Supplementary material for 3DV 2018 paper "Learning monocular depth estimation under unsupervised trinocular assumption"

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This document provides additional details and experimental results concerned with 3DV 2018 paper "Learning monocular depth estimation under unsupervised trinocular assumption". The supplementary material is organized as follows: Section 1 reports detailed explanation of the loss functions used at training time, Section 2 describes how we obtain \( d_c \) with 3Net and how we post-process it, Section 3 comments additional experiments on the Eigen split [1] assuming as maximum depth 50 meters and Section 4 collects additional qualitative results. Finally, Section 5 reports run time analysis for 3Net and [3].

1. Training losses

In the paper, all loss functions are computed at four scales, ranging from full image resolution to \( 1/8 \). The global loss function is defined as:

\[
L_{total} = \beta_{ap}(L_{ap}) + \beta_{ds}(L_{ds}) + \beta_{lcr}(L_{lcr})
\]

where \( L_{ap}, L_{ds} \) and \( L_{lcr} \) represent, respectively, the appearance, smoothness and consistency terms, while \( \beta_{ap}, \beta_{ds} \) and \( \beta_{lcr} \) are hyper-parameters. In particular, we set \( \beta_{ap} = \beta_{lcr} = 1 \) and \( \beta_{ds} = 0.1 \).

**Appearance Loss.** It measures the reconstruction error between a warped image and the original one. It is obtained by a weighted sum of a SSIM based score [7] and a L1 distance over pixel intensities.

\[
L_{ap}(I^l, I^r) = \frac{1}{N} \sum_{ij} \alpha \left( 1 - SSIM(I^l_{ij}, \hat{I}^r_{ij}) \right) + (1 - \alpha) ||I^l_{ij} - \hat{I}^r_{ij}||
\]

**Smoothness Loss.** This term favours the propagation of similar disparity values in low-textured regions, thus enforcing smoothness. It is obtained computing horizontal and vertical gradients on both disparity image and reference image, discouraging disparity smoothness in presence of strong image gradients.

\[
L_{ds}(d, I) = \frac{1}{N} \sum_{ij} |\partial_x d_{ij}^{l} e^{-||\partial_x t^l_{ij}||} + |\partial_y d_{ij}^{l} e^{-||\partial_y t^l_{ij}||}}
\]

**Left-Right Disparity Consistency Loss.** It enforces consistency between reference-to-target and target-to-reference disparity maps. It relies on the L1 distance between reference-to-target map and warped, according to the former, target-to-reference map.

\[
L_{lr}(d^l, d^r) = \frac{1}{N} \sum_{ij} |d^l_{ij} - d^r_{ij + d^l_{ij}}|
\]

2. Depth computation and post-processing

For the sake of clarity, we describe in detail how we combine \( d^{cl} \) and \( d^{cr} \) to obtain the final output map \( d^c \). In [3] the authors obtained \( d^l \) and \( d^l \) by processing, respectively, both \( I \) and its horizontally flipped version \( \hat{I} \). The two maps were combined as follows:

\[
d_{pp} = \omega \cdot d^l + (1 - \omega) \cdot \hat{d}^l
\]

with \( \omega \) obtained as:

\[
\omega = \begin{cases} 
0 & \text{if } j \leq 0.05 \\
1 & \text{if } j > 0.95 \\
0.5 & \text{otherwise}
\end{cases}
\]

being \( j \) normalized pixel coordinates.

Following this principle, we combine our \( d^{cl} \) and \( d^{cr} \) maps as follows:

\[
d^c = \omega \cdot d^{cr} + (1 - \omega) \cdot d^{cl}
\]
Running two forwards, we can post-process both intermediate maps and

\[
d_{pp}^{cr} = \omega \cdot d_{pp}^{cr} + (1 - \omega) \cdot d_{pp}^{cl}
\]
(8)

being \(d_{pp}^{cr}\) and \(d_{pp}^{cl}\) obtained as:

\[
d_{pp}^{cr} = \omega \cdot d_{pp}^{cr} + (1 - \omega) \cdot d_{pp}^{cl}
\]
(9)

\[
d_{pp}^{cl} = \omega \cdot d_{pp}^{cl} + (1 - \omega) \cdot d_{pp}^{cl}
\]
(10)

3. Depth estimation: additional experiments with 50m cap

We report additional experimental results on the Eigen split [1], evaluating depth maps up to a maximum distance of 50 meters as reported in some recent works [3, 8, 5, 9]. Table 1 contains a comparison between all previous works reporting this experiment as well and our best model, i.e. 3Net ResNet50 + pp. This further evaluation confirms, once again, the superiority of our technique with respect to all competitors.

<table>
<thead>
<tr>
<th>Method</th>
<th>Supervision</th>
<th>Train set</th>
<th>Abs Rel</th>
<th>Sq Rel</th>
<th>RMSE</th>
<th>RMSE log</th>
<th>(\delta &lt; 1.25)</th>
<th>(\delta &lt; 1.25^2)</th>
<th>(\delta &lt; 1.25^3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zhou et al. [9]</td>
<td>Temporal</td>
<td>E</td>
<td>0.201</td>
<td>1.391</td>
<td>5.181</td>
<td>0.264</td>
<td>0.696</td>
<td>0.900</td>
<td>0.966</td>
</tr>
<tr>
<td>Mahjourian et al. [5]</td>
<td>Temporal</td>
<td>E</td>
<td>0.155</td>
<td>0.927</td>
<td>4.549</td>
<td>0.231</td>
<td>0.781</td>
<td>0.931</td>
<td>0.975</td>
</tr>
<tr>
<td>Zhan et al. [8]</td>
<td>Stereo + Temp.</td>
<td>E</td>
<td>0.135</td>
<td>0.905</td>
<td>4.366</td>
<td>0.225</td>
<td>0.818</td>
<td>0.937</td>
<td>0.973</td>
</tr>
<tr>
<td>Godard et al. [3] ResNet50 + pp</td>
<td>Stereo</td>
<td>E</td>
<td>0.1217</td>
<td>0.7630</td>
<td>4.047</td>
<td>0.210</td>
<td>0.847</td>
<td>0.946</td>
<td>0.976</td>
</tr>
<tr>
<td>3Net ResNet50 + pp (ours)</td>
<td>Stereo</td>
<td>E</td>
<td>0.1207</td>
<td>0.7185</td>
<td>3.968</td>
<td>0.208</td>
<td>0.849</td>
<td>0.948</td>
<td>0.977</td>
</tr>
</tbody>
</table>

Table 1. Evaluation on the KITTI dataset [2] using the split of Eigen et al. [1], with maximum depth set to 50m. Results concern state-of-the-art techniques for unsupervised monocular depth estimation leveraging video sequences (Temporal), binocular stereo pairs (Stereo) and both cues (Stereo+Temp.).

Table 2. Run time comparison between Godard et al. [3] and 3Net running single and double forward on a CPU Intel Core i7-7700K.

<table>
<thead>
<tr>
<th>256 × 512</th>
<th>384 × 1280</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 ×</td>
<td>2×</td>
</tr>
<tr>
<td>[3] ResNet50</td>
<td>0.57s</td>
</tr>
<tr>
<td>3Net ResNet50</td>
<td>0.80s</td>
</tr>
</tbody>
</table>

Table 2. Run time comparison between Godard et al. [3] and 3Net running single and double forward on a CPU Intel Core i7-7700K.

Stereo pair (i) is made of two completely novel views synthesized by our network. The other two stereo pairs contain the input image and a novel image synthesized by 3Net.

Observing (a), (b) and (c) we can easily notice three different view points: the two virtual cameras are located at the left and right side of the real camera (i.e., the central one). The three maps in the middle column clearly show artifacts occurring near depth discontinuities and occlusions in (d) and (f) and how they are greatly dampen in the final output of our network (e). Finally, we can perceive how (g) and (i) share the same reference image (synthetic left) and how they compute different disparity values according to different baselines, narrow and wide, made available by the three-view virtual rig enabled by 3Net.

A video showing the performance of 3Net on the KITTI sequence 2011_10_03_drive_0047_sync [2] not part of the Eigen split imagery used for training is available at this link: https://www.youtube.com/watch?v= uMA5YWJME4M.

Finally, the source code is available at this link: https: //github.com/mattpoggi/3net

5. Runtime analysis

In this section, we briefly compare the runtime of 3Net compared to the models by Godard et al. [3]. On high-end GPUs (e.g., Titan X Pascal), the difference between the two models either running single or double forward is negligible, taking between 0.09 and 0.11 seconds both. Nevertheless, in case of applications deploying different architectures the margin rises.

In particular, Table 2 compares the execution times of the
Figure 1. Qualitative evaluation of 3Net. In the leftmost column, we show (always from top to bottom) synthetic left (a), real central (b) and synthetic right (c) view. In the middle column, $d^{l}$ (d), $d^{c}$ (e) and $d^{r}$ (f) depth maps computed by our network processing the input image. In the rightmost column, disparity maps obtained by the SGM algorithm [4] processing respectively, left-center (g), center-right (h) and left-right (i) stereo pair.

considered models using ResNet50 encoder on a CPU Intel Core i7-7700K. Times are averaged on the entire Eigen split testing set. We report numbers at 256 × 512 resolution (i.e., the dimensions used by [3] at inference time), as well as at full KITTI resolution, to stress how the difference between them increases with the image size. We can see how the second encoder in 3Net adds about 50% overhead, while 2× forwards usually doubles it. However, by recalling results reported in the main paper (Table 2, last 3 rows on bottom), 3Net ResNet50 running a single forward is more accurate and faster than [3] ResNet50 running two forwards.

**Acknowledgements**

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Figure 2. Qualitative evaluation of 3Net. In the leftmost column, we show (always from top to bottom) synthetic left (a), real central (b) and synthetic right (c) view. In the middle column, \(d^l\) (d), \(d^c\) (e) and \(d^r\) (f) depth maps computed by our network processing the input image. In the rightmost column, disparity maps obtained with SGM algorithm [4] processing respectively, left-center (g), center-right (h) and left-right (i) stereo pair.

References


