Deskewing by space-variant deblurring

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Introduction

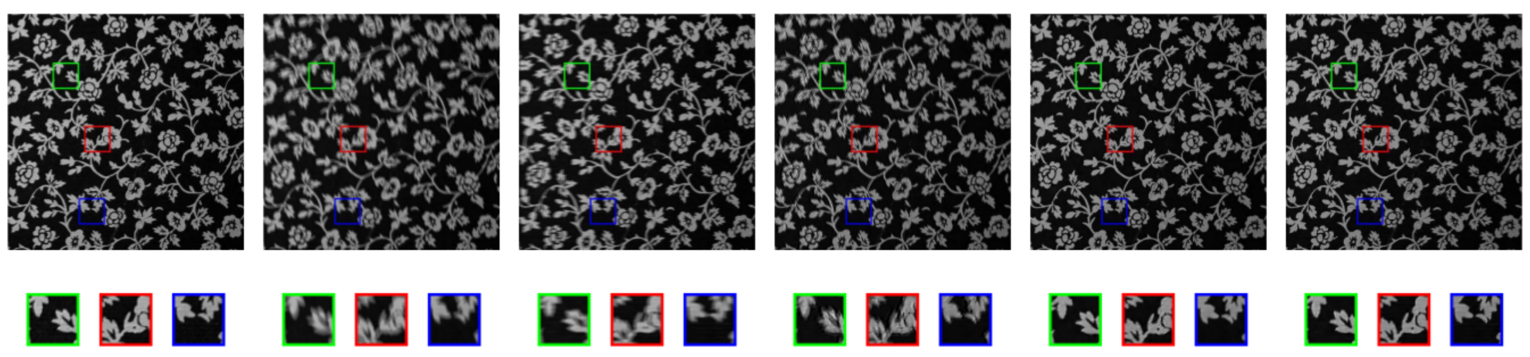
- Skew and motion blur are significant challenges when camera and scene of interest are in two different media.
- Skew occurs due to spatially varying refraction on a dynamic water surface
- Motion blur results from multiple intensities impinging on the imaging sensor during camera exposure time due to time varying refraction
- **We propose the concept of virtual depth map and also shot detection to initially segment an input video into groups of frames each of which conforms to a single virtual depth map.**
- **We then propose an alternating minimization scheme, to estimate the deskewed image.**

Proposed approach

Virtual depth map

- The attenuated cyclic water waves can be modeled as $h(\mathbf{x}, t) = A(\mathbf{x})\cos(\mathbf{x} - t)$.
- The warps induced at a pixel $\mathbf{x}$ can be derived as $w(\mathbf{x}, t) = \alpha\nabla h(\mathbf{x}, t) = \alpha\sqrt{\nabla A(\mathbf{x})^2 + A(\mathbf{x})^2}\cos(\mathbf{x} - t + \phi) = \alpha^1(\mathbf{x})p(\mathbf{x}, t)$
- Let $\mathbf{w_1}$ and $\mathbf{w_2}$ be the warps induced at pixels $\mathbf{x_1}$ and $\mathbf{x_2}$, respectively. For one cycle of $\mathbf{p}(\mathbf{x}, t)$, $\mathbf{w_2} = k\mathbf{w_1}$, where $k = \frac{\alpha_2^1}{\alpha_1^1}$.
- Hence, the set of warps induced by unidirectional cyclic attenuation waves at different pixel locations can be related by the scale factor k.
- The set of all scale factors with respect to one reference depth is the virtual depth $\mathbf{V_d}$.

Shot detection



(a) (b) (c) (d) (e) (f)

Figure 2: Significance of shot detection. (a) Ground truth. Blurred images generated by (b) segment 1, (c) segment 2. Restored observations: (d) without shot detection, (e) with shot detection for segment 1, and (f) with shot detection for segment 2.

Alternating Minimization

- Proposed cost function is

$$E(\hat{\mathbf{f}}, \hat{\mathbf{d}}_\mathbf{p}, \hat{\omega}) = \sum_{\delta^* \in \Theta} \lambda_{\delta^*} ||(\delta^* f) o T_{\omega}^{\mathbf{d}_\mathbf{p}} - \delta^* \mathbf{g}||_2^2 + \text{prior}(\mathbf{f}, \mathbf{d}_\mathbf{p}, \omega). \quad (1)$$

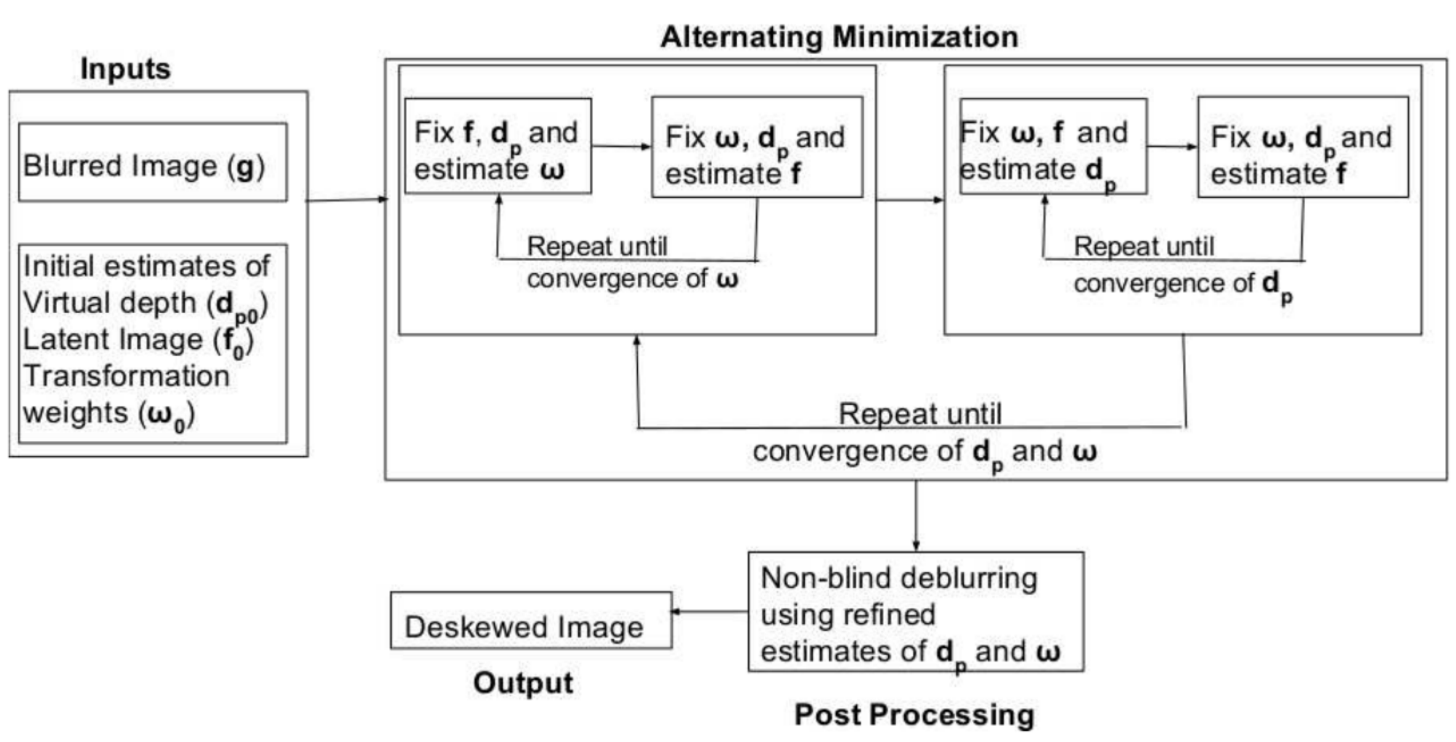
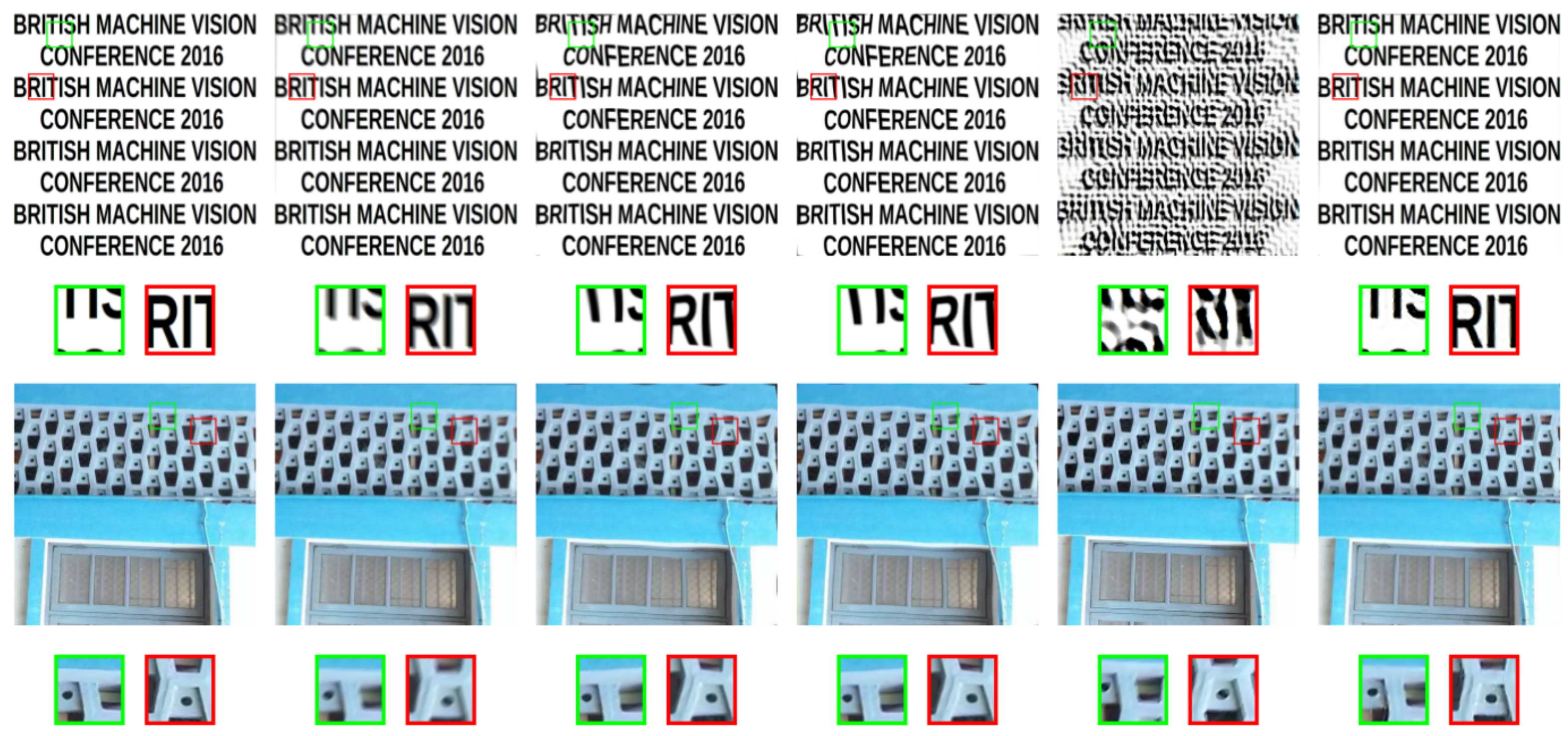


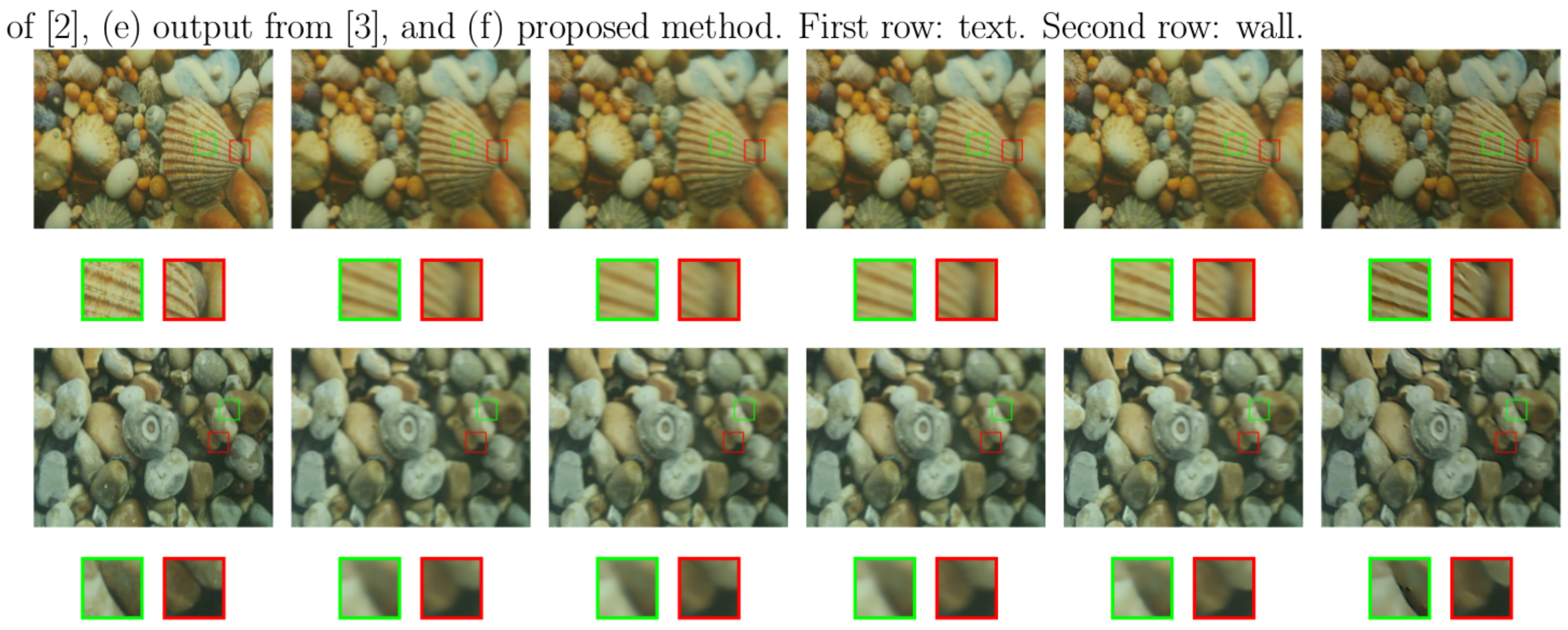
Figure 3: Block diagram of our proposed Alternating Minimization

Results



(a) (b) (c) (d) (e) (f)

Figure 4: Synthetic examples. (a) Focused observation, (b) blurred observation, (c) restored by [1], (d) output of [2], (e) output from [3], and (f) proposed method. First row: text. Second row: wall.

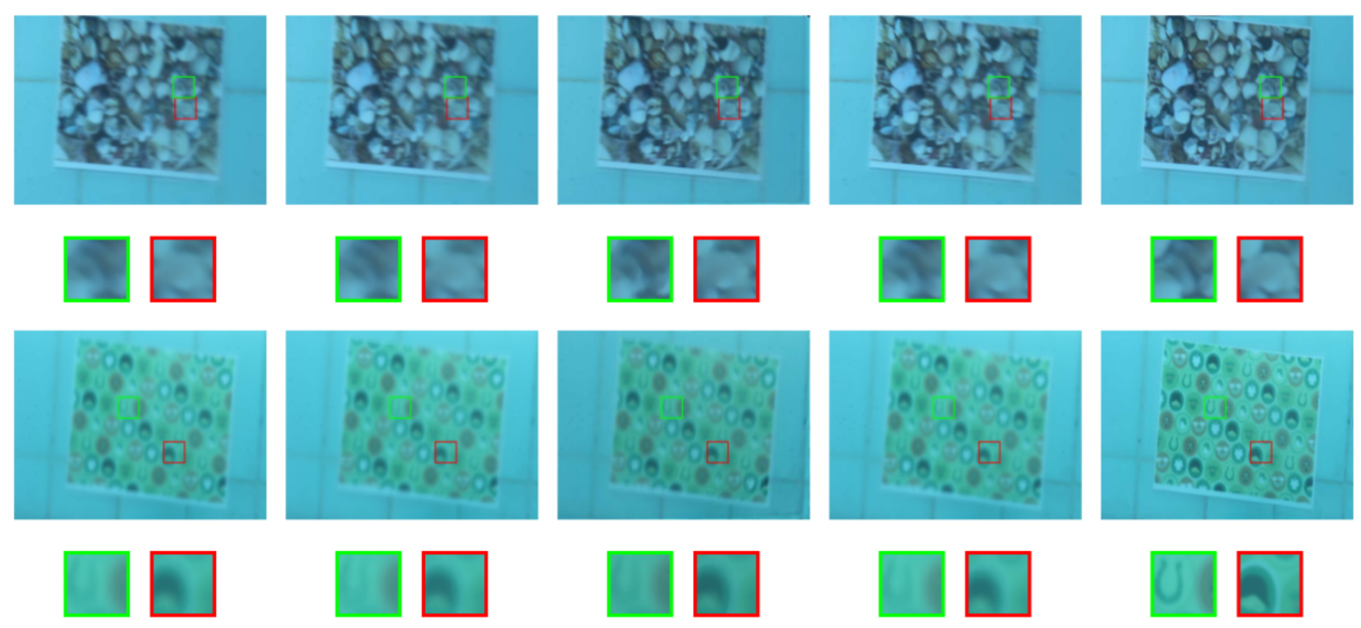


(a) (b) (c) (d) (e) (f)

Figure 5: Real indoor experiments. (a) Focused observation, (b) blurred observation, (c) restored by [1], (d) output of [2], (e) output from [3] and (f) proposed method. First row: shell. Second row: stones.

	PSNR (in dB)				SSIM				NMI			
	Tian et al. [1]	Oreifej et al. [2]	Xu et al. [3]	Proposed Method	Tian et al. [1]	Oreifej et al. [2]	Xu et al. [3]	Proposed Method	Tian et al. [1]	Oreifej et al. [2]	Xu et al. [3]	Proposed Method
Wall	20.9638	22.4273	13.0005	**22.8546**	0.9994	0.9996	0.9943	**0.9997**	1.0626	1.0148	0.8994	**1.0713**
Text	13.5681	13.5679	11.1212	**20.8162**	0.9975	0.9975	0.9798	**0.9997**	0.5770	0.5766	0.5290	**0.6107**
Shell	26.3070	26.6811	23.6328	**26.7811**	0.9984	0.9983	0.9986	**0.9999**	0.9760	0.9544	0.9544	**0.9820**
Stones	23.4497	28.2615	27.0457	**28.2815**	0.9995	0.9994	0.9993	**0.9998**	0.9727	1.0248	1.0045	**1.0250**

Table 2: Quantitative analysis for synthetic and real experiments.



(a) (b) (c) (d) (e)

Figure 6: Real outdoor experiment. (a) Blurred image. Output of: (b) [1], (c) [2], (d) [3], and (e) proposed method. First row: shell. Second row: band.

Conclusions

- By using the concept of virtual depth map and shot detection followed by an alternating minimization framework, we restore the input video from skew.
- Our approach outperforms state-of-the-art deskewing and space-variant deblurring approaches, both qualitatively and quantitatively.

References

1. Tian, Yuandong, et al. "Seeing through water: Image restoration using model-based tracking." ICCV 2009.
2. Oreifej, Omar, et al. "A two-stage reconstruction approach for seeing through water." CVPR 2011.
3. Xu, Li, et al. "Unnatural l0 sparse representation for natural image deblurring." CVPR 2013.