"Image de-fencing using RGB-D data"

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Masters thesis at IIT Kharagpur, India

(2013-2014)

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Abstract

Objective: De-fence images



- Capture multiple views of the same scene
- Use RGB-D data to detect fence
- Inpaint fence regions using Loopy Belief Propagation

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Objective:

To remove fence-like occlusions from images

Use cases:

- Personal videos with fence-like occlusions
- Surveillance: security footage with fence-like occlusions
- Tourist spots like museums or high towers with fences for safety

Previous work:

- Estimation from single image (not multi-modal)
 - via regular patterns^[1] (not all fences),
 - or graph cuts^[2] (not all fence pixels),
 - or through learning-based matting^[3] (requires heavy user input),
- Estimation from multiple images^[4] by inpainting not via an optimization-based framework

Our novelty:

Use of multi-modal information involving depth maps (from Microsoft Kinect) to detect fences, inpainting via an optimization-based framework



Source: Google I/O 2017

^[1] M. Park, K. Brocklehurst, Robert Collins, and Yanxi Liu, "Deformed lattice detection in real-world images using mean-shift belief propagation," IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI), vol. 31, no. 10, pp. 1804–1816, 2009.

^[2] Y. Boykov and V. Kolmogorov, "An experimental comparison of min-cut/max-flow algorithms," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 26, no. 9, pp. 1124–1137, 2004.

^[3] Y. Zheng and C. Kambhamettu, "Learning based digital matting," in IEEE International Conference on Computer Vision (ICCV), 2009, pp. 889–896

^[4] M. Park, K. Brocklehurst, R. T. Collins, and Y. Liu. "Image de-fencing revisited." In Asian Conference on Computer Vision, pages 422-434, 2011.

2. Our approach

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2. Our approach

Capture of multiple RGB-D images



Fence detection and alignment

Computation of pixel shift





with slight shift in camera position (choose one to de-fence)



using affine transformation



using ASIFT



using LBP

2. Our approach - Capture of multiple RGB-D images

Capture of multiple RGB-D images

Fence detection and alignment

Computation of pixel shift



- Multiple images of the same scene are captured with slight positional shift in the camera.
- We choose one image to de-fence, and use the rest to borrow information.
- Objects occluded in one image are revealed in another:



2. Our approach - Fence detection and alignment



2. Our approach - Computation of pixel shift

Capture of multiple RGB-D images Fence detection and alignment

Computation of pixel shift

• To borrow information of an occluded pixel from another image, the pixel shift between the images is needed

Assumption: Global shift

1) Naive way computationally intensive



2) Optical flow - cannot handle occlusions

3) **ASIFT**^[5]: [online demo]

- State-of-the-art (at the time)
- Can handle affine variations



[5] J. M. Morel and G.Yu, "ASIFT: A new framework for fully affine invariant image comparison," SIAM Journal on Imaging Sciences, vol. 2, no. 2, pp. 438–469, 2009.

Inpainting

2. Our approach - Inpainting

Capture of multiple RGB-D images Fence detection and alignment Computation of pixel shift

Inpainting

• De-fenced image is modelled as a Markov Random Field

• Degradation Model:
$$y_m = O_m . W_m . x + n_m$$

 \mathcal{Y}_m is the observed image,

x is the de-fenced image,

 W_m is the warp matrix: it describes the Pixel Shift,

 O_m is the occlusion matrix: it crops the non-fence regions from x,

 n_m is noise, assumed to be Gaussian.

• Objective function:

$$\mathbf{J}(\mathbf{x}) = ||\mathbf{y}_{\mathrm{m}} - \mathbf{O}_{\mathrm{m}} \cdot \mathbf{W}_{\mathrm{m}} \cdot \mathbf{x}||^{2} + \beta \sum_{c \in C} \mathbf{V}_{c}(\mathbf{x})$$

 $V_c(x)$ is the clique potential function:

$$V_{c}(x) = |x_{i,j} - x_{i-1,j}| + |x_{i,j} - x_{i+1,j}| + |x_{i,j} - x_{i,j-1}| + |x_{i,j} - x_{i,j+1}|$$

• J(x) is optimized to obtain MAP estimate x using **Loopy Belief Propagation**

2. Our approach - recap

Capture of multiple RGB-D images

Fence detection and alignment

nent

Computation of pixel shift

Inpainting



with slight shift in camera position (choose one to de-fence)



using affine transformation



using ASIFT



using LBP

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• Rectangular fence and single object, with varying material of object



RMSE \approx 3.1; pSNR \approx 38dB; SSIM \approx 0.87

 Rectangular and diagonal fences with two objects:

Using two pixel shifts one for the person, and one for the background.





RMSE ≈ 3.9 pSNR ≈ 36dB SSIM ≈ 0.79

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4. Comparison with other methods



Using Total Variation Inpainting using Split Bregman^[5]

• Uses single image to inpaint, fails for thick fences

Using Learning-Based Digital Matting^[6] on multiple images

 Uses single pixel shift, requires heavy user input, cannot handle multiple planes of depth



Using our approach

 Can handle thick fences and multiple planes of depth

[5] Getreuer, P., "Total variation inpainting using Split Bregman," Image Processing On Line, 2:147-157, 2012.

[6] [14] Khasare, V., and Sahay, R., "Seeing through the fence: image de-fencing using a video sequence," 2013 IEE International Conference on Image Processing, Restoration and Enhancement III.

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precautions

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5. Limitations and precautions

 Sufficient indoor illumination -Kinect fails to record depth in outdoor settings



• Sufficient camera translation - to obtain full information



• Sufficient fence dilation - to avoid errors in depth map



- Limited camera translation to avoid perspective distortion
 - If camera translation is too high, inpainting leads to a blurred image



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Some improvements -

• perform depth completion by fusing data from multiple recorded depth maps affected by occlusions

Conference Paper - S. Jonna, V. S. Voleti, R. R. Sahay, and M. S. Kankanhalli, "A multimodal approach for image de-fencing and depth inpainting," in Proc. Int. Conf. Advances in Pattern Recognition, 2015, pp. 1-6.

More work -

- made a dataset of captured occluded and unoccluded images
- proposed a robust algorithm to estimate optical flow under known fences/occlusions
- used the total variation of the unoccluded image and the completed depth map as regularization constraints
- used Split-Bregman iterative method to simultaneously de-fence and inpaint

Journal paper - S. Jonna, S. Satapathy, V. S. Voleti, R. R. Sahay, "Unveiling the scene - A Multimodal Framework for Simultaneous Image Disocclusion and Depth Map Completion using Computational Cameras"



@IIIT Hyderabad, India

• Using an assessor to filter video retrieval results



Movie translation with lip-sync



"A adE, priyA cheppunTundi kada"



Thank you.

voletiv.github.io

APPENDIX

Computation of Pixel Shifts



Since the superimposed image is not too blurry, we can conclude that the pixel shifts have been calculated accurately.

Superimposition of Reference Image and Shifted Test Image

Rectangular fence with single object: Board



Rectangular fence with single object: Poster



NATIONAL WORKSHOP ON BIOSTATISTICS Applications of Computational Statistics in Medicine & Biology

Rectangular fence with single object: Bedsheet



Rectangular fence with single object: Painting



Rectangular fence with two objects



Diagonal fence with two objects





Total Variation Inpainting using Split Bregman



Using Total Variation Inpainting using Split Bregman Using Proposed Algorithm



De-fencing using Learning-Based Matting





Using De-fencing using Learning-Based Matting Using Proposed Algorithm

Precautions

Sufficient fence dilation



Precautions

Sufficient camera translation



Precautions

Limited camera translation

