# Correspondence of Image Warping using Plane Constraints

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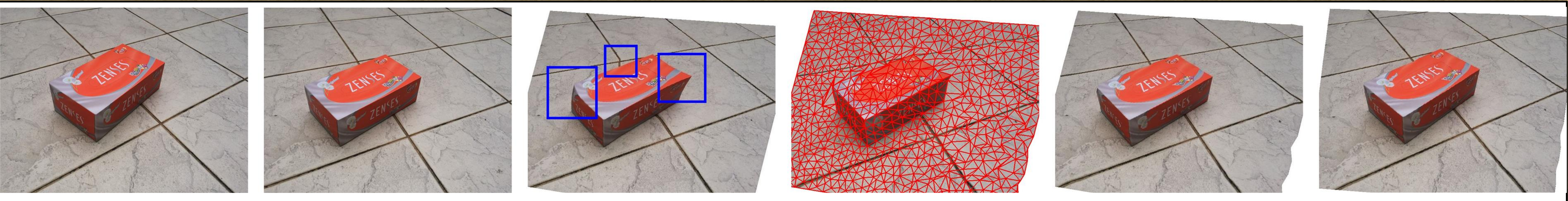

(a) (b) (c) (d) (e) (f)

**Figure 1**: *(a) Source image. (b) Target image. (c) Initial warping result. (d) Optimization result after 20 iterations. (e) Optimization result after 30 iterations.(f) Novel view by our method with α = 0.5.*

## Introduction

This paper presents a novel warping approach for IBR inspired by the previous method [Liu et al. 2009; Chaurasia et al. 2011]. Our main insight is that the previous warping method only considered feature correspondences and mesh regularization in the energy, and these two terms cannot guarantee the photo-consistency of corresponding triangles, hence may introduce ghost artifacts in the novel view. To avoid such artifacts, we propose a novel warping method that directly models on the triangle color similarities and tries to minimize the total color difference between two meshes.

In this paper, we propose an approach to optimize mesh correspondence between two images for warping. After optimization, the corresponding triangles have the most similar colors. We optimized color and plane constraints in an unified optimization framework. The experiments demonstrated the effectiveness of our method.

## Approach

The pixel-level color correspondence is easily trapped into local minima which cannot be solved by only constraining sparse and error-prone feature correspondences [Chaurasia et al. 2011]. We turn to indicate reliable high-level plane correspondences between images, which can provide stronger priors for better correspondences. The difficulty is how to optimize the low-level color correspondence and the high-level plane constraints in a unified framework. To solve the problem, we carefully design our optimization strategy:

$$E(\boldsymbol{H},\boldsymbol{V}) = \omega_{photo}E_{photo}(\boldsymbol{V}) + \omega_{plane}E_{plane}(\boldsymbol{H}) + \omega_{geom}E_{geom}(\boldsymbol{H},\boldsymbol{V}) + \omega_{bar}E_{bar}(\boldsymbol{V})$$

where $\boldsymbol{V}$ is the parameterized mesh overlaid on images, $\boldsymbol{H}$ is parameterized planes, $\omega_*$ are the weights, the photometric term $E_{photo}$ ensures triangle-to-triangle photo consistency of meshes, plane term $E_{plane}$ encodes high-level plane constraints, an additional geometric term $E_{geom}$ fuses the photometric and plane terms together, and a barrier term $E_{bar}$ prevents the fold-over of triangles. The four terms together constitute a complete warping system which is a typical non-linear least-squares problem, and can be solved by Gauss-Newton method.

- *Photometric term*

$$E_{photo}(\boldsymbol{V}) = \sum_i^N \sum_j^M \left|\hat{\Gamma}(\hat{p}_{i,j}) - \Gamma(p_{i,j})\right|^2$$

- *$N$: triangle number* *$M$: sample number*
- *$\hat{p}_{i,j}$: the $j^{th}$ sample in $i^{th}$ triangle in source image*
- *$p_{i,j}$: the $j^{th}$ sample in $i^{th}$ triangle in target image*
- *$\hat{\Gamma}(\hat{p})$: the greyscale intensity at point $\hat{p}$ in source image*
- *$\Gamma(p)$: the greyscale intensity at point $p$ in target image*

- *Plane term*

$$E_{plane} = \sum_i \sum_j^K \left|H_i(\boldsymbol{x}_j) - H_i^0(\boldsymbol{x}_j)\right|^2$$

- *$K$: sample number $x_j$: the $j^{th}$ sample on plane $i$*
- *$H_i^0$: initial homography of detected corresponding planes $\hat{\pi}_i$ and $\pi_i$*
- $H(\boldsymbol{x}) = H([x,y]) = [\frac{h_1x+h_2y+h_3}{h_7x+h_8y+1}, \frac{h_4x+h_5y+h_6}{h_7x+h_8y+1}]$

- *Geometric term*

$$E_{geom}(\boldsymbol{H},\boldsymbol{V}) = \sum_i \sum_{\hat{V}_j\in\hat{\pi}_i} |H_i(\hat{V}_j) - V_j|$$

- *$\hat{V}_j$: the $j^{th}$ vertex from the source mesh*
- *$V_j$: the $j^{th}$ vertex from the target mesh*
- *$\hat{\pi}_i$: the $i^{th}$ plane from the source image*

- *Barrier term*

$$E_{bar}(\boldsymbol{V}) = \sum_{j\in\Omega} \left(\phi_j\left(\lambda_j(\boldsymbol{V})\right)\right)^2$$

- *$\lambda_j(\boldsymbol{V})$: the area of the $j^{th}$ triangle in mesh $\boldsymbol{V}$*
- $\phi_j(x) = \begin{cases} \infty & x \le 0 \\ \frac{1}{g_j(x)} & 0 < x < s_j \\ 0 & x \ge s_j \end{cases}$
- $g_j(x) = \frac{x^3}{s_j^3} - \frac{3x^2}{s_j^2} + \frac{3x}{s_j}$, *where* $s_j = s\lambda_j(\boldsymbol{V}^0), s \in [0.1,1]$
- *$\boldsymbol{V}^0$: the initial mesh*

## Experiments

To evaluate the effectiveness of our approach, we ran a testing set of 3 pairs of images (BOX, PILLOW, BUILDING). The maximum size of the mesh triangles is the only parameter has to be tuned in our approach. Parameter settings and quantitative results are reported as follows.

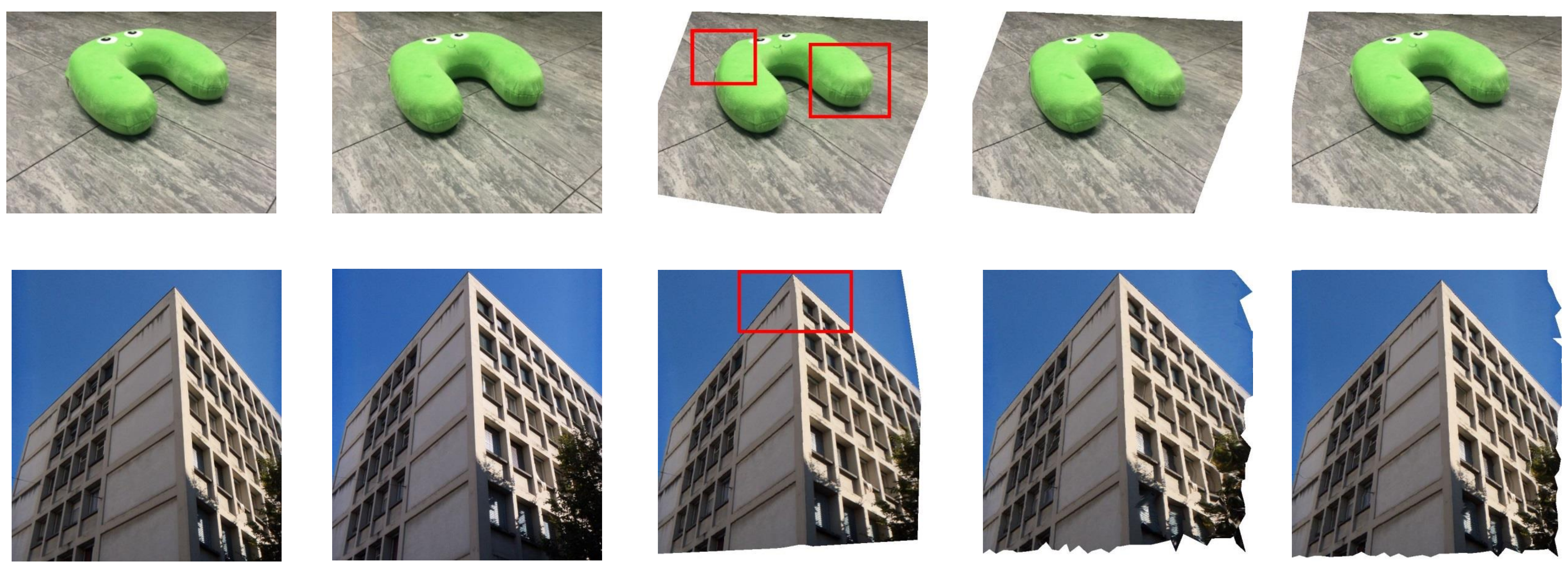

**Figure 2:** *From left to right: source image, target image, initial warping, our warping, novel view by our method with* $\alpha$ = 0.5.

| Name | Image size | Max. triangle size | Energy | | | |
|---|---|---|---|---|---|---|
| | | | Initial | 10 iter. | 20 iter. | 30 iter. |
| BOX | 800*600 | 500 | 4.16E+07 | 5.76E+06 | 4.82E+06 | 4.39E+06 |
| PILLOW | 600*400 | 800 | 2.17E+07 | 3.78E+06 | 3.06E+06 | 3.05E+06 |
| BUILDING | 660*714 | 200 | 1.64E+08 | 5.89E+07 | 5.68E+07 | 5.13E+07 |

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