Stereo image de-fencing using smartphones

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Problem statement

Left image Right image Disparity map

Goal: To build an effecient algorithm for the detection and removal of fences/occlusions from images/videos. We solve the identified problem in three phases:

- Robust segmentation of fences/occlusions
- Optical flow between the frames
- Information fusion using TV split Bregman

Model

The degradation model for the frames of the captured video is

$$\mathbf{y}_m^{obs} = \mathbf{O}_m \mathbf{y}_m = \mathbf{O}_m \mathbf{W}_m \mathbf{x} + \mathbf{n}_m \qquad (1)$$

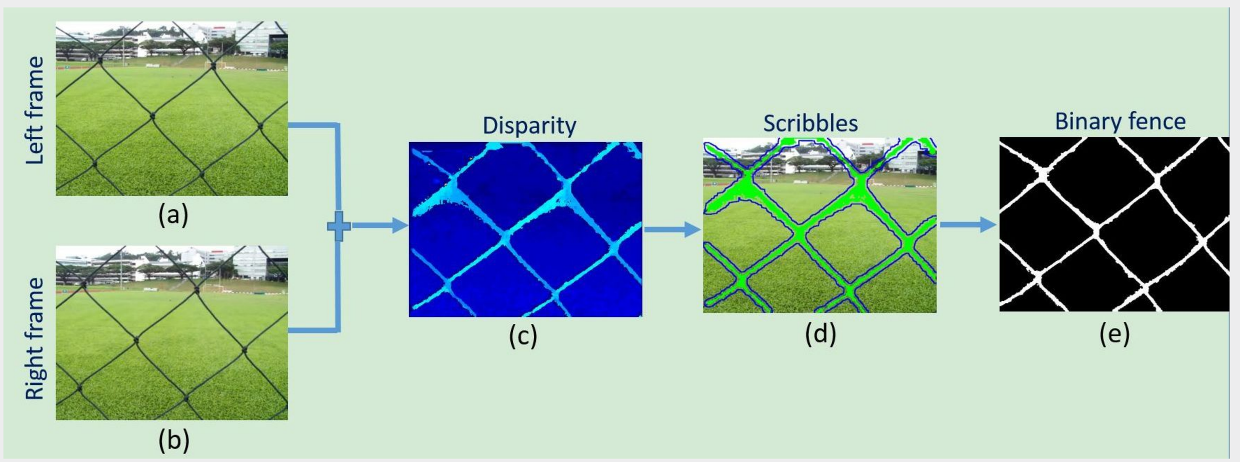
where $\mathbf{y}_m^{obs}$ is the m^{th} observation wherein the occluded pixels have been excluded using $\mathbf{O}_m$, $\mathbf{y}_m$, $m = 1, 2$ are the left and right images comprising the stereo pair, $\mathbf{O}_m$ is the fence mask corresponding to m^{th} image, $\mathbf{W}_m$ is the warp matrix, $\mathbf{x}$ is the de-fenced image and $\mathbf{n}_m$ is the Gaussian noise.

Fence detection using stereo

- Given a pair of images $\mathbf{y}_m$ (m=1,2), we want to compute the disparity map $\mathbf{D}$.
- We have exploited disparity/depth cue for the fence pattern segmentation.
- The authors in [1], trained two CNNs 'fast' and 'accurate' on pairs of small image patches.
- We employed 'fast' pre-trained model given below for matching cost computation in our work.

- Each sub-network in 'fast' CNN is made up of convolutional layers followed by ReLU layers.

Segmentation pipeline



- Exatrcted features from each one of the sub-network are used to compute cosine similarity.
- Robustly obtain the fence pixels by feeding automatically generated scribbles to mating.

Left image Right image Disparity map

Information fusion using total variation split Bregman

The de-fenced image is the solution of the following constrained optimization problem

$$\arg\min_{\mathbf{x}} \frac{1}{2} \sum_{m=1}^{p} \| \mathbf{y}_m - \mathbf{O}_m \mathbf{W}_m \mathbf{x} \|_2^2 + \mu \| \mathbf{d} \|_1 \qquad s.t.\ \mathbf{d} = \nabla \mathbf{x}$$

where p is the number of frames chosen from the video and μ is the regularization parameter. We employ the split Bregman (SB) iterative framework in [2] to solve the above problem.

$$\arg\min_{\mathbf{x}} \frac{1}{2} \sum_{m=1}^{p} \| \mathbf{y}_m - \mathbf{O}_m \mathbf{W}_m \mathbf{x} \|_2^2 + \mu \| \mathbf{d} \|_1 + \frac{\lambda}{2} \| \mathbf{d} - \nabla \mathbf{x} \|_2^2$$

where λ is the shrinkage parameter. The Bregman iterates to solve the above equation are as

$$[\mathbf{x}^{k+1}, \mathbf{d}^{k+1}] = \arg\min_{\mathbf{x},\mathbf{d}} \frac{1}{2} \sum_{m=1}^{p} \| \mathbf{y}_m - \mathbf{O}_m \mathbf{W}_m \mathbf{x}^k \|_2^2 + \mu \| \mathbf{d}^k \|_1 + \frac{\lambda}{2} \| \mathbf{d}^k - \nabla \mathbf{x}^k + \mathbf{b}^k \|_2^2$$

$$\mathbf{b}^{k+1} = \nabla \mathbf{x}^{k+1} + \mathbf{b}^k - \mathbf{d}^{k+1}$$

We can now split the above problem into two sub-problems as

Sub Problem 1:

$$[\mathbf{x}^{k+1}] = \arg\min_{\mathbf{x}} \frac{1}{2} \sum_{m=1}^{p} \| \mathbf{y}_m - \mathbf{O}_m \mathbf{W}_m \mathbf{x}^k \|_2^2 + \frac{\lambda}{2} \| \mathbf{d}^k - \nabla \mathbf{x}^k + \mathbf{b}^k \|_2^2$$

This sub-problem is solved by a steepest descent method.

Sub Problem 2:

$$[\mathbf{d}^{k+1}] = \arg\min_{\mathbf{d}} \mu \| \mathbf{d}^k \|_1 + \frac{\lambda}{2} \| \mathbf{d}^k - \nabla \mathbf{x}^{k+1} + \mathbf{b}^k \|_2^2$$

The above sub-problem can be solved by applying the shrinkage operator as follows

$$\mathbf{d}^{k+1} = shrink(\nabla \mathbf{x}^{k+1} + \mathbf{b}^k, \frac{\lambda}{\mu})$$

$$\mathbf{d}^{k+1} = \frac{\nabla \mathbf{x}^{k+1} + \mathbf{b}^k}{| \nabla \mathbf{x}^{k+1} + \mathbf{b}^k |} * max(| \nabla \mathbf{x}^{k+1} + \mathbf{b}^k | - \frac{\lambda}{\mu}, 0)$$

The update for $\mathbf{b}$ is as $\mathbf{b}^{k+1} = \nabla \mathbf{x}^{k+1} + \mathbf{b}^k - \mathbf{d}^{k+1}$. We tune the parameters μ, λ to obtain the best estimate of the de-fenced image.

References

[1] J. Zbontar and Y. LeCun *Stereo matching by training a convolutional neural network to compare image patches*, JMLR (2016).

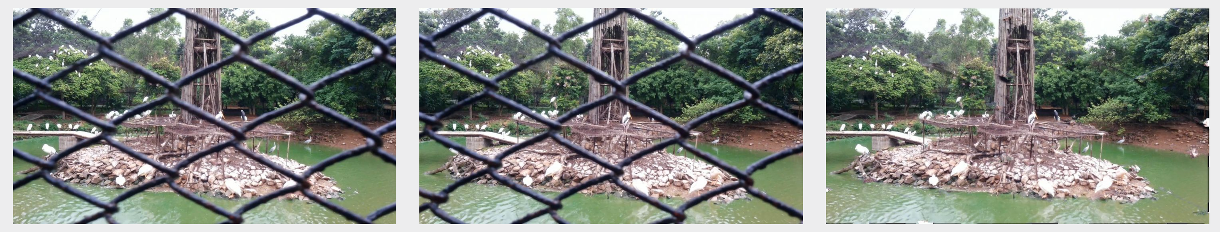
[2] T. Goldstein and S. Osher: *The split Bregman method for l1 regularized problems*, SIAM J. Imag. Sci. (2009).

[3] Y. Mu, W. Liu, and S. Yan *Video de-fencing*, TCSVT (2014).

[4] T. Xue, M. Rubinstein, C. Liu, and W. T. Freeman *A computational approach for obstruction-free photography*, TOG (2015).

[5] R. Yi, J. Wang, and P. Tan *Automatic fence segmentation in videos of dynamic scenes*, in CVPR (2016).

Experimental results



(a) (b) (c)

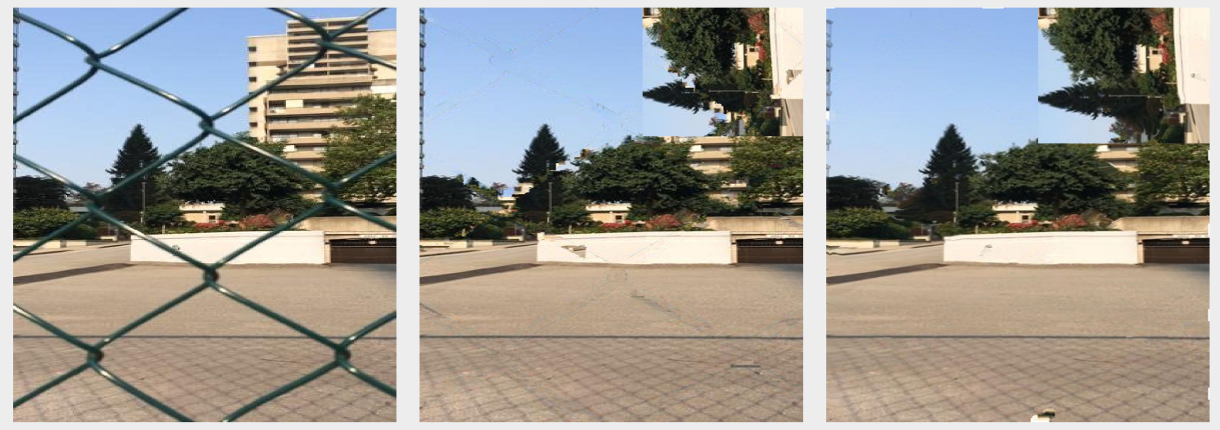
(a), (b) Two fenced observations from a video captured by us using a smartphone. (c) De-fenced image obtained by the proposed technique.

Input Mu et al. [3] Proposed

Comparison with the video de-fencing algorithm in [3].

Input Xue et al. [4] Ours

Comparison with the computational approach proposed in [4].



Input Yi et al. [5] Ours

Comparison with the state-of-the-art image de-fencing algorithm in [5].

Conclusions

- Presented a novel algorithm for fence segmentation and removal using a stereo-pair.
- We harnessed disparity cue for robust fence pixel identification.
- Computed the motion between the frames using optical flow.
- Formulated an optimization framework and the ill-posed inverse problem is solved using SB.
- We compare with several state-of-the-art works for image de-fencing.