Spring: A High-Resolution High-Detail Dataset and Benchmark for Scene Flow, Optical Flow and Stereo – Supplementary Material –

In the following, we provide additional information regarding the Spring dataset and benchmark. In this context, we present further example sequences and visualizations of the methods we evaluated, we continue the discussion of results from the main paper, list additional evaluation results excluding the sky region, and show screenshots of the benchmark website.

1. Further examples of the Spring dataset

In Fig. 1, we show further example sequences of the Spring dataset that illustrate its *wide variety of content*. For each sequence, we show the left and right image of the stereo camera, the corresponding left and right disparity, the change of the left and right disparity both in forward and backward temporal direction, as well as the left and right optical flow also both in forward and backward temporal direction, accordingly.

2. Visual benchmark results

Moreover, for the stereo, optical flow and scene flow tasks, we show disparity/flow and error visualizations of the methods we evaluated in Figs. 2 to 4.

3. Further discussion of results

Optical Flow. For optical flow, we can see that the handling of high-resolution inputs plays an important role for the performance on our benchmark. Many of the evaluated networks estimate the optical flow on a lower resolution, followed by a learned upsampling; FlowFormer [2], RAFT [11] and GMA [6] work on 1/8th of the original resolution, GMFlow [14] on 1/4th. The best-performing MS-RAFT+ [4, 5] works on an even higher resolution, 1/2 of the original resolution, also followed by a learned upsamling. In general, methods with learned upsampling lead the benchmark, a strategy closely related to FlowNet2 [3] ranking third. Their architecture consists of modules predicting optical flow on 1/4th of the original resolution, but then uses a fusion module that given nearest-neighbor upsampled inputs predicts results on the original resolution. In contrast, the coarse-to-fine pyramid strategy of SPyNet [9] as well as the purely bilinear $4 \times$ upsampling of PWCNet [10] did not yield as good results as the aforementioned strategies.

When comparing EPE results from our benchmark to EPE results from the Sintel benchmark, it is noticeable that numbers on our benchmark are on a lower level. We attribute this mainly to the fact that the Sintel dataset has a focus on action sequences with very strong motion, while Spring addresses high-resolution and high-detail content. Although there are also several high-speed scenes in Spring, they cover a smaller part of the dataset. Further, with the super-resolution ground truth, Spring uses a more permissive evaluation methodology than Sintel.

Stereo. In case of stereo, one can observe that the best performing methods on the Spring benchmark operate on moderately subsampled versions of the input images -i.e. typically 1/3 or 1/4 of the original resolution – while they rely on hierarchical concepts at the same time. More precisely, ACVNet [13] uses three-level adaptive patch matching with attention-based feature concatenation, RAFT-Stereo [7] exploits a four-level correlation pyramid, multi-level recurrent update operators and a three level coarse-to-fine estimation scheme, and LEAStereo [1] learns a compact network with 2-level feature extractor and 3-level matching module based on a neural architecture search. GA-Net [15] which ranks last in the Spring benchmark is the only network that directly operates on the original resolution. While it considers guided aggregation layers, however, it does not exploit hierarchical concepts. From all considered methods, ACVNet performs best. This can not only be seen from the corresponding table in the main paper, but also from a visual comparison of the results in Fig. 2. While it shows slight upsampling artefacts, ACVNet seems most robust regrading the background estimation, potentially due to the attentionbased feature concatenation.

Scene Flow. In case of scene flow, two of the considered approaches (RAFT-3D [12], M-FUSE [8]) rely on a RGB-D setting. This in turn requires the pre-computation of stereo results before estimating the scene flow. In contrast, CamliFlow seeks to better preserve the 3D structure of the scene by integrating LiDAR input that is converted to point clouds. However, in case of stereo input, CamliFlow also has to rely on external stereo results before constructing these point clouds. Interestingly, all three approaches show problems with different components of the scene flow. M-FUSE that extends RAFT-3D by considering temporal in-

formation and using LEAStereo as a stereo baseline shows only moderately accurate results for the optical flow - although the stereo input seems be of good quality. In contrast, RAFT-3D that relies on GA-Net shows larger errors in the stereo estimation that eventually propagate to the overall scene flow. Finally, CamliFlow has severe problems obtaining useful disparity estimates for the second frame pair, most probably due to the same difficulties as RAFT-3D with the underlying GA-Net approach. Another observation that might explain the comparably poor performance of CamliFlow is its dedicated background estimation module. Since it is trained on Cityscapes and KITTI it is likely not to generalize to other type of data. In terms of overall accuracy, M-FUSE slightly outperforms MS-RAFT. In contrast, CamliFlow gives significantly worse results. As in the the stereo case, these findings are not only reflected in the corresponding results in the main paper. They can also be seen from the visual comparison in Fig. 4.

4. Additional results for non-sky regions

As described in the main paper, we provide additional evaluation results that consider *non-sky pixels only*. The corresponding rankings for stereo, optical flow and scene flow can be found in Tabs. 1 to 3. As expected, the difficulty decreases such that the overall errors are lower, resulting in a few ranking order changes. The largest decrease is noticeable for the stereo benchmark, showing that the sky regions are particularly difficult for the current set of methods. At the same time, it is expected that future stereo methods trained on datasets with sky regions will perform better.

5. Screenshots of the benchmark website

Finally, in Figs. 5 to 12, *screenshots* of the Spring benchmark website are shown. These screenshots include the benchmark start page (Fig. 5), the current benchmark rankings for stereo (Fig. 6), optical flow (Fig. 7), and scene flow (Fig. 8), the benchmark evaluation sites of the three leading methods, i.e. ACVNet (Fig. 9), MS-RAFT+ (Fig. 10), and M-FUSE (Fig. 11), as well as the benchmark page to sign up for an evaluation account (Fig. 12).

References

- Xuelian Cheng, Yiran Zhong, Mehrtash Harandi, Yuchao Dai, Xiaojun Chang, Hongdong Li, Tom Drummond, and Zongyuan Ge. Hierarchical neural architecture search for deep stereo matching. In *Proc. Conference on Neural Information Processing Systems (NeurIPS)*, pages 22158–22169, 2020. 1
- [2] Zhaoyang Huang, Xiaoyu Shi, Chao Zhang, Qiang Wang, Ka Chun Cheung, Hongwei Qin, Jifeng Dai, and Hongsheng

Li. FlowFormer: a transformer architecture for optical flow. In *Proc. European Conference on Computer Vision (ECCV)*, 2022. 1

- [3] Eddy Ilg, Nikolaus Mayer, Tonmoy Saikia, Margret Keuper, Alexey Dosovitskiy, and Thomas Brox. FlowNet 2.0: Evolution of optical flow estimation with deep networks. In Proc. IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pages 2462–2470, 2017. 1
- [4] Azin Jahedi, Maximilian Luz, Lukas Mehl, Marc Rivinius, and Andrés Bruhn. High resolution multi-scale RAFT (Robust Vision Challenge 2022). In *arXiv preprint 2210.16900*. arXiv, 2022. 1
- [5] Azin Jahedi, Lukas Mehl, Marc Rivinius, and Andrés Bruhn. Multi-scale RAFT: Combining hierarchical concepts for learning-based optical flow estimation. In *Proc. IEEE International Conference on Image Processing (ICIP)*, pages 1236–1240, 2022. 1
- [6] Shihao Jiang, Dylan Campbell, Yao Lu, Hongdong Li, and Richard Hartley. Learning to estimate hidden motions with global motion aggregation. In *Proc. IEEE/CVF International Conference on Computer Vision (ICCV)*, 2021. 1
- [7] Lahav Lipson, Zachary Teed, and Jia Deng. RAFT-Stereo: Multilevel recurrent field transforms for stereo matching. In International Conference on 3D Vision (3DV), 2021. 1
- [8] Lukas Mehl, Azin Jahedi, Jenny Schmalfuss, and Andrés Bruhn. M-FUSE: Multi-frame fusion for scene flow estimation. In Proc. IEEE/CVF Winter Conference on Applications of Computer Vision (WACV), 2023. 1
- [9] Anurag Ranjan and Michael J. Black. Optical flow estimation using a spatial pyramid network. In Proc. IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2017. 1
- [10] Deqing Sun, Xiaodong Yang, Ming-Yu Liu, and Jan Kautz. PWC-Net: CNNs for optical flow using pyramid, warping, and cost volume. In Proc. IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2018. 1
- [11] Zachary Teed and Jia Deng. RAFT: recurrent all-pairs field transforms for optical flow. In *Proc. European Conference* on Computer Vision (ECCV), pages 402–419, 2020. 1
- [12] Zachary Teed and Jia Deng. RAFT-3D: Scene flow using rigid-motion embeddings. In Proc. IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pages 8375–8384, 2021. 1
- [13] Gangwei Xu, Junda Cheng, Peng Guo, and Xin Yang. Attention concatenation volume for accurate and efficient stereo matching. In Proc. IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2022. 1
- [14] Haofei Xu, Jing Zhang, Jianfei Cai, Hamid Rezatofighi, and Dacheng Tao. GMFlow: Learning optical flow via global matching. In Proc. IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2022. 1
- [15] Feihu Zhang, Victor Prisacariu, Ruigang Yang, and Philip H. S. Torr. GA-Net: Guided aggregation net for end-to-end stereo matching. In *Proc. IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 185– 194, 2019. 1



Figure 1. Example sequences from the Spring dataset. *First row*: Left and right images of the stereo camera, *second row*: Corresponding left and right disparity, *third row*: Change in disparity for forward left, backward left, forward right and backward right, *fourth row*: Optical flow visualization for forward left, backward left, forward right and backward right. Please note that we show the disparity change for visualization purposes while the dataset contains the target frame disparity.



Figure 2. Visualizations from the stereo benchmark. Top row: predicted disparity, bottom row: absolute error visualization and color code.



Figure 3. Visualizations from the optical flow benchmark. Top row: predicted optical flow, bottom row: EPE error visualization.

Table 1. Stereo results on our benchmark. We show additional evaluation metrics computed only on the non-sky pixels of the dataset.

				1px					Abs	D1
Method	total	low-det.	high-det.	matched	unmat.	s0-10	s10-40	s40+	1105	21
RAFT-Stereo	9.92	9.56	32.14	8.46	43.39	5.16	9.99	17.03	0.68	3.67
ACVNet	11.16	10.77	35.13	9.44	50.63	6.32	11.33	18.12	1.14	4.59
LEAStereo	16.73	16.36	39.65	14.91	58.50	7.63	13.84	39.39	2.44	7.42
GANet	18.42	18.03	42.16	16.51	62.09	7.32	16.41	41.48	2.59	7.77



Figure 4. Visualizations from the scene flow benchmark. *From top to bottom*: predicted reference disparity, reference disparity error, predicted target disparity, target disparity error, predicted optical flow, optical flow error, combined scene flow error.

					1px						EPE	Fl	WAUC
Method	total	low-det.	high-det.	matched	unmat.	rigid	non-rigid	s0-10	s10-40	s40+	212	••	
MS-RAFT+	4.84	4.46	61.80	4.18	32.41	1.84	25.96	1.43	4.93	34.60	0.63	2.08	93.64
RAFT	5.25	4.86	64.30	4.47	37.74	2.15	27.08	1.75	5.15	36.39	0.71	2.09	92.28
FlowFormer	5.50	5.11	64.30	4.75	36.60	2.16	29.07	2.09	5.54	35.37	0.69	2.14	92.50
GMA	5.61	5.21	66.41	4.83	38.31	2.40	28.24	2.27	5.28	36.06	0.87	2.23	91.93
FlowNet2	6.04	5.65	64.31	5.05	47.31	2.72	29.39	1.72	5.72	45.05	0.84	2.27	91.62
GMFlow	8.95	8.50	76.64	7.65	63.10	4.94	37.24	4.01	9.66	50.34	0.94	2.75	82.98
SPyNet	25.83	25.49	77.88	24.58	77.74	21.46	56.61	19.68	23.42	87.28	3.23	8.72	70.71
PWCNet	81.57	81.57	81.76	81.37	90.07	82.07	78.09	80.57	82.09	88.82	2.25	4.17	46.40

Table 2. Optical flow results on our benchmark. We show additional evaluation metrics computed only on the non-sky pixels of the dataset.

Table 3. Scene flow results on our benchmark. We show additional evaluation metrics computed only on the non-sky pixels of the dataset.

					1px						SF	1nx ^{D1}	1nx ^{D2}	1nx ^{Fl}
Method	total	low-det.	high-det.	matched	unmat.	rigid	non-rigid	s0-10	s10-40	s40+	51	1PA	1PA	1pA
M-FUSE (F)	31.36	30.68	64.35	28.79	67.90	25.39	73.36	14.08	23.58	67.67	13.05	16.73	21.26	18.38
RAFT-3D (K)	33.23	32.68	60.54	30.54	71.57	27.94	70.51	28.43	24.22	62.19	13.20	27.96	28.64	11.82
CamLiFlow (F)	46.85	46.34	72.05	44.75	76.75	42.82	75.24	11.98	42.44	89.06	31.88	18.42	40.62	21.79
M-FUSE (K)	60.03	59.81	70.98	58.26	85.25	57.42	78.41	78.19	48.97	74.81	20.36	49.10	54.22	19.50
RAFT-3D (F)	77.57	77.43	84.67	77.14	83.63	78.25	72.80	80.42	81.66	63.87	67.58	18.42	72.27	48.80
CamLiFlow (K)	84.35	84.21	91.19	83.55	95.65	83.00	93.85	55.39	87.79	99.85	69.03	27.96	74.99	67.72



Figure 5. Spring benchmark: Start page.

					PH	< 1 I	VC	-					
				Dat	acot \$	2. Ronc	hma	rk					
				Dui	user	x Dene	iiiiiu						
				LI	Metic J. Schewalfor	is, A. Johesh, Y. Naliv	șiko, A Brahn						
				Download	times /	And the second second	cece flow	T- Avenue					
				Dominous		pota non	CALIN FROM	200116					
												1	estuser@univi
	Name	1µx	Tpx	1px	1px	3,8.8	1px	1,84	1px	100.43	184	Abs	01
			140-94125	right becau	mounee	annestones	inter sky	ay .	30.10	110100	100*		
1	ACVNet	14.772	14.432	35.273	12.600	57.894	11.163	69.621	18.385	11.346	18.145	1.516	5.346
	+ submitted by spring norm (Gampani Ku, Junda Dr	ang Rang Euro, and Kin Y	ang Nataralan Cancelana	eien Volume for Accurat	a and Officient Stews Mater	ing" in ETDOM OF	nheieres en Camp	uter iteen and ite	nen langeiten	(NH); 1622		
2	BALT-Stargo	15.273	14.983	32.776	13.394	52.582	9.924	26.571	22.588	10.018	17.086	3.025	8.625
	Budenitised by spring insure.	Lahas Lipson, Zashary	Tees, and jis Deng. WAI	T Server Multimet Berury	ant Lais Tarolows &	r Seens Matching 7 in Inter	utional Conference	n Wilson (De	3124				
3	LEAStereo	19.888	19.547	40.396	17.611	65.086	16.735	67.805	19.076	13.861	39.412	3.884	9.194
	submitted by spring inset	Nation Chang View 2	horg Alebrank Earand	Norbas Sal, Karper Dar	g Hargeburg Li, Tore D	rummersel, and Zengevan D	. Tileserhind Neur	ni Antoine Se	and dar George States	e Mering " in 6	2026 Plinus		
4	MILLSEID (SF)	19.888	19.547	40.396	17.611	65.086	16.735	67.805	19.076	13.861	39.412	3.884	9.194
	automitiani key spring tauna	Lakas Mells Aan jahe	a prey schedules are	Andres Bruhn, "Bir Cole, 1	Auto-frame fragements a	core from Edimation." In E	LECCI Weber Confe	rance on Applicati	ens of Computer 1	Non (NAC) 212	A		
5	SANG	25.225	22.912	42.064	20.976	67.878	18,418	96.274	24,299	16.427	41,/099	4.594	10.393
6	946T-10 (D)/SEI	23.225	22 912	42.054	23.976	47 878	10.410	96.274	24 285	16.477	41,000	4 594	10 292
	automation in spring town	Jachery feed, and ba	Dane, TAVI JD Some P	ow yong Rep-Mation End	bookings," In 1985-CVF I	Conference on Computer W	ine and Pattern Aug	option CPTS 2	10.				
7	CamURow (F) (SF)	23,225	22.912	42.054	20.976	67.878	18.418	96.274	24,285	16.427	41,499	4.594	10.393
	* submitted to spring team 1	Heborg Lin, Teo Lo, Y	Part Pro. So Line Worses Line	end pain then "Cartofic	. beredore (anos	-LOAR Fusion for Ising Out	at they are some if	ion Estimation," in	BLOCH Cartine	na en Camputar	Vision and Patter	heapiton 6	wines, 2002.
	CamURow (K) (SFI	32,309	32,096	45.189	30.071	76.734	27.953	98,355	39,354	22.522	48,158	7.042	14.174
	+ submitted by spring team (Haborg Lin, Tao Lin, W	hai ha jia Liu. Morgie Liu	and signs then "Carelina	e beredine Cares	-LOAR Fusion for paint Opt	at free and Scene if	low Estimation," in	ELDON Confine	nce en Camputor	Vision and Pattor	keopitor t	wP49.2022
9	RAFT-SD (K) [SF]	32.309	32.096	45,189	30.071	75.734	27.953	98.355	39.354	22.522	48.158	7.042	14.174
	nuterities by spring team	Zachary Tensi, and Jie	Darg WAITID Some II	on using Digit Advisor Erri	issisings." in 200 Cull i	Conference on Computer W	ion and Pattern Re-	option (CHI), 3	21				
	0 MEUSE IKUISEI	52,232	52.185	55.051	50.647	83.685	49.104	99.771	80.774	34.056	52.347	7.890	19.836

Figure 6. Spring benchmark: Stereo ranking.

					3	ГГ			1.							
					Dat	acot \$	2. D	anch	ma	k						
					Dui	userc	x De	incri	mui	~						
					1.1	dent, J. Schwalfus	is, A johed	, r. Nateoyea,	A Brohn							
				Dov	beoinv	Stereo O	ptical Flow	Scene	Flow	Submit						
															test	nergyrn
	Name	1px totol A	1px low-detail	1px Neb-detail	1px matched	1px anmatched	1px circle	tpx pan-cipid	1px nat sky	1px sky	1µx x0-10	1px x10.40	1µx 140+	DE	п	нию
1	MS-RAFT+	5.724	5.370	61.497	5.041	33.954	3.047	25.973	4.840	19.150	2.055	5.022	38.315	0.643	2.189	92.888
	Danformari i govgas	4.610	6.1.64	64 310	5 754	27.764	2 5 7 7	20.084	8 6 m	11 959	1.001	5.690	25.244	0.778	1.984	01.670
-	 Admitted by spring into 	m Danyang li	org, Kerys Sti, Ox	e Durg Garg liveg	to Our Deve	iorguei (in, jilorg lie	antiiengite	rgii Visafarner	ATweetermer	and	Optical line	In Sumpson i	onlenence on	Computer Vision	1004 202	
3	Doublet2	6.710	6.346	64.061	5.691	48.892	3.711	29.404	6.039	16.908	1.862	5.816	43.653	1.040	2.823	50.907
	I submitted by spring into	en Corylig Nik	niaus Mayor, Toronay	Sakin, Margar Koup	er, Aleury Gennutes	ity and Domes line "	Combine 2.0-1	ministran of Optical I	Institution	aith Deep lars	units" in ETT	Contenance or	Computerille	in and famous i	languiton (CV	10,207
4	LAL1	6.790	0.425	64.087	5.222	39.481	4.107	27.068	5.250	30.183	3.134	5.301	41.405	1.436	3.198	50.920
5	GMA	7.074	6.699	66.203	6.281	39.892	4.276	28.247	5.614	29,263	3.645	5.389	40.327	0.914	3.079	50.722
	I submitted by spring too	m Shihoo Jung	Dylar Campbell Ya	Gu Hangslung Li. and	Robard Helloy 1	inarrang to Antimutu He	alden Multions	with Dodar Mation	Appropriation." In	BBLOT HO	national Card	eramia an Gam	nder Vann (K	206 2021.		
6	GVEIow	10.355	9.935	76.613	9.060	63.949	6.800	37.258	8.952	31.680	5.412	9.901	52.944	0.945	2.952	82.337
7	PACT 10 (0) ISE	13 952	13 539	E0.454	12 663	EC 2CA	8 932	52.013	11.822	dr. d79	8 895	14 726	54 703	2 528	6.009	81.267
	* automational lay spring taxe	m Zachary Teo	L and Ju Dung, TAV	12D Scine flow using	RgoMiton End	oodrags," In SELECT C	ion for small on	Computer Vision an	d fattare facos	How COTING	1021					
8	M-FUSE (F) [SF]	20.376	19.993	80.798	19.382	61.415	15.312	58.668	18.381	\$0.653	9.734	29.588	84.458	2.948	8.791	76.550
	* submitted by spring too	en Lukus Mehr	Alm jaheab, Janny Sc	mature and Andrea	Dute, "M-LSE B	uto-france fusion for Se	core from Estim	nation." In EELCON	Winter Contere	nce on Applica	tions of Comp	Aprilippe (MP	05.2523			
9	M-FUSE (K) [SF]	20.979	20.600 Attribute immovid	E0.743	19.942	63.882	15.953 one line (no	59.005	19.500 Winter Content	43.455	10.131 tere et Corre	30.966	84.713	2.526	8.480	76.182
10	CamLiBow(D(SF)	24.012	23.694	74.084	23.112	61.234	21.203	45.265	21.791	57.763	15.394	33.769	69.710	27.374	17,216	74.082
	Endersitied by spring into	en Haborg Lin,	Tan ke, Yibut ibu, jin i	As Merginia and Spe	Dan Vanidina	himinal lanes	10423.444	for joint Optical Elev	a and Scene Die	a Differention/	A REDCH CO	elevence an Co	mpatter Vision	and Fattern Rev	option (1976)	2920.
11	SPythet	29.963	29.661	77,450	28.783	78.766	26.442	56.601	25.832	92.738	24.803	24.201	88.714	4.162	12.865	67.150
12	RAFT-SD IFLISE	48.066	47.883	76.933	47.662	64.791	48,200	47.056	48.798	36.942	42.335	68.531	40.645	4.784	34.921	50.685
	 A submitted by spring into 	m Zachary Tea	4. and Ja Dang, "AA"	11D Some Time using	Digit Abrian Dela	enderge." in 2015 Cut of	Conference on	Computer Union an	of Pathern Decog	patter (CVPR) :	48.000	00.001	40.040	45.04	Jan Jan	20000
13	CamUElow/80 (SF)	69.685	69.533	93.651	69.179	90.611	67.381	87.114	67.724	99.492	62.899	79.497	99.903	127.387	60.485	30.635
		en Helong Lis.	Teo Lo, Vitus Ro, Sa I	As When is and the		e Belmetional Camera	LOAK Fusion				IN BEECON CO			and Pattern Rec	spinon (CPR)	2902

Figure 7. Spring benchmark: Optical flow ranking.

					-	SP	R		V	G							
					D	aldse	ιà	Ben	um	uri	<						
						L. Mehr, J. Sci	tenaļšizzs, A	Johesti, Y. Nis	lionyko, A B	raha							
					Download	Stereo	Optio	al Row	Scene Flor		abmit						
																14523	Der Burner
	Nome	cooal +	iper-detail	high-detail	matched	sumstched	rigid	non-rigid	net sky	sky	\$0.10	\$10.40	540+	SF	7px 01	1px 32	Tpx ^{FI}
1	M-EUSE.(E)	34.896	34.298	64.324	32.028	71.943	29.810	73.377	31.355	88.712	29.890	23.911	69.148	16.103	19.888	24.256	20.374
15	DATE 3D 40	27.262	14 Th	60.007	24.240	77.004	33.044	20.022	33.334	00.534	43 700	DATAS	63.04.4	17.247	22.200	33.040	12.002
1	696130.00	31.202	30.799	00.227	54.540	75.021	34,600	10.522	33-231	98.331	43.757	24.549	03.914	17.345	36.343	34.940	13.912
5	Corri (Elen (E)	50.092	19.643	71.984	47 795	79.636	46.754	25.367	46.0.10	69.252	21 115	42 699	99.550	24161	22 225	44.105	24.012
	I sales that ity arr	ing learn False	rwin letin Was	No. In Los Warris Li.	rd Like Own V	riden Birning	Cameralich	Fundament for Sales 2	what free and	lorne filme Int	instan' hill	IS Cif Carder	rea on Comp	star librar and	Paters Inco	ration (C)PE.	A-4-9-A
	M-RUSE IKI	62,490	62,291	72.356	60.574	87.247	60.385	78.416	60.032	99,850	82.966	49,200	25.963	25,232	\$2.232	\$7.029	20.979
	1 submitted by opt	ing team Lake	Stehl, Auto Jahmil, J	my lobration, are	Andres Bruter, 'M	PULL Mate have for	sites for Low-w	ten Internation." In	III.OF NYS	Cardwana	an Application	s of Computer	Voir (MC)	2023.			
5	RAFT-3D.(F)	78.822	78.753	82.195	78.329	85.191	79.618	72,799	77.570	97,838	84.329	81.680	65.478	66.879	23.225	73.426	48.066
	1 million about the sport	ing team Deth	ary feed, and its Out	g 1997.30 Scane F	owvering Rigid Mo	tor Endeddings," in 1	ILLCA Carto	ence en Campute	Vicion and Patt	en keopite	or (NPR, 192						

Figure 8. Spring benchmark: Scene flow ranking.

			Download So	reo Optical Row	Scene Flow	Submit			testaser@university-domain
ACVN	et								
Nov. 1, 2022	2 p.m. — Public by spring team Gan	gwei Xu, Junda Cheng, Per	g Guo, and Xin Yang. '9	tsention Concatenation V	olume for Accurate an	nd Efficient Stereo	Matching." In IEE	UCWF Conference	on Computer Vision
BR DR	secognition (Cavid, 20	22							
Stereo	1px	1pe	1pe	1px	tax.	fpr	1px	1pe	tps:
tistel 14.772	four-detail 14.432	bigh-decoil 35.273	natched 12.600	samutched 57,094	net sty 11.163	sky 09.621	s0-10 18.386	s10-40 11.346	s43+ 18.145
tatal 1.516	low-deteil 1.483	high-deteil 3.506	matched 0.938	assetched 13.002	net sky 1.144	aky 7,170	1.852	1.183	1.873
81 8968/ 5.346	D1 Jow-detail 5.266	01 bigb-decoil 10.178	01 matched 3.804	D1 anmetched 35.948	01 not aky 4.586	81 aky 16.895	01 x0-10 5.618	01 x10-40 5.310	D1 140+ 4.938
						2 4	23		
						0.2			
W.	Reference	e trase	3	Deparity 1 visuals	alon	2	198 Y	1	2
(Street									- 1 12
ie.	Briterere	e Frane		Departy Lyssals	aton		50.	22	
and the		a Form		Poorts I visual					
1		m					S.		1 P
	A for the second	e France		Eperty 1 Yourk					3
CON ST							1.00		P.1.
	Arteres	a France		Disparity 1 visuals	stor				62
		*				*	and the second s		
	Beforeno	e France		Departy 1 visuals	ation			X	
		e fore							
	2		Marrie Walt			10.00	2		
	Reference	e france		Departy 1 Vool	ator		2	sparity 1 error	
			7						
		500	7	and a state	7		Carles Contraction		10

Figure 9. Spring benchmark: Example of stereo result.



Figure 10. Spring benchmark: Example of optical flow result.

											Not logged in
M-FU	SE (F)										
ev 1 2022	2 am - Pater										
submitte	d by spring team Luka	s Mehl, Azin Jahedi, J	nny Schmalfiz	ss, and Andrés Brut	hn. W-RUSE: Multi-Ir	ame Fusion for Sce	ne Row Estimatio	in." In IEEE/CV	F Winter Co	nference on Ap	plications of
cene H	low	fax	tax	fer	tax	fer	144	far	fex	far	for
odal 14.895	Jow-detail 34,298	Ngb-detail 64.324	matched 32.028	unmotched 71.943	rigid 29.810	non-rigid 73-377	net sky 31.355	sky 88.712	35-10 29.890	23.911	240+ 69.148
y otal	5.F Jow-detail	s# Nati-detail	s# matched	SF unmotched	Tpx chaid	1pr ren-ripld	SF ReCally	SF SRV	5F 50-10	SF 510-40	5/ 540+
6.103	15.748	33.553	13.554	49.034	12.847	40.735	13.050	62.502	14,262	8.188	38.919
isparit	ty 1										
pr oda/	1px low-detail	1pm high-detoil	2	at chevel	Ipx anmatched	1px not sky	1px sky	1px 50-10		1px s10-40	Tpx s40+
9.888	12.547	40.396	1	7.611	65.086	16.735	67.835	19.03	6	13.861	39.412
lðs otal	Abs low-detail	Abs high-detail	A	hs vatched	Abs annotched	Abs net sky	Abs sky	A85 50-50		Abs s10-40	Abs \$40+
	5.00U	5.934 01	2	1	a1.465	2.443 D1	25.771	5.64 D1		01	D1
kitel	1000-detail 9.116	high-detail 13.884	7	atched 321	annatched 46.378	800 sky 7,417	sky 36.191	9.60		s10-40 6.293	s40+ 17.062
ien ar fe											
nsparit	ty Z	1pm		м	1pe	1pr	Tpy	1,0.0		1pv	fax
506a/ 24.256	low-detail 23.925	high-decall 44.192	2	atched 1.867	anesatched 63.259	not sky 21.262	sky 69.755	23.3	7	s10-40 17.005	\$40+ 47.656
las total	Abs low-detail	Abs high-detail	4	hs atched	Abs anenatched	Abs not sky	Abs sky	Abs 10-10		Abs 110-40	Abs 240+
L059	4.035	6.114	2	975	21.928	2.616	25.854	5.57		1.903	7.682
52 todaf	D2 how-detail	D2 high-detail		2 otched	D2 ammatched	D2 net sky	02 sky	502 50-70		02 \$10-40	52 540+
ptical	Flow					1.					
px otat 10.374	ngte Now-detail 19.995	nys-detell 80.335	npx motched 19.582	fpr unmatched 01.415	15.312	tpar men-right 58.008	fдя лот sky 18.381	sky 50.053	7px s0-10 2.734	1px s10-40 29.588	540+ 841.458
PE otal	EPE Jour-detail 2.833	EPE Ng8-detail 21.047	EPE motched 2.678	EPE unmatched 14,103	EPE rigid 2.106	EPE non-rigid 9.317	EPE net sky 2.003	EPE sky 17.308	ере s0-10 1.051	EFE 510-40	EPE 540+ 22.886
Fr total	FI Jose-detail	FI Nigh-detail	FI matched	FI unmatched	FI rinid	FI non-rield	FI net sky	FI sky	FI 50-10	FI \$10-42	FI 540+
8.791	8.495	55.544	8.111	36.942	6.205	28.360	6.792	39.181	3.447	10.080	50.018
NRUC total	NAUC Jour-detail	WAUC Ngh-detail	wAuC matched	WAUC unmotched	WAUC rigid	MHUC non-rigid	WAUC net sky	ницс лку	WHUC a0-10	10-40	WAOC 240+
Refere	ce frame Departs	- Manufactor		Provertire	vauriuston D	3	Towytustus		S		and how env
Refere	rce frame Disparity	1 visualization	Doparity 1 erro	Departy 2	visualization	spanity 2 error	Rev vbuilize	Con	Devero		cere how enor
Referen	t Doparty	1 vouelization		r Departy 2	Visualization		Flow vousilize	600	Howerro		cere flow error
Adare	nce Frame Etiganty	I Visuelization	Departy Leve	r Departy 2		aparty 2 error	Fiew visualize	eon I	Pow erro		cere for erer
Referen	nce France Dogarty	I visualization	Disparity 1 error	r Dequirity 2	Visualization	Isparity 2 error	Piew vesseles		Plow erro Plow erro		cere flow error
Referen	Ke Frans	Visuelization		e Depurty 2	visuelization	tipanty 2 atter	Perevenuela	eon	Pow erro		Cene Tow error
Referen	rce frame Desparity	T Visualization	Disparity 1 erro	r Departy 2	visualization D	sparity 2 error	Plew vessilies		Howers		cere flow error
Referen	nce Frame Departy	1 visualization	Disparity 1 erro	r Departy 2	visualization 0	rsparity 2 error	Plaw vecaliza		Row erro		cene flow error

Figure 11. Spring benchmark: Example of scene flow result.

		L. Ment, J. Schenapters, A. Jones	i, Y. Nolivojsko, A. Bruhn		
	Download	Stereo Optical Flow	Scene flow Submit		
					Not logged in
Sign up					
In order to submit your own results to t by our team. Do not register multiple to	he benchmark, you need to sign up. Nest	Please register below and confi	rm your mail address by clicking or	the link we send you. Afterw	ards, your account will be verified
Email address*;					
	Please use your univ	ersity/organisation mail addres	s		
Getversity/Organization*:					
Datversity/Organization*:					
University/Organization*:					
University/Organization*: Personal website:					
University/Organization*: Personal website:					
Detersity.iDependodien*: Personal website: Description*:					
Untversity/Organization*: Persenel website: Description*:					
Ontversity/Organization 1; Personal methodice: Description 1;					
Ontwisigningenbodden"; Persiseet website: Description";	Prese provide a brie	f Justification of why you need	KCers 10 the benchmark.		
Oliverstylligheekstoler*: Perseel welste: Description*: Perseel welste: Perseel welste:	Plase provde a brie	t justification of why you need .	eccess to the benchmark.		

Figure 12. Spring benchmark: Registration form.