# Solving the multi-way matching problem by permutation synchronization

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## 1 Experiments

In the supplement, we further elaborate on our experiments, describe the challenges associated with various datasets and present additional results.

### 1.1 Stereo matching

As discussed in the main paper, we consider the task of aligning landmarks in 2D images from **CMU hotel** dataset. Dataset includes $m = 101$ frames of a video sequence of a toy hotel. We used all hand labeled nodes in each frame ($n = 30$). For image pair $(\mathcal{I}_i, \mathcal{I}_j)$, pairwise linear assignment of keypoints (Kuhn-Munkres algorithm) provided relative baseline to compare our results against. Normalized error of recovered matchings is shown in Fig. 1 as the number of images increases. The blue curve gives the normalized error of recovered correspondences using permutation synchronization and the red curve presents the normalized error for the baseline method. It is evident that our method outperforms the baseline method which degrades progressively as the number of images increases in the dataset. This is due to the fact that the appearance (or descriptors) of keypoints differ considerably for large offset pairs (which is likely when the image set is larger), and many false matches are found for such pairs. On the other hand, our method improves as the size of the image set increases. Qualitative results are shown in Fig. 2.

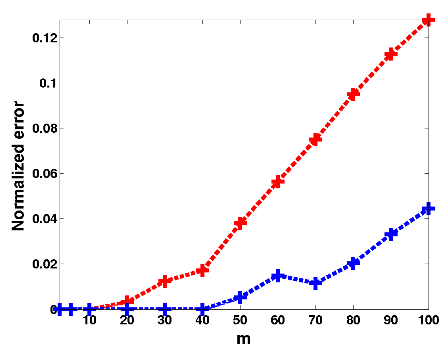
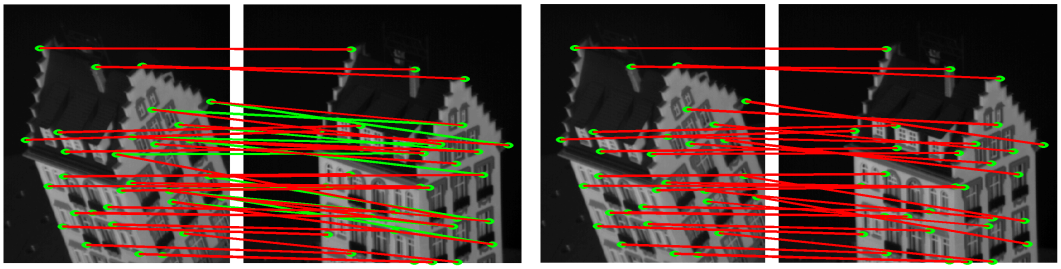



Figure 1: Normalized error as $m$ increases on the Hotel dataset. Permutation Synchronization (blue) vs. the pairwise Kuhn-Munkres baseline (red).

**Repetitive Structures.** Next we considered two datasets with repetitive structures in the scene causing severe geometric ambiguities and serious occlusion (due to varying camera angle). One of these datasets called **Building**, had several "similar looking" landmark points (based on local context) in the scene, see Fig. 3. We identified 25 such keypoints, and hand annotated them across all images. It is known that even sophisticated features like SIFT fail to resolve geometrics ambiguities

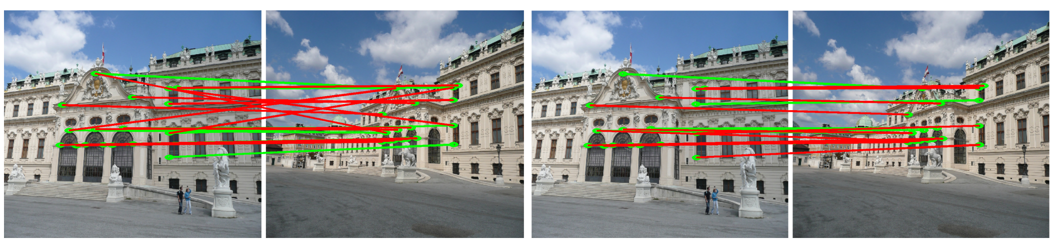


(a) (b)

Figure 2: Representative image pairs from the Hotel datasets. (Green circles) Landmark points, (green lines) ground truth matchings, (red lines) found matches. (a) Pairwise linear assignment. (b) Permutation snchronization. Note less visible green is good (b).

Figure 3: Subset of images from Building dataset with multiple instances of similar structure.

and often pairwise matching procedures provide wrong matches, largely due to the presence of similar looking landmarks (and feature descriptors) in the scene. In our experiments, we found that the proposed method resolve geometric ambiguities by enforcing mutual consistency and robustly handles occlusion because of evidence derived from the large number of additional images in the set, Fig. 4 (b).

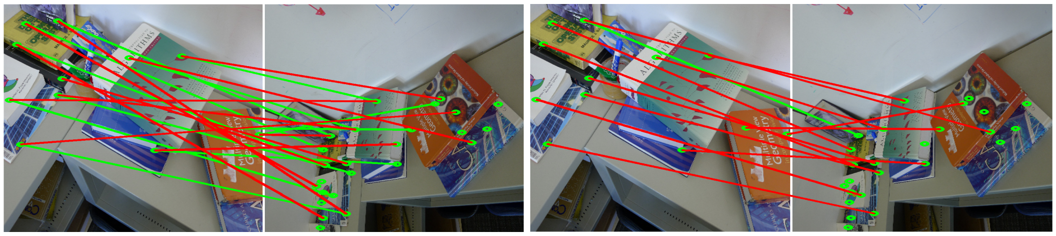


(a) (b)

Figure 4: Matches for a representative image pair from Building dataset. (Green circles) landmark points, (green lines) ground truth matchings, (red lines) found matches. (a) Pairwise linear assignment, (b) permutation synchronization. Note that less visible green is better (b).

We made a similar observation on a second dataset called **Books**. This dataset include images of a "L" shaped study table with multiple instances of "similar" looking books on the table, Fig. 5. Because of heavy occlusion and *multiple instances* of similar objects, data suffer severe geometrical ambiguities. Permutation synchronization method exploit mutual consistency very efficiently, and outperform the pairwise matching procedure on this dataset too. Qualitative results on a representative image pair are shown in Fig. 6.

Figure 5: Multiple views of "L" shaped study table from Books dataset.



(a) (b)

Figure 6: A representative image pair matching from Books dataset. (Green circles) landmark points, (green lines) ground truth matchings, (red lines) found matches. (a) Pairwise linear assignment, (b) permutation synchronization. Note that less visible green is better (b).

### 1.2 Keypoint matching with nominal user supervision

In this section, we focus on a matching problem that involve multiple graphs. Datasets for such problems do not suffer the kind of challenges that are mentioned in the previous section. However, the problem is challenging nonetheless because graphs are not extracted under controlled background. Even sophisticated features like Shape context, usually provide less informative keypoint characterization. Our experimental results show that the proposed permutation synchronization method along with little supervision improved accuracy to a great extent. We considered "Touring bike" dataset from **Caltech 256 dataset** in our experiments, Fig. 7a. For each image, graph was extracted by identifying 6 interest points that correspond to the bike frame, Fig. 7b (red). Each interest point was characterized using SUSAN corner detector's output, Fig. 7b (blue). As before, the baseline was pairwise linear assignment. Results on a representative triplet are shown in Fig. 7 as the degree of supervision varies.

(a) "Touring bike" dataset.

(b) SUSAN detector output.

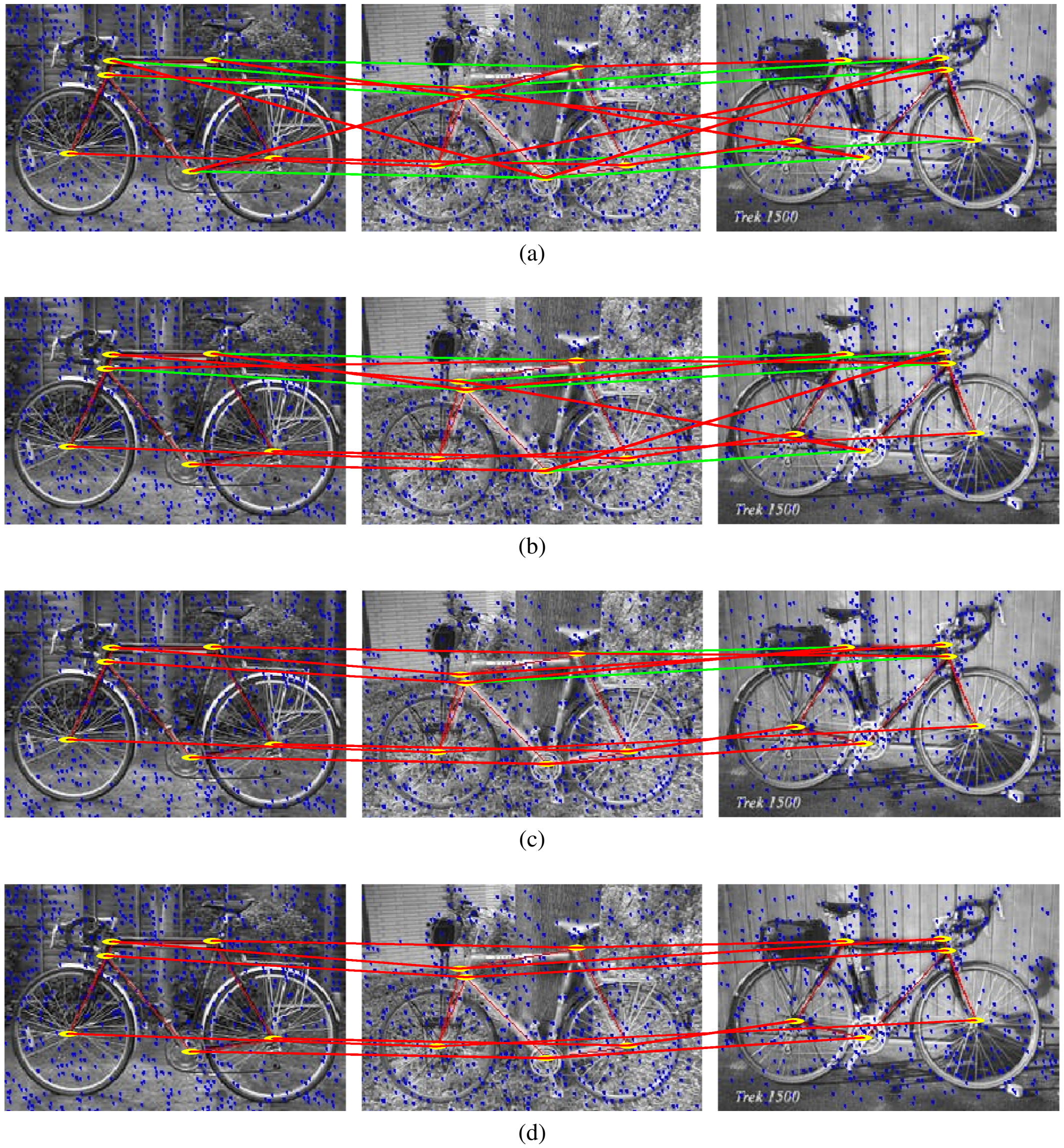



Figure 7: Recovered matches using permutation synchronization for a representative graph triplet. (yellow circles) Landmark points, (green lines) ground truth matchings, (red lines) found matches.(a) supervision = 0.1, (b) supervision = 0.2, (c) supervision = 0.3, (d) supervision = 0.4.