Variational Simultaneous Stereo Matching and Defogging in Low Visibility

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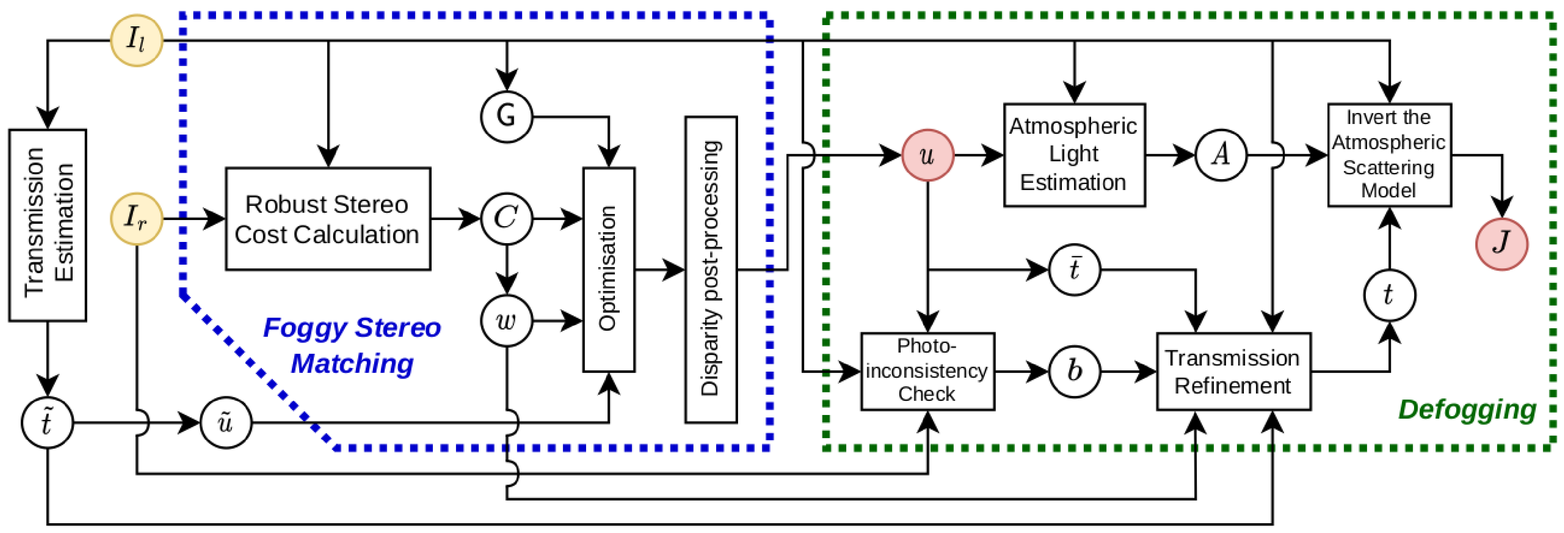
Introduction

- PROBLEM: We seek to estimate *a dense disparity map* and *a defogged image* from *a rectified stereo pair of foggy images*.
- RESEARCH GAP: Existing stereo matching algorithms are predominantly developed under the assumption of *clear* scenes. Meanwhile, most of the literature on defogging addresses *single* images only. There is very *little* work that tackles the two problems *simultaneously*.
- MOTIVATION: These two tasks are closely linked by scene *depth*, which can be inferred from *disparity* and *scattering*, respectively.
- SOLUTION: We propose a novel algorithm which *effectively exploits this underlying connection* and *improves both results*. It is based on *variational continuous optimisation* and *does not require large scale training data*, the acquisition of which is not always possible outdoors.

Method



Input:

- I_l Left foggy image
- I_r Right foggy image

Output:

- u Left dense disparity map
- J Left defogged image

$$I_l, I_r, J \in \mathbb{R}^{H\times W\times 3}$$

$$\tilde{t}, \bar{t}, t \in [0,1]^{H\times W}$$

$$A \in \mathbb{R}^3$$

$$\tilde{u}, u, w, b \in [0,1]^{H\times W}$$

$$\mathsf{G} : \mathbb{R}^{H\times W\times 2} \rightarrow \mathbb{R}^{H\times W\times 2}$$

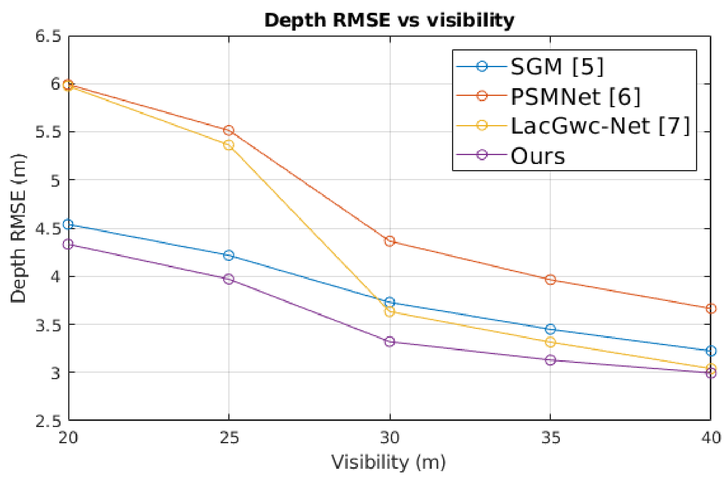
$$C \in \mathbb{R}^{H\times W\times |\Gamma|}$$

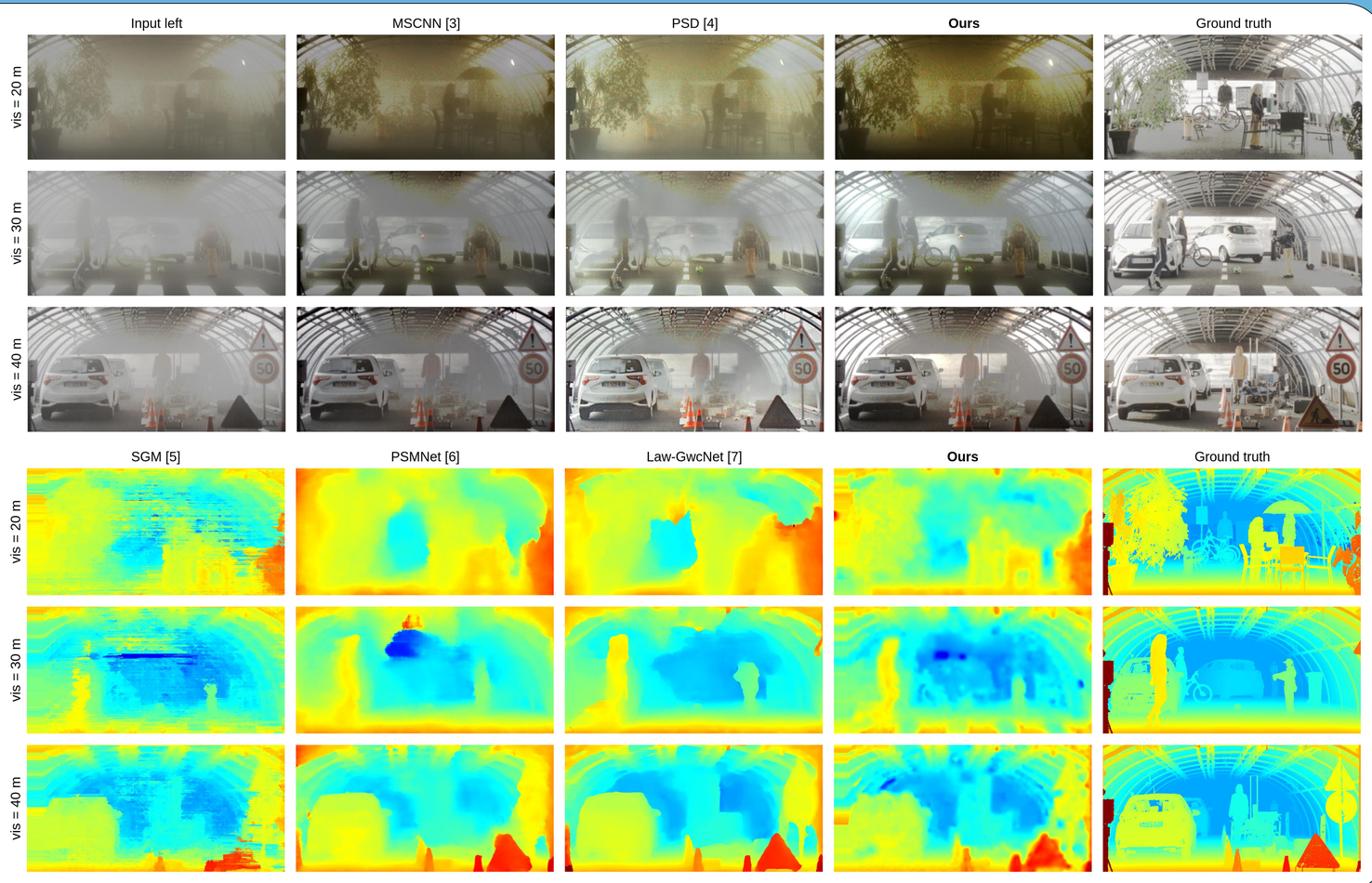
$$\Gamma = \{0, 1, \cdots, \gamma_{\max}\}$$

- Our two-stage system consists of a *Foggy Stereo Matching* module and a *Defogging* module.
- The Foggy Stereo Matching module has the following features which get seamlessly incorporated into our disparity optimisation process.
  - An anisotropic weighting scheme to allow for *non-uniform penalty parameters at different pixel locations*.
  - A customised regularisation term which effectively injects disparity cues from scattering by *encouraging gradient alignment*.
- Within the Defogging module we leverage a *photo-inconsistency check* and perform a *transmission refinement* to enable the recovered depth information to assist defogging.

Results

- We evaluate our method qualitatively and quantitatively on *both synthetic* data (VKITTI2 [1], shown in paper) and *real* data (PAD [2], shown in paper and here).
- Our algorithm *outperforms* comparative methods in all metrics on depth estimation, and produces *visually more appealing* defogged images, especially *in extremely low visibilities*.





Future Work

- Use motion information embedded in consecutive frames and incorporate more matching constraints to improve depth estimation results
- Adopt a more sophisticated fog model (*e.g.* blurring and fog inhomogeneity) to better recover intensity images

References

[1] Cabon *et al.*, "Virtual KITTI 2", arXiv preprint arXiv:2001.10773, 2020.
[2] Gruber *et al.*, "Pixel-accurate depth evaluation in realistic driving scenarios," 3DV'19
[3] Ren *et al.*, "Single image dehazing via multi-scale convolutional neural network", ECCV '16
[4] Chen *et al.*, "PSD: Principled synthetic-to-real dehazing guided by physical priors", CVPR'21
[5] Hirschmuller, "Stereo processing by semiglobal matching and mutual information", PAMI'07
[6] Chang and Chen, "Pyramid stereo matching network", CVPR'18
[7] Liu *et al.*, "Local similarity pattern and cost self-reassembling for deep stereo matching networks", AAAI'22

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