SDRSAC: Semidefinite-Based Randomized Approach for Robust Point Cloud Registration without Correspondences Supplementary Material

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1. Extension of the algorithm to the case of known correspondences

As mentioned in the main paper, our algorithm (SDR-SAC) can be extended easily to registration problems with known correspondences. Such extension can be done easily with a slight modification to the original algorithm. In this section, we discuss in details a new algorithm to enable SDRSAC for problems where putative correspondences are known (we call the new algorithm CSDRSAC – SDRSAC with correspondences). Also, we will provide some preliminary experiment results where show that CSDRSAC performs much better than RANSAC [1].

1.1. Algorithm

The main idea of the extension is to make use of the information provided by the a priori putative set of correspondences to obtain the subset \mathcal{D}' , instead of sampling from \mathcal{D} (Line 5 in the SDRSAC algorithm described in the main paper). Specifically, the algorithm can be described as Alg. 3

1.2. Experiments

In this section, we compare CSDRSAC against RANSAC [1]. For input data, we use the Standford 3D dataset and the UWA datasets. The keypoints were generated and matched using the data and code provided by [?]. For each pair of shapes, a set of N = 2000 putative correspondences are supplied to the algorithms. The number correspondences and run time for five pairs are shown in the Table 1 and the alignment results are displayed in Fig. 1. Note that the number of correspondences are measured based on the original point clouds instead of the feature set. Apparently, CSDRSAC performs much better than RANSAC. This suggest that CSDRSAC is a promising method, which deserves further investigation to develop better randomized algorithm for registration problems with known correspondences.

Algorithm 3 CSDRSAC

- **Require:** Input data S and D, max_iter, size of sampled subsets N_{sample}
- 1: iter $\leftarrow 0$; best_score $\leftarrow 0$;
- 2: while iter < max_iter do
- 3: $\mathcal{S}' \leftarrow \text{Randomly sample from } \mathcal{S} \text{ with } |\mathcal{S}'| = N_{\text{sample}}$
- 4: $\mathcal{D}' \leftarrow \text{Correspondences of } \mathcal{S}' \text{ where } \mathcal{D}' \subseteq \mathcal{D}$
- 5: $\{\mathcal{M}, \mathbf{R}, \mathbf{t}\} \leftarrow$ SDRMatching $(\mathcal{S}, \mathcal{D}, \mathcal{S}', \mathcal{D}')$ /*As Alg.2 in main paper */
- 6: if $|\mathcal{M}| > \text{best_score}$ then
- 7: best_score $\leftarrow |\mathcal{M}|; \mathbf{R}^* \leftarrow \mathbf{R}; \mathbf{t}^* \leftarrow \mathbf{t}$
- 8: **end if**
- 9: iter \leftarrow iter + 1
- 10: $T \leftarrow$ Number of iterations that satisfies the stopping criterion.
- 11: **if** iter $\geq T$ **then**
- 12: return
- 13: **end if**
- 14: end while
- 15: return Best transformation(R*, t*), best_score

2. More experiments on registration problems without correspondences

In this section, we provide more results for registration problem without correspondences. These experiments were setup with the same settings as described in Section 4 in the main paper. The results are shown in Table 2. As can be seen in Table 2, our method consistently provides comparable results compared to other state-of-the-art methods on point cloud registration without correspondences.

References

 M. A. Fischler and R. C. Bolles. Random sample consensus: a paradigm for model fitting with applications to image analysis and automated cartography. *Communications of the ACM*, 24(6):381–395, 1981.



Figure 1. Examples of point clouds aligned by CSDRSAC. From left to right: T-rex; Dragon; Armadillo

		Bunny	Armadillo	Dragon	Buddha	Chicken	T-rex
SDRSAC	#Corrs	6850	6898	6828	6739	7260	6531
	Time (s)	14.56	15.73	15.28	13.46	16.65	12.25
RANSAC	#Corrs	6530	6793	6818	6695	6956	6521
	Time (s)	195.5	420.27	153.93	445.37	156.61	352.52

Table 1. Experiment results for CSDRSAC and RANSAC. For each pair of input data, N = 2000 key points were used for registration

Pairs		SDRSAC	4PCS	S-4PCS	ICP	TrICP	IRLS	GoICP	TrGoICP
Office2_1	#Corrs	8962	7644	8335	8505	8615	8575	953	5685
Office2_2	Time(s)	10.15	10.52	10.68	4.32	5.15	11.15	40.4	35.5
Office2_5	#Corrs	5630	4337	4301	1887	3206	4976	3813	2811
Office2_6	Time(s)	8.65	10.52	10.35	4.26	4.65	12.53	30.1	28.5
Office2_10	#Corrs	5975	5604	5275	1881	2714	2272	2840	3338
Office2_11	Time(s)	7.39	10.19	10.35	4.48	5.25	22.5	29.5	28.5
Living2_20	#Corrs	3787	3662	3347	2227	2368	2267	1990	3300
Living2_21	Time(s)	8.65	10.25	10.12	4.65	4.13	4.45	32.5	29.3
Living2_5	#Corrs	3862	3523	3545	1358	1456	1286	1618	2553
Living2_6	Time(s)	6.8	10.25	10.65	4.35	4.56	8.78	33.5	30.2
Living2_47	#Corrs	2892	2788	2392	587	614	374	379	1688
Living2_48	Time(s)	11.85	15.95	15.23	4.56	4.67	29.75	39.5	42.6

Table 2. Results for real data experiments. For each pairs, the first row is the number of correspondences (#Corrs) and the second row shows the run time in second. Note that S-4PCS represent Super4PCS