules:

The **embedding** module produces image descriptors for left and right images, and the (non-parametric) **matching** module performs an explicit correlation between shifted descriptors to compute a cost volume for every disparity Dosovitskiy et al. [2015], Mayer et al. [2016], Pang et al. [2017], Jie et al. [2018], Liang et al. [2018]. This matching module may be absent, and concatenated left-right descriptors directly fed to the **regularization** module Kendall et al. [2017], Chang and Chen [2018], Zhong et al. [2017]. This strategy uses more context, but the deep network implementing such a module has a larger memory footprint as shown in Table 1. In this work we reduce memory use without sacrificing accuracy by introducing a matching module that compresses concatenated left-right image descriptors into compact matching signatures.

The **regularization** module takes the cost volume, or the concatenation of descriptors, regularizes it, and outputs either disparities Mayer et al. [2016], Dosovitskiy et al. [2015], Pang et al. [2017], Liang et al. [2018], or a distribution over disparities Kendall et al. [2017], Zhong et al. [2017], Jie et al. [2018], Chang and Chen [2018]. In the latter case, sub-pixel disparities can be computed as a weighted average with SoftArgmin, which is sensitive to erroneous minor modes in the inferred distribution.

This **regularization** module is usually implemented as a hourglass deep network with shortcut connections between the contracting and the expanding parts Mayer et al. [2016], Dosovitskiy et al. [2015], Pang et al. [2017], Kendall et al. [2017], Zhong et al. [2017], Chang and Chen [2018], Liang et al. [2018]. It composed of 2D convolutions and not treat all disparities symmetrically in
some models, which makes the network over-parametrized and prohibits the change of the disparity range without modification of its structure and re-training. Or it can use 3D convolutions that treat all disparities symmetrically. As a consequence these networks have less parameters, but their disparity range is still non-adjustable without re-training due to SoftArgmin as we show in § 3.3. In this work, we propose to use a novel sup-pixel MAP approximation for inference which computes a weighted mean around the disparity with maximum posterior probability. It is more robust to erroneous modes in the distribution and allows to modify the disparity range without re-training.

Finally, some methods also have a refinement module, that refines the initial low-resolution disparity relying on attention map, computed as left-right warping error. The training of end-to-end networks is usually performed in fully supervised manner (except of Zhong et al. [2017]).

All described methods use modest-size image patches during training. In this work, we show that training on a full-size images boosts networks ability to utilize large context and improves its accuracy. The methods, even the ones producing disparity distribution, rely on \( L^1 \) loss, since it allows to train network to produce sub-pixel disparities. We, instead propose to use more “natural” sub-pixel cross-entropy loss that ensures faster converges and better accuracy.

Our contributions can be summarize as follows:

1. We decrease the memory footprint by introducing a novel bottleneck matching module. It compresses the concatenated left-right image descriptors into compact matching signatures, which are then concatenated and fed to the hourglass network we use as regularization module, instead of the concatenated descriptors themselves as in Kendall et al. [2017], Chang and Chen [2018]. Reduced memory footprint allows to process larger images and to train on a full-size images, that boosts networks ability to utilize large context.

2. Instead of computing the posterior mean of the disparity and training with a vanilla \( L_1 \) penalty Chang and Chen [2018], Jie et al. [2018], Zhong et al. [2017], Kendall et al. [2017] we propose for inference a sub-pixel MAP approximation that computes a weighted mean around the disparity with maximum posterior probability, which is robust to erroneous modes in the disparity distribution and allows to modify the disparity range without re-training. For training we similarly introduce a sub-pixel criterion by combining the standard cross-entropy with a kernel interpolation, which provides faster convergence rates and higher accuracy.

In the experimental section, we validate our contributions. In § 3.2 we show how the reduced memory footprint allows to train on full-size images and to leverage large image contexts to improve performance. In § 3.3 we demonstrate that, thanks to the proposed sub-pixel MAP and cross-entropy, we are able to modify the disparity range without re-training, and to improve the matching accuracy. Than, in § 3.4 we compare our method to state-of-the-art baselines and show that it has smallest 3-pixels error (3PE) and second smallest mean absolute error (MAE) on the FlyingThings3D set and ranked third and fourth on KITTI’15 and KITTI’12 sets respectively.

2 Method

2.1 Network structure

Our network takes as input the left and right color images \( \{ \mathbf{x}^L, \mathbf{x}^R \} \) of size \( W \times H \) and produces a “cost tensor” \( C = \text{Net}(\mathbf{x}^L, \mathbf{x}^R \mid \Theta, D) \) of size \( \frac{D}{2} \times W \times H \), where \( \Theta \) are the model’s parameters, and \( D \in \mathbb{N} \) is the maximum disparity.

The computed cost tensor is such that \( C_{k,i,j} \) is the cost of matching the pixel \( \mathbf{x}^L_{i,j} \) in the left image to the pixel \( \mathbf{x}^R_{i-2k,j} \) in the right image, which is equivalent to assigning the disparity \( d_{i,j} = 2k \) to the left image pixel.

This cost tensor \( C \) can then be converted into an a posterior probability tensor as

\[
P(d \mid \mathbf{x}^L, \mathbf{x}^R) = \text{softmax}(-C).
\]
Figure 1: Network structure and processing flow during training and inference. Input / output quantities are outlined with thin lines, while processing modules are drawn with thick ones. Following the vocabulary introduced in §1 the yellow shapes are embedding modules, the red rectangle the matching module and the blue shape the the regularization module. The matching module is a contribution of our work, as in previous methods [Kendall et al. 2017, Chang and Chen 2018] left and shifted right descriptors are directly fed to the regularization module (hourglass network). Note that the concatenated compact matching signature tensor is a 4D tensor represented here as 3D by combining the feature indexes and disparities along the vertical axis.

The overall structure of the network and processing flow during training and inference are shown in Figure 1 and we can summarize for clarity the input/output to and from each of the modules:

- The embedding module takes as input a color image $3 \times W \times H$, and computes an image descriptor $32 \times \frac{W}{4} \times \frac{H}{4}$.
- The matching module takes as input, for each disparity $d$, a left and a (shifted) right image descriptor both $32 \times \frac{W}{4} \times \frac{H}{4}$, and computes a compact matching signature $8 \times \frac{W}{4} \times \frac{H}{4}$. This module is unique to our network and described in details in §2.2.
- The regularization module is a hourglass 3D convolution neural network with shortcut connections between the contracting and the expanding parts. It takes a tensor composed of concatenated compact matching signatures for all disparities of size $8 \times \frac{D}{4} \times \frac{W}{4} \times \frac{H}{4}$, and computes a matching cost tensor $C$ of size $\frac{D}{2} \times W \times H$.

Additional information such as convolution filter size or channel numbers is provided in the Supplementary materials.

According to the taxonomy in [Scharstein and Szeliski; 2001] all traditional stereo matching methods consist of (1) matching cost computation, (2) cost aggregation, (3) optimization, and (4) disparity refinement steps. In the proposed network, the embedding and the matching modules are roughly responsible for the step (1) and the regularization module for the steps (2-4).

Besides the matching module, there are several other design choices that reduce test and training memory footprint of our network. In contrast to [Kendall et al. 2017] we use aggressive four-times sub-sampling in the embedding module, and the hourglass DNN we use for regularization module produces probabilities only for even disparities. Also, after each convolution and transposed convolution in our network we place Instance Normalization (IN) [Ulyanov et al. 2016] instead of Batch Normalization (BN) as show in the Supplementary materials, since we use individual full-size images during training.

2.2 Matching module

The core of state-of-the-art methods [Kendall et al. 2017, Zhong et al. 2017, Jie et al. 2018, Chang and Chen 2018] is the 3D convolutions Hourglass network used as regularization module, that takes as input a tensor composed of concatenated left-right image descriptor for all possible disparity values. The size of this tensor makes such networks have a huge memory footprint during inference.

We decrease the memory usage by implementing a novel matching with a DNN with a “bottle-neck” architecture. This module compresses the concatenated left-right image descriptors into a compact matching signature for each disparity, and the results is then concatenated and fed to the Hourglass module. This contrasts with existing methods, which directly feed the concatenated descriptors [Kendall et al. 2017, Zhong et al. 2017, Jie et al. 2018, Chang and Chen 2018].
Figure 2: Comparison the proposed Sub-pixel MAP with the standard SoftArgmin: (a) in presence of a multi-modal distribution SoftArgmin blends all the modes and produces an incorrect disparity estimate. (b) when the disparity range is extended (blue area), SoftArgmin estimate may degrade due to additional modes.

This module is inspired by CRL Pang et al. [2017] and DispNetCorr1D Pang et al. [2017], Mayer et al. [2016] which control the memory footprint (as shown in Table 1) by feeding correlation results instead of concatenated embeddings to the Hourglass network and by Zagoruyko and Komodakis [2015] that show superior performance of joint left-right image embedding. We also borrowed some ideas from the bottleneck module in ResNet He et al. [2016], since it also encourages compressed intermediate representations.

2.3 Sub-pixel MAP

In state-of-the-art methods, a network produces an posterior disparity distribution and then use a SoftArgmin module Kendall et al. [2017], Zhong et al. [2017], Jie et al. [2018], Chang and Chen [2018], introduced in Kendall et al. [2017], to compute the predicted sub-pixel disparity as an expectation of this distribution:

\[
\hat{d} = \sum_{d} d \cdot P(d = d | x^L, x^R).
\]

This SoftArgmin approximates a sub-pixel maximum a posteriori (MAP) solution when the distribution is unimodal and symmetric. However, as illustrated in Figure 2, this strategy suffers from two key weaknesses: First, when these assumptions are not fulfilled, for instance if the posterior is multi-modal, this averaging blends the modes and produces a disparity estimate far from all of them. Second, if we want to apply the model to a greater disparity range without re-training, the estimate may degrade even more due to additional modes.

The authors of Kendall et al. [2017] argue that when the network is trained with the SoftArgmin, it adapts to it during learning by rescaling its output values to make the distribution unimodal. However, the network learns rescaling only for disparity range used during training. If we decide to change the disparity range during the test, we will have to re-train the network.

To address both of these drawbacks, we propose to use for inference a sub-pixel MAP approximation that computes a weighted mean around the disparity with maximum posterior probability as

\[
\tilde{d} = \sum_{d: |\hat{d} - d| \leq \delta} d \cdot P(d = d | x^L, x^R), \quad \text{where} \quad \hat{d} = \arg\max_{1 \leq d \leq D} P(d = d | x^L, x^R),
\]

with \(\delta\) a meta-parameter (in our experiments we choose \(\delta = 4\) based on small scale grid search experiment on the validation set). The approximation works under assumption that the distribution is symmetric in a vicinity of a major mode.

In contrast to the SoftArgmin, the proposed sup-pixel MAP is used only for inference. During training we use the posterior disparity distribution and the sub-pixel cross-entropy loss discussed in the next section.

2.4 Sub-pixel cross-entropy

Many methods use the \(L^1\) loss Chang and Chen [2018], Jie et al. [2018], Zhong et al. [2017], Kendall et al. [2017], even though the “natural” choice for the network that produces the posterior distribution is a cross-entropy. The \(L^1\) loss is often selected because it empirically Kendall et al. [2017] performs
better than cross-entropy, and because when it is combined with SoftArgmin, it allows to train a network with sub-pixel ground truth.

In this work, we propose a novel sub-pixel cross-entropy that provides faster convergence and better accuracy. The target distribution of our cross-entropy loss is a discretized Laplace distribution centered at the ground-truth disparity $d^{gt}$, shown in Figure 3 and computed as

$$Q^{gt}(d) = \frac{1}{N} \exp \left( -\frac{|d - d^{gt}|}{b} \right),$$

where $N$ is a normalization constant computed as

$$N = \sum_i \exp \left( -\frac{|i - d^{gt}|}{b} \right),$$

where $b$ is a diversity of the Laplace distribution (in our experiments we set $b = 2$, reasoning that the distribution should reasonably cover at least several discrete disparities). With this target distribution we compute cross-entropy as usual

$$L(\Theta) = \sum_d Q^{gt}(d) \cdot \log P(d = d | x^L, x^R, \Theta).$$ (2)

The proposed sub-pixel cross-entropy is different from soft cross entropy Luo et al. [2016], since in our case probability in each discrete location of the target distribution is a smooth function of a distance to the sub-pixel ground-truth. This allows to train the network to produce a distribution from which we can compute sub-pixel disparities using our sub-pixel MAP.

3 Experiments

Our experiments are done with the PyTorch framework PyTorch. We initialize weights and biases of the network using default PyTorch initialization and train the network as shown in Table 2. During the training we normalize training patches to zero mean and unit variance. The optimization is performed with the RMSprop method with standard settings.

| Mode       | FlyingThings3D       | KITTI       |
|------------|----------------------|-------------|
| Lr. schedule | 0.01 for 120k, half every 20k | 0.005 for 50k, half every 20k |
| Iter. #    | 160k                 | 100k        |
| Tr. image size | 960 x 540 full-size | 1164 x 330 |
| Max disparity | 255                 | 255         |
| Augmentation | not used            | mixUp [Zhang et al. 2018], anisotropic zoom, random crop |

We guarantee reproducibility of all experiments in this section by using only available data-sets, and making our code available online under open-source license after publication.

3.1 Datasets and performance measures

We used three data-sets for our experiments: KITTI'12 Geiger et al. [2012] and KITTI'15 Menze and Geiger [2015], that we combined into a KITTI set, and FlyingThings3D Mayer et al. [2016] summarized in Table 2. KITTI'12, KITTI'15 sets have online scoreboards [KITTY].

The FlyingThings3D set suffers from two problems: (1) as noticed in Pang et al. [2017], Zhang et al. [2018], some images have very large (up to $10^3$) or negative disparities; (2) some images are rendered with black dots artifacts. For the training we use only images without artifacts and with disparities $\in [0, 255]$.

We noticed that this is dealt with in some previous publications by processing the test set using the ground truth for benchmarking, without mentioning it. Such pre-processing may consist of ignoring pixels with disparity $> 192$ [Chang and Chen 2018], or discarding images with more than 25% of pixels with disparity $> 300$ [Pang et al. 2017, Liang et al. 2018]. Although this is not commendable, for the sake of comparison we followed the same protocol as Chang and Chen [2018] which is the method the closest to ours in term of performance. In all other experiments we use the unaltered test set.
We make validation sets by withholding 500 images from the FlyingThings3D training set, and 58 from the KITTI training set, respectively.

Table 3: Datasets used for experiments. During benchmarking, we follow previous works and use maximum disparity, that is different from absolute maximum for the datasets, provided between parentheses.

| Dataset          | Test # | Train # | Size       | Max disp.  | Ground truth          | Web score |
|------------------|--------|---------|------------|------------|-----------------------|-----------|
| KITTI            | 395    | 395     | 1226 × 370 | 192 (230)  | sparse, ≤ 3 px.       | ✓         |
| FlyingThings3D   | 4370   | 25756   | 960 × 540  | 192 (6773) | dense, unknown        | ✓         |

We measure the performance of the network using two standard measures: (1) 3-pixel-error (3PE), which is the percentage of pixels for which the predicted disparity is off by more than 3 pixels, and (2) mean-absolute-error (MAE), the average difference of the predicted disparity and the ground truth. Note, that 3PE and MAE are complimentary, since 3PE characterize error robust to outliers, while MAE accounts for sub-pixel error.

3.2 Training on full-size images

In this section we show the effectiveness of training on full-size images. For that we train our network till convergence on FlyingThings3D dataset with the $L^1$ loss and SoftArgmin twice, the first time we use $512 \times 256$ training patches randomly cropped from the training images as in Kendall et al. [2017], Chang and Chen [2018], and the second time we used full-size $960 \times 540$ training images. Note, that the latter is possible thanks to the small memory footprint of our network.

As seen in Table 4, the network trained on small patches, performs better on larger than on smaller test images. This suggests, that even the network that has not seen full-size images during training can utilize a larger context. As expected, the network trained on full-size images makes better use of the said context, and performs significantly better.

3.3 Sub-pixel MAP and cross-entropy

Figure 4: Example of disparity estimation errors with the SoftArgmin and sup-pixel MAP on FlyingThings3d set. The first column shows image, the second – ground truth disparity, the third – SoftArgmin estimate and the fourth sub-pixel MAP estimate. Note that SoftArgmin estimate, though completely wrong, is closer to the ground truth than sub-pixel MAP estimate. This can explain larger MAE of the sub-pixel MAP estimate.

Figure 5: Comparison of the convergence speed on FlyingThings3d set with sub-pixel cross entropy and $L^1$ loss. Note that with the proposed sub-pixel cross-entropy loss (blue) network converges faster.

Table 4: Error of the proposed PDS network on FlyingThings3d set as a function of training patch size. The network trained on full-size images (highlighted), outperforms the network trained on small image patches. Note, that in this experiment we used SoftArgmin with $L^1$ loss during training.

| Train size       | Test size    | 3PE, [%] | MAE, [px] |
|------------------|--------------|----------|-----------|
| $512 \times 256$ | $512 \times 256$ | 8.63     | 4.18      |
| $512 \times 256$ | $960 \times 540$ | 5.28     | 3.55      |
| $960 \times 540$ | $960 \times 540$ | 4.50     | 3.40      |
In this section, we firstly show the advantages of the sub-pixel MAP over the SoftArgmin. We train the our PDS network till convergence on FlyingThings3D with SoftArgmin, $L^1$ loss and full-size training images and then test it twice: the first time with SoftArgmin for inference, and the second time with our sub-pixel MAP for inference instead.

As shown in Table 5, the substitution leads to the reduction of the 3PE and slight increase of the MAE. The latter probably happens because in the erroneous area SoftArgmin estimate are completely wrong, but nevertheless closer to the ground truth since it blends all distribution modes, as shown in Figure 4.

Table 5: Performance of the sub-pixel MAP estimator and cross-entropy loss on FlyingThings3d set.

| Loss                           | Estimator            | 3PE, [%] | MAE, [px] |
|-------------------------------|----------------------|----------|-----------|
| **Standard disparity range**  |                      |          |           |
| $L^1$ + SoftArgmin            | SoftArgmin           | 4.50     | 3.40      |
| $L^1$ + SoftArgmin            | Sub-pixel MAP        | 4.22     | 3.42      |
| Sub-pixel cross-entropy.      | Sub-pixel MAP        | 3.80     | 3.63      |

| **Increased disparity range** |                      |          |           |
| $L^1$ + SoftArgmin            | SoftArgmin           | 5.20     | 3.81      |
| $L^1$ + SoftArgmin            | Sub-pixel MAP        | 4.27     | 3.53      |

When we test the same network with the disparity range increased from 255 to 511 pixels the performance of the network with the SoftArgmin plumments, while performance of the network with sub-pixel MAP remains almost the same as shown in Table 5. This shows that with Sub-pixel MAP we can modify the disparity range of the network on-the-fly, without re-training.

Next, we train the network with the sub-pixel cross-entropy loss and compare it to the network trained with SoftArgmin and the $L^1$ loss. As show in Table 5 the former network has much smaller 3PE and only slightly larger MAE. The convergence speed with sub-pixel cross-entropy is also much faster than with $L^1$ loss as shown in Figure 4. Interestingly, in Kendall et al. [2017] also reports faster convergence with one-hot cross-entropy than with $L^1$ loss, but contrary to our results, they found that $L^1$ provided smaller 3PE.

### 3.4 Benchmarking

In this section we show the effectiveness of our method, compared to the state-of-the-art methods. For KITTI, we computed disparity maps for the test sets with withheld ground truth, and uploaded the results to the evaluation web site. For the FlyingThings3D set we evaluated performance on the test set ourselves, following the protocol of [Chang and Chen 2018] as explained in §3.1.

**FlyingThings3D set** benchmarking results are shown in Table 1. Notably, the method we propose has lowest 3PE error and second lowest MAE. Moreover, in contrast to other methods, our method has small memory footprint, number of parameters, and it allows to change the disparity range without re-training.

**KITTI’12, KITTI’15** benchmarking results are shown in Table 6. The method we propose ranks third on KITTI’15 set and fourth on KITTI’12 set, taking into account state-of-the-art results published a few months ago or not officially published yet iResNet-i2 [Liang et al. 2018], PSMNet [Chang and Chen 2018] and LRCR [Hie et al. 2018] methods.

### 4 Conclusion

In this work we addressed two issues precluding the use of deep networks for stereo matching in many practical situations in spite of their excellent accuracy: their large memory footprint, and the inability to adjust to a different disparity range without complete re-training.
Table 6: KITTI'15 (top) and KITTI'12 (bottom) snapshots from 15/05/2018 with top-10 methods, including published in a recent months on not officially published yet: iResNet-i2 Liang et al. [2018], PSMNet Chang and Chen [2018] and LRCR Jie et al. [2018]. Our method (highlighted) is 3rd in KITTI'15 and 4th in KITTI'12 leader boards.

| #  | dd/mm/yy | Method                        | 3PE (all pixels), [%] | Time, [s] |
|----|----------|-------------------------------|-----------------------|-----------|
| 1  | 30/12/17 | PSMNet Chang and Chen [2018]  | 2.16                  | 0.4       |
| 2  | 18/03/18 | iResNet-i2 Liang et al. [2018]| 2.44                  | 0.12      |
| 3  | 15/05/18 | PSN (proposed)                | 2.58                  | 0.5       |
| 4  | 24/03/17 | CRL Pang et al. [2017]        | 2.67                  | 0.47      |
| 5  | 27/01/17 | GC-NET Kendall et al. [2017]  | 2.87                  | 0.9       |
| 6  | 15/11/17 | LRCR Jie et al. [2018]        | 3.03                  | 49        |
| 7  | 15/11/16 | DRR Gidaris and Komodakis [2017]| 3.16               | 0.4       |
| 8  | 08/11/17 | SoSMnet Zhong et al. [2017]   | 3.40                  | 0.8       |
| 9  | 15/12/16 | L-ResMatch Shaked and Wolf [2017]| 3.42          | 48        |
| 10 | 26/10/15 | Displets v2 Güney and Geiger [2015]| 3.43       | 265       |

| #  | dd/mm/yy | Method                        | 3PE (non-occluded), [%] | Time, [s] |
|----|----------|-------------------------------|-------------------------|-----------|
| 1  | 31/12/17 | PSMNet Chang and Chen [2018]  | 1.49                    | 0.4       |
| 2  | 23/11/17 | iResNet-i2 Liang et al. [2018]| 1.71                    | 0.12      |
| 3  | 27/01/17 | GC-NET Kendall et al. [2017]  | 1.77                    | 0.9       |
| 4  | 15/05/18 | PSN (proposed)                | 1.92                    | 0.5       |
| 5  | 15/12/16 | L-ResMatch Shaked and Wolf [2017]| 2.27          | 48        |
| 6  | 11/09/16 | CNNF+SGM Zhang and Wahi [2018]| 2.28                    | 71        |
| 7  | 15/12/16 | SGM-NET Seki and Pollefeys [2017]| 2.29       | 67        |
| 8  | 08/11/17 | SoSMnet Zhong et al. [2017]   | 2.30                    | 0.8       |
| 9  | 27/04/16 | PBCP Seki and Pollefeys [2016]| 2.36                    | 68        |
| 10 | 26/10/15 | Displets v2 Güney and Geiger [2015]| 2.37       | 265       |

We showed that by carefully revising conventionally used networks architecture to control the memory footprint and adapt analytically the network to the disparity range, and by using a new loss and estimator to cope with multi-modal posterior and sub-pixel accuracy, it is possible to resolve these practical issues and reach state-of-the-art performance.

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