# Multiple Combined Constraints for Image Stitching

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## Motivation

- Single global homography is only suitable for concentric and planar condition.
- Some more flexible models, such as: spatially-varying model and mesh-based warping model, are used to handle more complex scenes.
- More constraints are required to estimate such a model with high degree of freedom (DoF).

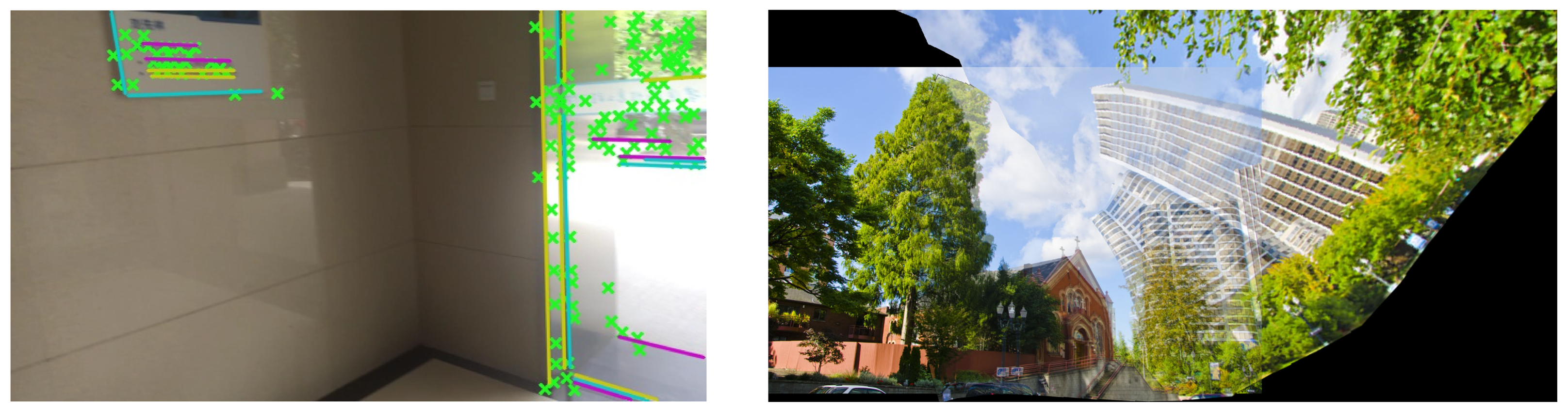

Figure 1: An illustration of the limitation when geometric constraint and photometric constraint are used for image stitching.

- Geometric constraints (e.g., point and line correspondences) usually are spatially biased [1] and are insufficient for low-texture scenes.
- Photometric constraints are sensitive to displacements, moving objects, and occlusions. They are not suited for parallax-tolerant image stitching.

## Our Idea

- Based on the observation that geometric and photometric constraints are complementary. We propose to combine them together in a unified content-preserving warping (CPW) framework.

| | **Geometric Constraints** | **Photometric Constraints** |
|---|---|---|
| Unbiased Distribution | - | ✓ |
| Parallax Tolerance | ✓ | - |

Table 1: A comparison of two kinds of constraints.

- Overall Objective Function

$$E = \alpha E_f + \beta E_l + \gamma E_p + \delta E_c + \eta E_s$$

- $E_f$ and $E_l$ are two geometric terms based on point and line correspondences respectively.
- $E_p$ is the photometric term, in which a high-order component is appended to overcome the illumination consistency limitation.

$$E_p = E_{pm} + \lambda E_{pg}$$

- $E_c$ and $E_s$ are two smoothness terms that preserve image content and reduce distortion during image warping.
- The overall function is quadratic and can be easily minimized by any sparse linear system.

## Quantitative Comparison

- Evaluation metric. The RMSE of one minus normalized cross correlation (NCC) over a local window for all pixels in image overlapping region is used to measure the quality of stitching result quantitatively:

$$RMSE(\hat{I}_s, I_t) = \sqrt{\frac{1}{N}\Sigma_{\Omega}(1.0 - NCC(\mathbf{p}_s, \mathbf{p}_t))}$$

- Evaluation on low-texture images.


Figure 2: The dataset of our comparative experiments on low-texture images.

| | method | | | | method | | |
|---|---|---|---|---|---|---|---|
| Data | APAP[2] | DF-W[3] | Proposed | Data | APAP[2] | DF-W[3] | Proposed |
| *cabinet* | 4.55 | 2.63 | **1.33** | *bench* | 4.01 | 7.12 | **3.64** |
| *desk* | 6.17 | 4.89 | **1.59** | *bridge* | 7.95 | 6.60 | **4.49** |
| *four* | 6.92 | 2.36 | **0.98** | *girl* | 5.20 | **4.81** | 5.05 |
| *roof* | 7.82 | 2.25 | **1.52** | *park* | 11.07 | 8.18 | **5.85** |
| *shelf* | 8.76 | 1.54 | **0.83** | *road* | 2.28 | 4.59 | **1.67** |
| *window* | 5.78 | 4.94 | **1.95** | *villa* | 6.72 | **5.20** | 5.41 |

Table 2: The RMSE([0,255]) for three compared methods on low-texture image pairs.

- Evaluation on large-parallax images.

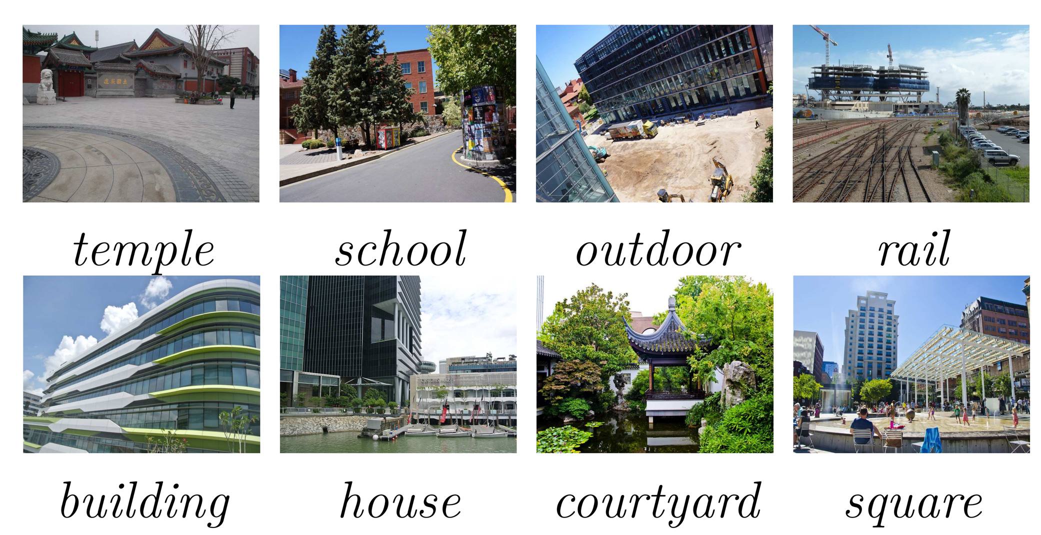


Figure 3: The dataset of comparative experiments on large-parallax images.

| | method | | | | method | | |
|---|---|---|---|---|---|---|---|
| Data | APAP[2] | MPA[4] | Proposed | Data | APAP[2] | MPA[4] | Proposed |
| *temple* | 6.39 | 4.65 | **2.57** | *school* | 12.20 | **9.73** | 10.85 |
| *outdoor* | 11.90 | 10.40 | **6.75** | *rail* | 14.80 | 11.80 | **9.81** |
| *building* | 6.68 | 4.94 | **3.74** | *house* | 19.80 | 18.00 | **14.57** |
| *courtyard* | 38.30 | 32.50 | **29.17** | *square* | 19.90 | 16.80 | **12.55** |

Table 3: The RMSE([0,255]) for three compared methods on large-parallax image pairs.

## Qualitative Comparison

- Only geometric constraints.
- Geometric constraints followed by photometric constraints.
- Geometric constraints combined with photometric constraints.

Figure 4: Qualitative comparisons between between methods with three different constraint combinations. **First Row:** Results with geometric constraints; **Second Row:** Results with geometric constraints followed by photometric constraints; **Third Row:** Results with geometric constraints combined with photometric constraints.

## References

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