Linear stereo matching Supplementary material

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1. Experimental results

With this supplementary material we include additional experimental results, full resolution disparity maps and error maps computed according to the Middlebury metric [3].

In the paper, we provided experimental results according to the Middlebury dataset and metric [3] of four stereo algorithms. These results correspond to the linear stereo algorithm proposed in our paper and to the adaptive-weight algorithm described in [4]. Each one of the two algorithms is tested without (referred, respectively, as LinearS and AdaptW) and with (referred, respectively, as P-LinearS and P-AdaptW) the disparity refinement step described in the paper composed of *intensity consistent* disparity selection (IC) [1] and *locally consistent* disparity selection (LC) [2].

For a more detailed analysis of the effects of the disparity refinement pipeline proposed based on IC and LC, we provide in this supplementary material the results of applying IC on the raw disparity maps provided by LinearS and AdaptW (referred here, after IC step, as I-LinearS and I-AdaptW). As described in Section 2.5.2 in [1], IC uses two segmented images. One is obtained applying *mean shift* segmentation to the reference image of the stereo pair (we use the parameter values proposed in [1]: $\sigma_r = 4$, $\sigma_s = 5$, and segments smaller than 100 pixels are not considered). The other segmented image is obtained clustering connected pixels with similar disparity within each segment. This is done by allowing neighboring pixels in the disparity map to vary by one pixel, considered. Further details of this method can be found in [1]. The mean shift segmented images can be found in the first column of Figure 1 and the segmented disparity maps according to the disparity map computed by LinearS can be found in the second column of Figure 1. Black pixels in Figure 1 represent segments not considered in the IC refinement step according to the size constraints previously described. For what concerns LC [2], the optimal parameters found are 39×39 windows with $\gamma_s = 22$, $\gamma_c = 23$, $\gamma_m = 5$ and T = 60 for P-LinearS and 39×39 windows with $\gamma_s = 13$, $\gamma_c = 35$, $\gamma_m = 8$ and T = 50 for P-AdaptW.

Algorithm	Tsukuba			Venus			Teddy			(Average percent of		
											bad pixels		
	nonocc	all	disc	nonocc	all	disc	nonocc	all	disc	nonocc	all	disc	
AdaptW	3.46	4.06	8.90	0.92	1.49	8.67	7.53	14.1	17.2	2.55	8.03	7.24	7.01
LinearS	3.63	4.39	9.61	2.10	2.81	17.0	9.14	15.5	21.1	2.84	8.53	8.15	8.73
I-AdaptW	3.69	4.13	8.54	0.57	0.89	5.47	6.69	13.3	16.0	2.80	8.08	7.78	6.50
I-LinearS	3.62	4.20	7.50	1.22	1.68	9.34	7.14	13.6	17.2	2.75	8.23	7.83	7.03
P-AdaptW	1.62	2.09	5.78	0.18	0.36	2.16	6.37	11.6	14.9	2.87	8.80	7.14	5.33
P-LinearS	1.10	1.67	5.92	0.53	0.89	5.71	6.69	12.0	15.9	2.60	8.44	6.71	5.68

Table 1. Performance comparison of aggregation methods using colour input images, pre and post-processing.

The results of the six proposed algorithms are summarized in Table 1. The performance of the algorithms is measured using the percentages of bad pixels considering all pixels ("all"), considering only non-occluded regions ("nonocc") and considering only pixels near depth discontinuities ("disc"). A detailed description of these parameters and the whole dataset used for this experiments can be found in [3]. The resulting disparity maps can be found in Figures 2-7. According to Table 1, and the disparity maps in Figures 2-7, IC and LC turn to be effective refinement techniques for both algorithms. In particular,

IC eliminates large erroneous patches (e.g. the upper-right corner in Tsukuba and the patch to the right of the teddy bear in Teddy are specially remarkable since they appear in most local stereo matching algorithms) and coarsely redefines some blurred disparity edges (e.g. on the Tsukuba statue head and Venus disparity edges for LinearS). According to Figures 2-7 and Table 1 LC solves small erroneous disparity patches and accurately refines disparity edges.

Finally, in Figure 8 we report a screenshot of the Middlebury ranking captured on February 23^{rd} , 2011. This figure allows us to compare the performance of the proposed P-LinearS algorithm with other state-of-the-art approaches.

References

- H. Hirschmüller. Stereo processing by semiglobal matching and mutual information. *IEEE Trans. Pattern Analysis and Machine Intelligence*, 30(2):328–341, 2008.
- [2] S. Mattoccia. A locally global approach to stereo correspondence. In Proc. IEEE Int. Workshop on 3D Digital Imaging and Modeling, pages 1763–1770, 2009. 1
- [3] D. Scharstein and R. Szeliski. Middlebury stereo evaluation version 2, http://vision.middlebury.edu/stereo/eval. 1
- [4] K.-J. Yoon and I. S. Kweon. Adaptive support-weight approach for correspondence search. *IEEE Trans. Pattern Analysis and Machine Intelligence*, 28(4):650–656, 2006.



Figure 1. Segmented maps computed using mean shift segmentation (left column) and disparity segmentation based on the mean shift maps and the disparity maps produced by LinearS (right column).



Figure 2. Disparity maps computed by LinearS (left column) and error maps according to the Middlebury website (right column).



Figure 3. Disparity maps computed by AdaptW (left column) and error maps according to the Middlebury website (right column).



Figure 4. Disparity maps computed by I-LinearS (left column) and error maps according to the Middlebury website (right column).



Figure 5. Disparity maps computed by I-AdaptW (left column) and error maps according to the Middlebury website (right column).



Figure 6. Disparity maps computed by P-LinearS (left column) and error maps according to the Middlebury website (right column).



Figure 7. Disparity maps computed by P-AdaptW (left column) and error maps according to the Middlebury website (right column).

Error Threshold = Error Threshold	Sort by nonocc				Sort by all					Sort b	y disc				
Algorithm	Avg.	<u>Tsukuba</u> ground truth			<u>Venus</u> ground truth			<u>Tedity</u> ground truth			<u>Cones</u> ground truth			Average percent of bad pixels (<mark>explanation</mark>)	
	Rank	<u>nonocc</u>	all V	<u>disc</u>	nonocc	all V	<u>disc</u>	nonocc	all V	<u>disc</u>	nonocc	all V	<u>disc</u>		
ADCensus [94]	5.3	<u>1.07</u> 11	1.48 9	5.73 13	<u>0.09</u> 1	0.25 6	1.15 t	<u>4.10</u> 4	6.223	10.94	<u>2.42</u> 3	7.25 5	6.954		3.97
AdaptingBP [17]	6.6	<u>1.11</u> 13	1.37 5	5.79 14	<u>0.10</u> 2	0.21 3	1.44 3	<u>4.22</u> 6	7.06 6	11.87	<u>2.48</u> 4	7.92 9	7.327		4.23
CoopRegion [41]	6.7	<u>0.87</u> 2	1.16 1	4.61 1	<u>0.11</u> 3	0.21 2	1.54 5	<u>5.16</u> 14	8.31 9	13.0 11	<u>2.79</u> 12	7.184	8.01 16		4.41
DoubleBP [35]	9.1	<u>0.88</u> 4	1.29 2	4.764	<u>0.13</u> 6	0.45 16	1.87 10	<u>3.53</u> 3	8.30 8	9.63 <mark>2</mark>	<u>2.90</u> 17	8.78 24	7.79 13		4.19
RDP [102]	9.7	<u>0.97</u> 7	1.396	5.00 6	<u>0.21</u> 20	0.38 14	1.89 11	<u>4.84</u> 8	9.94 15	12.69	<u>2.53</u> 5	7.697	7.38 8		4.57
OutlierConf [42]	10.2	<u>0.88</u> 3	1.438	4.743	<u>0.18</u> 14	0.26 8	2.40 18	<u>5.01</u> 10	9.12 12	12.8 10	<u>2.78</u> 11	8.57 20	6.995		4.60
SubPixDoubleBP [30]	13.6	<u>1.24</u> 21	1.76 23	5.98 16	<u>0.12</u> 5	0.46 18	1.74 8	<u>3.45</u> 2	8.38 10	10.0 3	<u>2.93</u> 19	8.73 23	7.91 15		4.39
SurfaceStereo (79)	14.3	<u>1.28</u> 26	1.65 15	6.78 30	<u>0.19</u> 16	0.28 9	2.61 25	3.12 1	5.10 t	8.65 1	<u>2.89</u> 16	7.95 11	8.26 21		4.06
WarpMat [55]	15.9	<u>1.16</u> 14	1.354	6.04 17	<u>0.18</u> 15	0.24 6	2.44 20	<u>5.02</u> 11	9.30 13	13.0 13	<u>3.49</u> 27	8.47 19	9.01 33		4.98
ObjectStereo [98]	16.2	<u>1.22</u> 20	1.62 11	6.36 <mark>22</mark>	<u>0.59</u> 43	0.69 32	4.61 43	<u>4.13</u> 5	7.597	11.26	<u>2.20</u> 1	6.993	6.36 1		4.46
Undr+OvrSeq [48]	21.0	<u>1.89</u> 48	2.22 41	7.22 38	<u>0.11</u> 4	0.22 4	1.34 2	<u>6.51</u> 26	9.98 16	16.4 29	<u>2.92</u> 18	8.00 12	7.90 14		5.39
GC+SeqmBorder [57]	21.5	<u>1.47</u> 37	1.82 25	7.86 45	<u>0.19</u> 17	0.31 10	2.44 20	<u>4.25</u> 7	5.55 <mark>2</mark>	10.9 5	<u>4.99</u> 62	5.78 t	8.66 27		4.52
GlobalGCP [104]	22.1	<u>0.87</u> 1	2.54 44	4.69 2	<u>0.16</u> 12	0.53 21	2.22 16	<u>6.44</u> 23	11.5 23	16.2 26	<u>3.59</u> 30	9,49 35	8.95 32		5.60
CostFilter [95]	22.4	<u>1.51</u> 39	1.85 29	7.61 42	<u>0.20</u> 19	0.39 15	2.42 19	<u>6.16</u> 21	11.8 26	16.0 <mark>23</mark>	<u>2.71</u> 9	8.24 15	7.66 12		5.55
AdaptOvrSeqBP [33]	23.3	<u>1.69</u> 41	2.04 36	5.64 11	<u>0.14</u> 8	0.20 1	1.47.4	<u>7.04</u> 40	11.1 19	16.4 31	<u>3.60</u> 32	8.96 28	8.84 29		5.59
<u>P-LinearS (99)</u>	23.6	<u>1.10</u> 12	1.67 16	5.92 15	<u>0.53</u> 40	0.89 39	5.71 48	<u>6.69</u> 32	12.0 32	15.9 <mark>22</mark>	<u>2.60</u> 6	8.44 18	6.71 3		5.68
PlaneFitBP [32]	25.2	<u>0.97</u> 9	1.83 26	5.26 9	<u>0.17</u> 13	0.51 20	1.717	<u>6.65</u> 30	12.1 33	14.7 15	<u>4.17</u> 49	10.7 47	10.6 44		5.78
<u>GeoSup [64]</u>	25.5	<u>1.45</u> 35	1.83 27	7.71 44	<u>0.14</u> 9	0.267	1.90 12	<u>6.88</u> 37	13.2 41	16.1 25	<u>2.94</u> 20	8.89 26	8.32 23		5.80
SymBP+occ [7]	25.8	<u>0.97</u> 7	1.75 22	5.09 8	<u>0.16</u> 10	0.33 12	2.19 15	<u>6.47</u> 25	10.7 17	17.0 39	<u>4.79</u> 57	10.7 49	10.9 48		5.92
ASSM [97]	26.8	<u>1.28</u> 27	1.69 18	6.44 <u>25</u>	<u>0.64</u> 47	1.11 46	5.61 47	<u>6.51</u> 26	11.5 22	16.4 32	<u>2.81</u> 13	8.07 13	7.196		5.77
GeoDif [103]	27.3	<u>1.88</u> 47	2.35 42	7.64 43	<u>0.38</u> 32	0.82 35	3.02 29	<u>5.99</u> 18	11.3 20	13.3 14	<u>2.84</u> 14	8.33 16	8.09 17		5.49
AdaptDispCalib [36]	28.4	<u>1.19</u> 17	1.427	6.15 19	<u>0.23</u> 22	0.34 13	2.50 23	<u>7.80</u> 47	13.6 46	17.3 46	<u>3.62</u> 33	9.33 33	9.72 37		6.10
Segm+visib [4]	28.8	<u>1.30</u> 29	1.57 10	6.92 36	<u>0.79</u> 61	1.06 44	6.76 56	<u>5.00</u> 9	6.54 4	12.38	<u>3.72</u> 35	8.62 22	10.2 41		5.40
C-SemiGlob [19]	29.0	<u>2.61</u> 63	3.29 54	9.89 58	0.25 25	0.57 23	3.24 31	<u>5.14</u> 13	11.8 25	13.0 11	2.77 10	8.35 17	8.20 18		5.76

Figure 8. Position of P-LinearS in the Middlebury ranking as of February 23^{rd} , 2011.