



# Stereoscopic Image Completion and Depth Recovery

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1. Background
   - Stereoscopic Media Processing
2. Related Work
   - Single Image Completion
   - Stereoscopic Image Completion
3. Methodology
   - Completion via optimization
   - Metric for patch distance
   - Iterative color and depth synthesis
   - Parameters
   - Results
4. Conclusions

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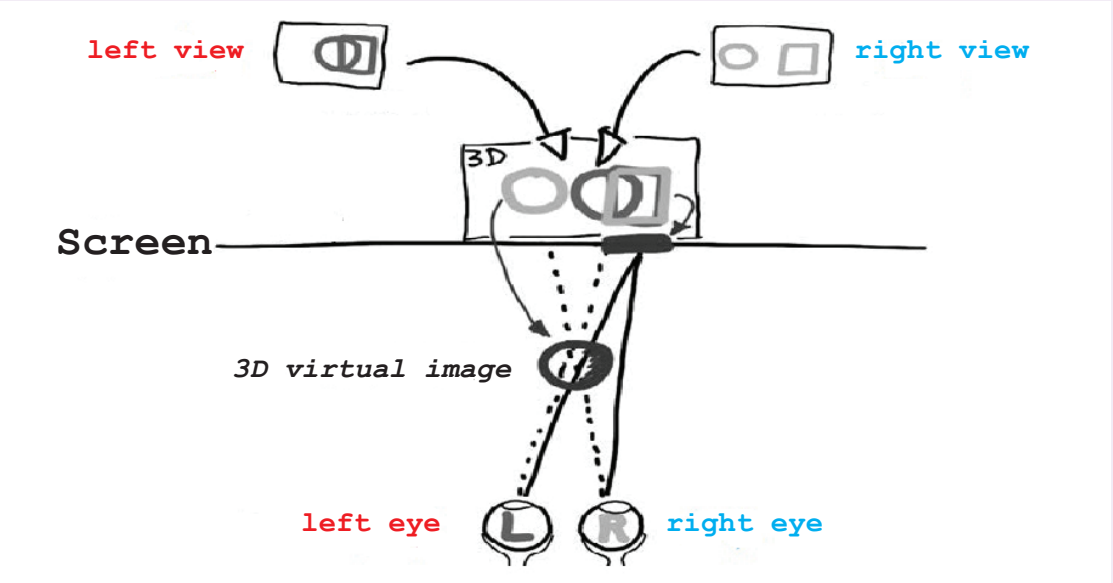
## Stereopsis

- Stereopsis, is the *impression of depth* that is perceived when a scene is viewed by someone with two eyes and normal binocular vision.
- The two views are slightly different, characterized by disparity, or horizontal parallax.




(a) Stereopsis

## Development of capture technology

- consumer cameras and smart phones bloom the stereoscopic media.



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## Applications

- Digital entertainment(films, games), 3DTV broadcast, medical diagnosis/surgery, etc.


New need for stereoscopic media processing!

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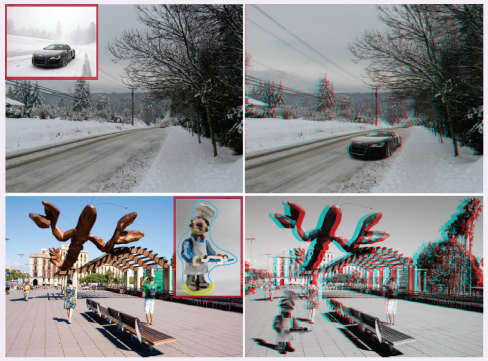
## Rules for handling 3D contents

- Additional information, i.e., disparity (depth), is available and should be accounted.
- Stereopsis should be kept after processing.
- e.g. Copy and Paste: [Lo10][a], [Luo12][b], [Tong13][c].

(a) Lo10

(b) Luo12



(c) Tong13

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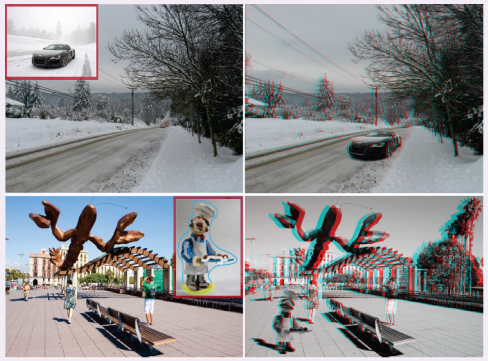

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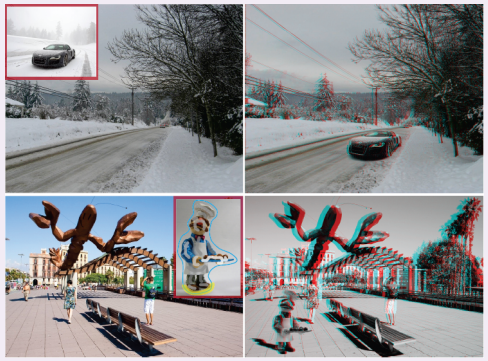

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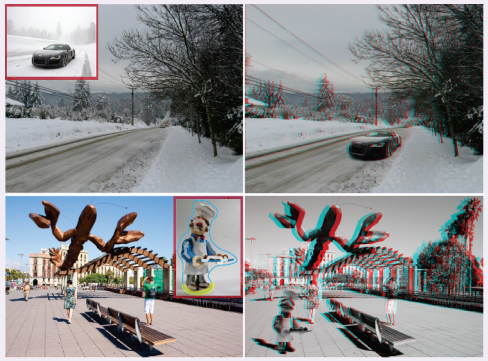

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## Do not directly apply 2D editing tools to 3D

(a) Original images with masks(green)

(b) Single Image Completion

(c) Basic rotation result

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## How to fill the "holes"?

- Diffusion-based, peeling onions: Bertalmio00[a]
- Exemplar-based, assigning sources to targets: Criminisi03[b], Sun05[c], Komodakis07[d], He12[e]

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## Frontal-parallel scenes

- Depth assumption: the "holes" should be filled with content from further regions than the original ones.
- Measure depth similarity.
- Wang08[a], half occlusion, greedily search, depth-assist texture synthesis.
- Morse12[b], pre-computing depth maps[Bertalmio00[c]], stereo propagation.

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[a] Wang, L., Jin, H., Yang, R., and Gong, M.: Stereoscopic inpainting: joint color and depth completion from stereo images. In: IEEE CVPR, pp. 1–8, 2008.

[b] Morse, B., Howard, J., Cohen, S., and Price, B.: Patchmatch-based content completion of stereo image pairs. In: 3DIMPVT, pp. 555–562, 2012.

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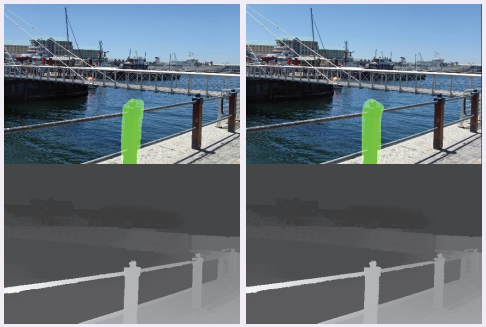
## Problem description



- Input image pair $(I^l, I^r)$, with disparity maps $(D^l, D^r)$ and holes $(\Omega^l, \Omega^r)$.
- Denote $(\Psi^l, \Psi^r) \triangleq (I^l \setminus \Omega^l, I^r \setminus \Omega^r)$, source regions.
- Completed color images $(\hat{I}^l, \hat{I}^r)$ and disparity maps $(\hat{D}^l, \hat{D}^r)$.

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$$SCC(\hat{I}^l, \hat{I}^r, \hat{D}^l, \hat{D}^r | \Psi^l, \Psi^r, \Omega^l, \Omega^r, D^l, D^r) = \sum_{t \in \Omega^l \cup \Omega^r} \min_{s \in \Psi^l \cup \Psi^r} \tilde{d}(t, s) + \lambda_{sc} \cdot \sum_{t \in \Omega^l \cup \Omega^r} \tilde{d}(t, M(t)) \quad (1)$$

- The stereoscopic image completion is then formulated as an optimization to maximize the coherence and stereo consistency of the completion results.
- $\tilde{d}(\cdot, \cdot)$ is a measure of difference between patches concerning about both appearance and depth.
- $M(\cdot)$ define a mapping for stereo correspondences between $\hat{I}^l$ and $\hat{I}^r$ with disparity maps $(\hat{D}^l, \hat{D}^r)$.

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# Metric for patch distance

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$$\tilde{d}(p_1, p_2) = (1 - \lambda_g) d_c(p_1, p_2) + \lambda_g \cdot d_g(\vec{G}(p_1), \vec{G}(p_2)) \quad (2)$$

$$d_g(\vec{g_1}, \vec{g_2}) = \sum_{\vec{x}} \|\vec{g_1}(\vec{x}) - \vec{g_2}(\vec{x})\| \quad (3)$$

- gradient domain, free of the depth assumption.
- suitable for both frontal-parallel and non-frontal-parallel scenes.

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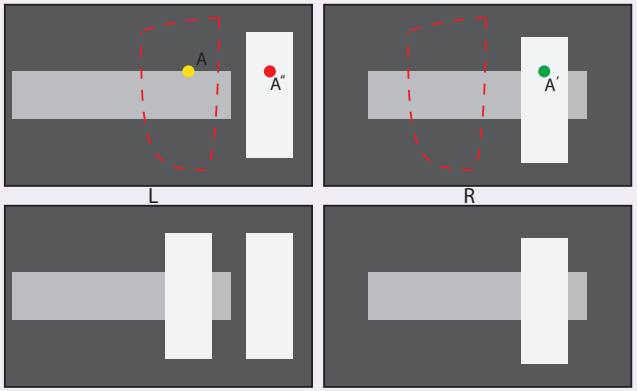
## Depth inconsistency in stereo propagation

- $DI(p)$ denotes the depth inconsistency at location $p$, defined as the shift between $p$ and its stereo reflection.




## Cost of selecting $s$ for $t$

$$F(s,t) = \mathcal{L}_{\lambda_{ic}}\Big(\mathcal{L}_{\lambda(s,t)}\big(\tilde{d}(s,t), \tilde{d}(t, M(t))\big), DI_\epsilon(t)\Big) \quad (4)$$

$$\mathcal{L}_\lambda(A,B) \triangleq (1-\lambda)\cdot A + \lambda \cdot B.$$

$$\lambda(s,t) = \lambda_m \cdot e^{-DI_\epsilon(t)} \quad (5)$$

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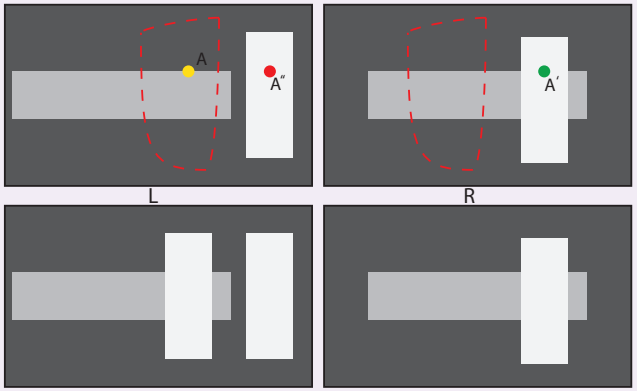


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## Conditions of iterative algorithm for Eq. 1

- For each point $p$ in $\Omega^l \cup \Omega^r$:[a]
  - (i). All patches containing $p$ appear exactly somewhere in $\Psi^l \cup \Psi^r$;
  - (ii). All patches containing $p$ agree on the values at $p$.
- An iterative algorithm based on PatchMatch[b] is adopted to satisfy the two conditions by propagating the optimized candidate patches from neighbors.

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[a] Wexler, Y., Shechtman, E., and Irani, M.: Space-time completion of video. IEEE Trans. Pattern Anal. Mach. Intell. 29(3), 463–476, 2007.

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## Scan order and initialization

- Compute the scanning priorities as in Criminisi03[a], outside in and along structures.
- Mutual initialization:
  $p(x,y) \in \Psi^l$ and $(x + D^l(x,y), y) \in \Omega^r$ or
  $p(x,y) \in \Psi^r$ and $(x + D^r(x,y), y) \in \Omega^l$.

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## Stereoscopic patch refinement

Refine $p \in \Omega^l \cup \Omega^r$ from the following candidates:

- $p$
- $p$'s 4-connected neighbors (only those with higher priority than $p$)
- $p$'s stereo-corresponding point in the other view

Then a random jump around the current best one.

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## Color and depth update

- Color is averaged.
- Depth is "shifted" before averaged:

$$\overrightarrow{d}(s,t) = \sum_{v \in \mathcal{N}_t} w_{s,t}(v) \cdot (d_{s+v} - d_{t+v}) \tag{6}$$

$$w_{s,t}(v) = \frac{g_x(\|v\|/\sigma_x) g_c(\|\boldsymbol{c}_{t+v} - \boldsymbol{c}_s\|/\sigma_c)}{\sum_{u \in \mathcal{N}_t} g_x(\|u\|/\sigma_x) g_c(\|\boldsymbol{c}_{t+u} - \boldsymbol{c}_s\|/\sigma_c)} \tag{7}$$

$$\hat{d}_t = d_s - \overrightarrow{d}(s,t) \tag{8}$$

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## Color and depth update

- Color is averaged.
- Depth is "shifted" before averaged:

$$\overrightarrow{d}(s,t) = \sum_{v \in \mathcal{N}_t} w_{s,t}(v) \cdot (d_{s+v} - d_{t+v}) \tag{6}$$

$$w_{s,t}(v) = \frac{g_x(\|v\|/\sigma_x) g_c(\|\boldsymbol{c}_{t+v} - \boldsymbol{c}_s\|/\sigma_c)}{\sum_{u \in \mathcal{N}_t} g_x(\|u\|/\sigma_x) g_c(\|\boldsymbol{c}_{t+u} - \boldsymbol{c}_s\|/\sigma_c)} \tag{7}$$

$$\hat{d}_t = d_s - \overrightarrow{d}(s,t) \tag{8}$$

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- *CIE L*a*b** color space, color images and disparity maps are normalized into $[0, 1]$
- Patch size: $15 \times 15$
- $\lambda_g$: $0.1 \sim 0.2$, $\varepsilon = 3.0$, $\lambda_m = 0.35$, $\lambda_{ic} = 0.2$
- $\sigma_x = 0.2$, $\sigma_c = 0.1$
- no more than 20 iterations

# Parameters

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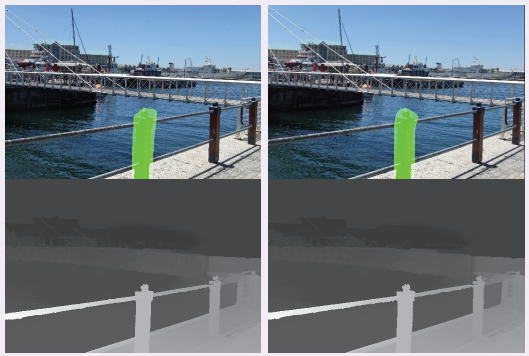
## Non-frontal-parallel



(a) Input images with mask(green) and disparity maps

(b) Left and right completion results

(c) Result anaglyph

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## Non-frontal-parallel

Inputs

Results

(a)

Inputs

Results

(b)

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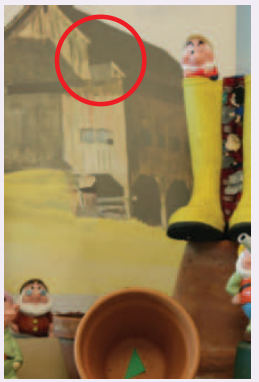
## Frontal-parallel

(a) Original images with masks(green), and disparity maps(inset)

(b) result analyph of our method

(c) Competion results of our method



(d) From Morse *et al.*

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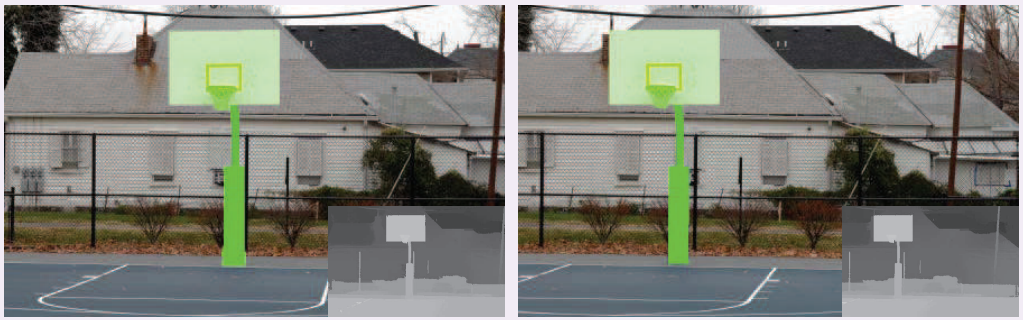
## Frontal-parallel



(a) Original images with masks(green), and disparity maps(inset)

(c) From Morse *et al.*

(b) Completion results of our method

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## Frontal-parallel

(a) Original images with masks(green), and disparity maps(inset)

(b) Completion results of our method

(c) From Morse *et al.*

(d) From Wang *et al.*

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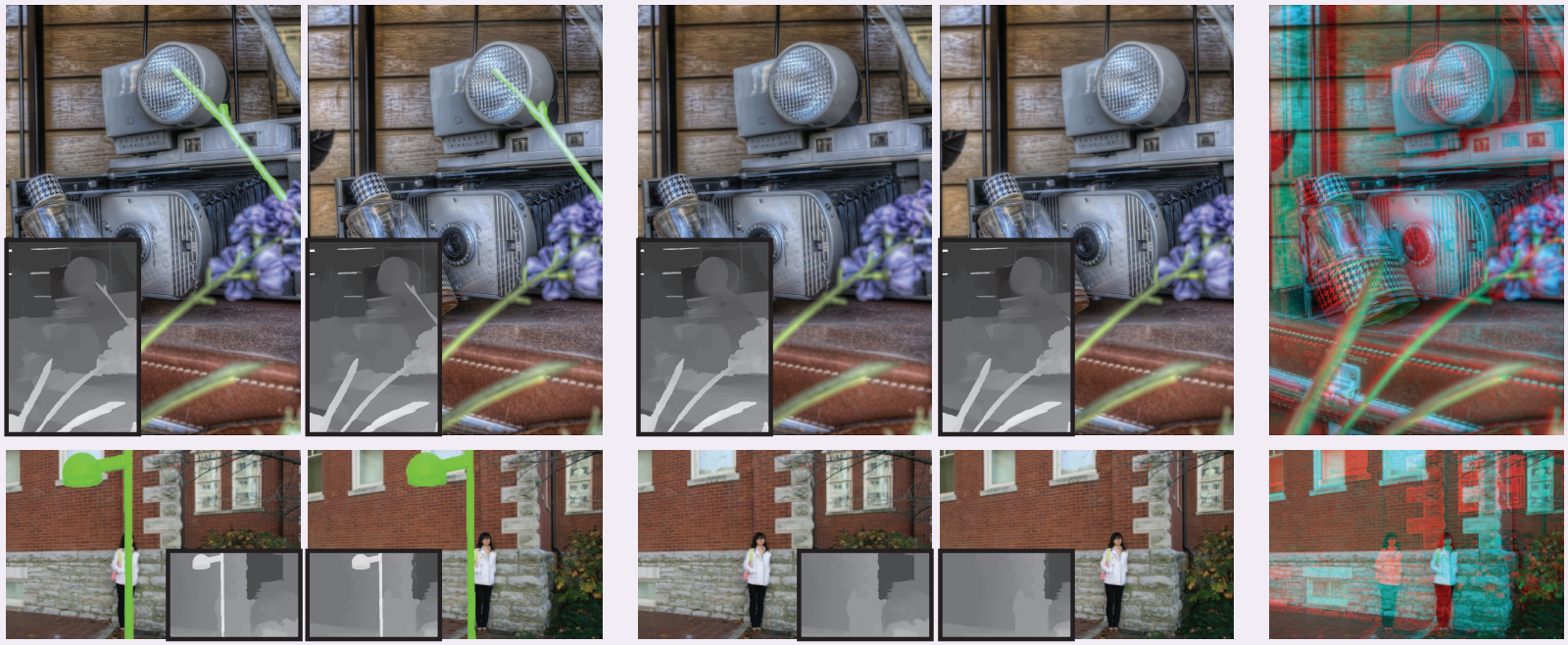







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- A patch-based refine scheme which produces stereoscopically consistent results and can be used to handle the depth inconsistency problem.
- A depth gradient domain patch distance metric, which is suitable for completing both frontal-parallel and non-frontal-parallel scenes.
- A disparity estimation method, which estimates disparity using depth shift in local feature space, facilitating simultaneously images and depth map completion.

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# Thanks!
# Questions?