Matching-space Stereo Networks for Cross-domain Generalization

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Code: https://github.com/ccj5351/MS-Nets

1. Motivation

- Annotated data for stereo matching is challenging to collect
  - ➢ Expensive LiDAR, Stereo Camera Rig
  - ➢ Ground truth depth is **sparse**
- SOTA deep networks generalize poorly to unseen domain
  - ➢ E.g., PSMNet suffers large accuracy drops moving from synthetic (pretrained on Scene Flow) to real scenes (KT15)

Left Image — Disparity Map by PSMNet

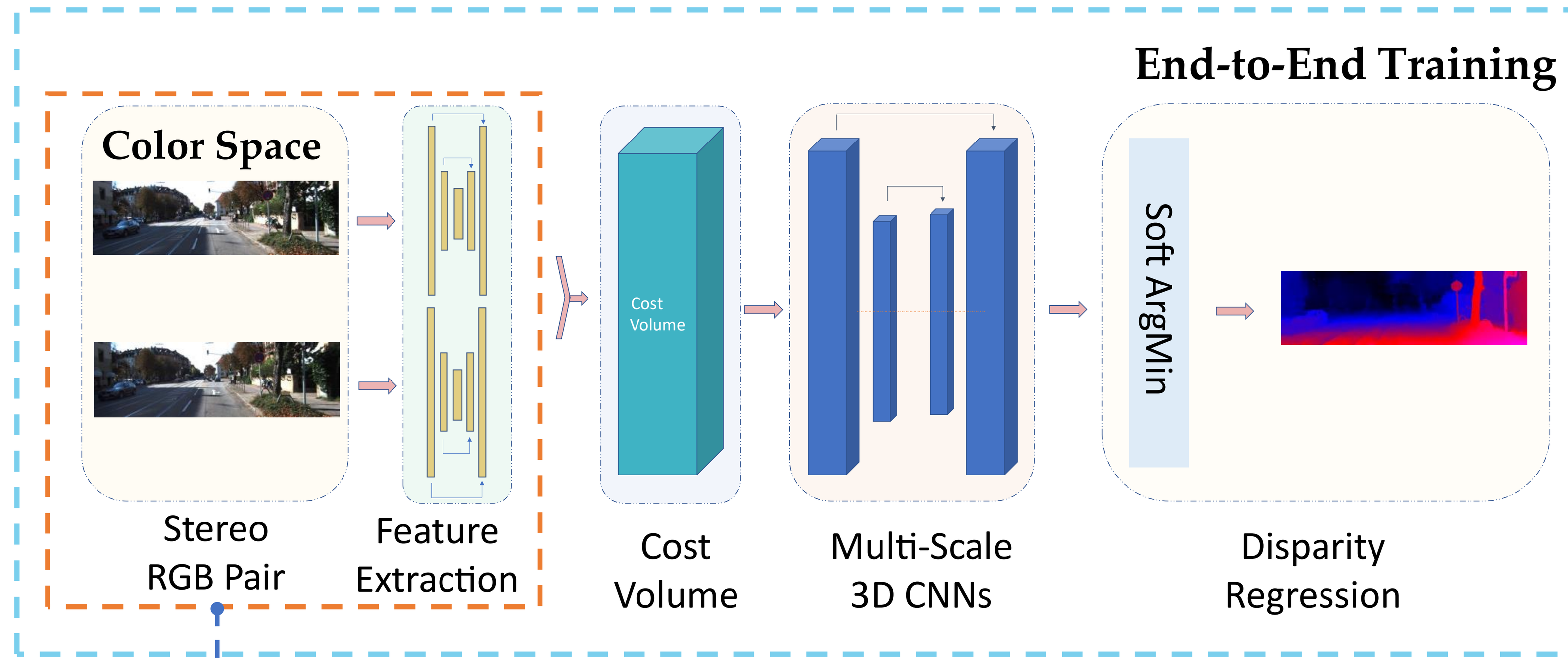
- **Domain generalization**
  - ➢ Methods that generalizes well without adaptation is a solution
  - ➢ Effective in continuously changing environments, e.g. autonomous driving, without re-training or adaptation
- **Goal**
  - ➢ Sacrifice as little accuracy as possible to attain generalization

2. Over-specialization to Color Space

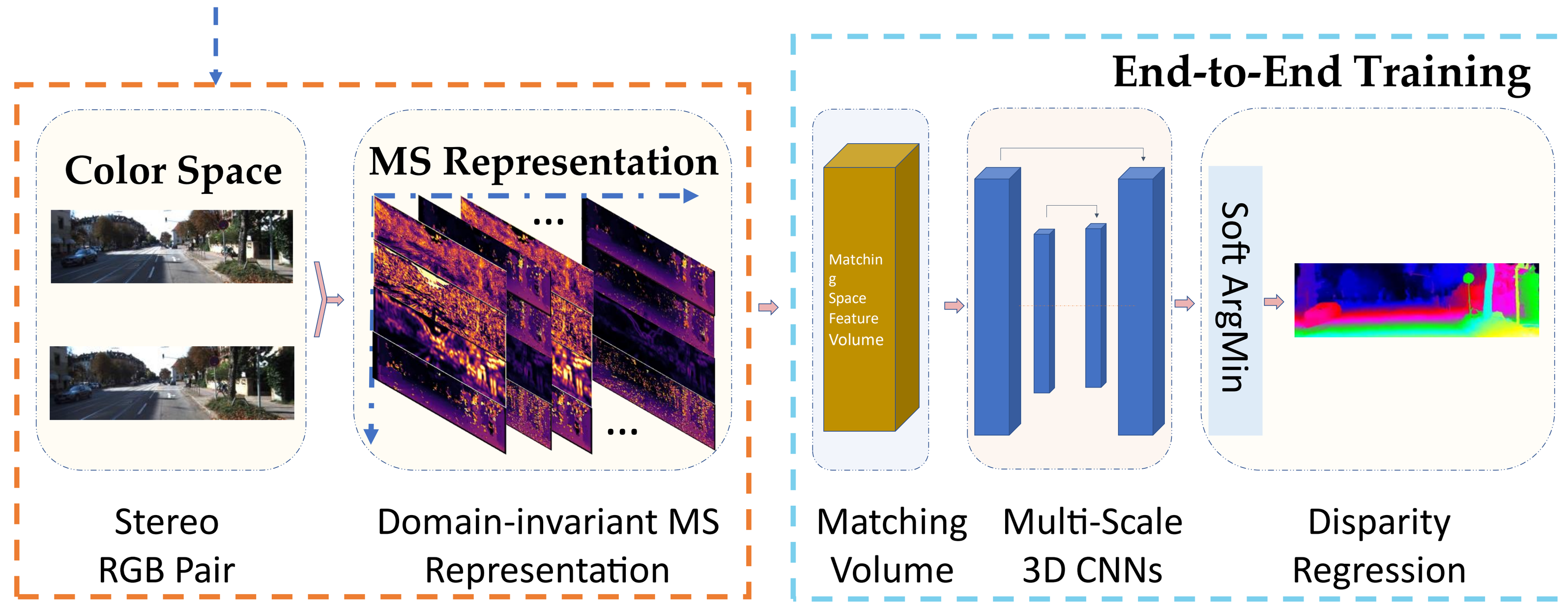
- Learning process is driven by image content
- Better generalization can be achieved by choosing a representation **insensitive** to common variations of RGBs

3. Matching Space Stereo Networks

- Replace learning-based feature extraction from RGB with matching functions and confidence measures
- Move learning from color space to Matching Space (MS), avoiding overspecialization to domain specific features
- Modify GCNet and PSMNet architectures to accept MS inputs
  - ➢ PSMNet allocates 63.5% of parameters to unary feature extraction
  - ➢ GCNet allocates 88.5% of parameters to 3D convolutions



(a) Conventional End-to-end 3D Convolutional Networks for Stereo Matching



(b) Our Matching Space (MS) End-to-End Stereo Networks for Cross-domain Generalization

4. Matching Functions and Confidences

- Four matching functions and the associated confidence scores
- Matchers include
  - ➢ normalized cross correlation (NCC)
  - ➢ zero-mean sum of absolute differences (ZSAD)
  - ➢ census transform (CENSUS)
  - ➢ absolute differences of the horizontal Sobel operator (SOBEL)
- Confidence scores
  - ➢ each matcher's likelihood, a confidence measure of each disparity for a given pixel
  - ➢ obtained by converting the cost curve to a probability density function for each disparity under consideration

$$L_z(x_L, y, d) = \frac{\exp\left(-\frac{(C_z(x_L,y,d)-C_{z,min})^2}{2\sigma_z^2}\right)}{\sum_i \exp\left(-\frac{(C_z(x_L,y,d_i)-C_{z,min})^2}{2\sigma_z^2}\right)}$$

5. Experimental Results

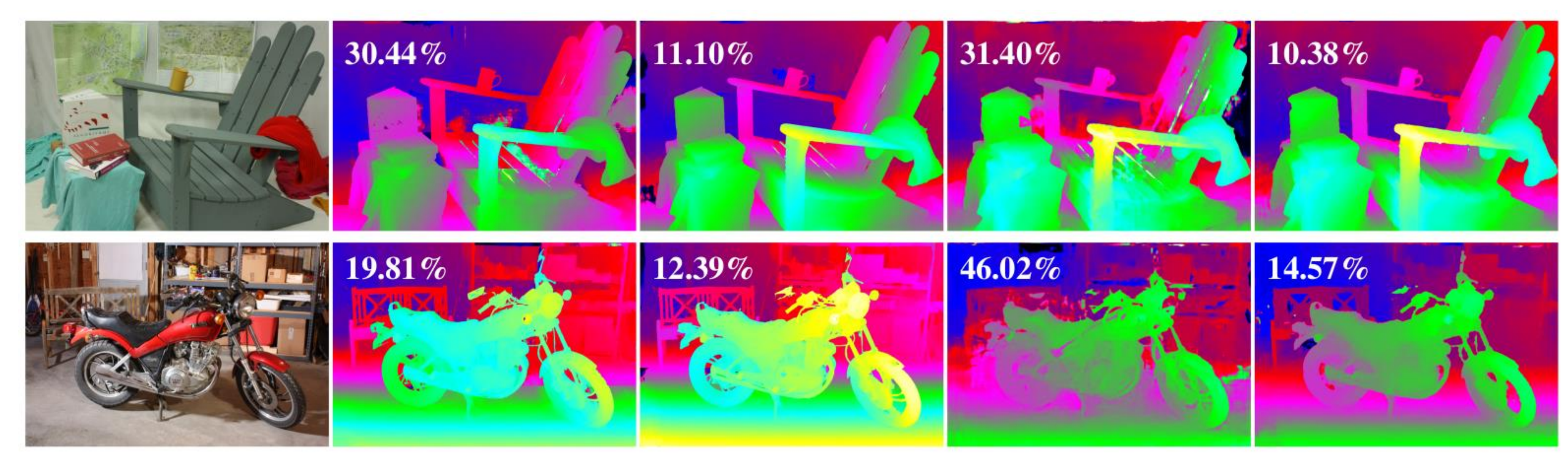
- **Domain Generalization Training and Evaluation**
  - ➢ Networks are trained in source domain Scene Flow
  - ➢ Evaluated in target domains (KITTI 2012&2015, Middlebury 2014 and ETH3D Low-res two view datasets) without finetuning or adaptation
- **Sim2Real (sf-all → real)**

Target domains	Models (Sim2Real)			
	GCNet	MS-GCNet(Ours)	PSMNet	MS-PSMNet(Ours)
KT12	6.22	**5.51**	27.02	**13.97**
KT15	14.68	**6.21**	26.62	**7.76**
MB	30.42	**18.52**	26.92	**19.81**
ETH3D	**8.03**	8.84	18.91	**16.84**

- **Evaluation on Real Benchmark KITTI 2015**

Models	All-D1 %			Noc-D1 %		
	bg	fb	all	bg	fg	All
MS-GCNet(Ours)	2.58	6.83	3.29	2.19	5.59	2.75
GC-Net	2.21	6.16	2.87	2.02	5.58	2.61
MS-PSMNet(Ours)	2.15	5.01	2.63	1.99	4.52	2.41
PSM-Net	**1.86**	**4.62**	**2.32**	**1.71**	**4.31**	**2.14**

- **Qualitative Results on Middlebury**



Input — GCNet — MS-GCNet (Ours) — PSMNet — MS-PSMNet (Ours)

- **Comparison with SOTA 2D and 3D architectures**

Target Domains	MAD-Net	Disp-Net	CRL	iRes-Net	Seg-Stereo	Edge-Stereo	GWC-Net	GA-Net	HD3	DSM-Net	MS-GCNet	MS-PSMNet
KT12	39.17	12.54	9.07	7.90	12.80	12.27	20.20	10.10	23.60	6.20	**5.51**	13.97
KT15	43.98	12.88	8.88	7.42	11.23	12.47	22.70	11.70	26.50	6.50	**6.21**	7.76