CVPR 2023, VANCOUVER, CANADA

3D Registration with Maximal Cliques

Xiyu Zhang, Jiaqi Yang*, Shikun Zhang, Yanning Zhang

Northwestern Polytechnical University

1. Problem definition

 Given putative correspondences, 3D registration aims at estimating the sixdegree-of-freedom (6-DoF) pose between two point clouds
 Correspondences can be generated by matching geometric or deep learned 3D features



$$\mathbf{R} \in SO(3)$$
$$\mathbf{t} \in \mathbb{R}^3$$

6DoF pose transformation



2. Challenges

Outliers are the main concern

- Data nuisances (noise, resolution variation, limited overlap, etc)
- Limited distinctiveness of point cloud features



3. Existing solutions

□ Two main categories 1. Deep learned SpinNet, CVPR2021 GeoTransformer, CVPR2022 PointDSC, CVPR2021 Module N. NSM Module Hypothesis Selection Weighted LS Sunnort Patch a Reference End-to-end registration Learn features Learn to find inliers Massive training data (with labels) WARNING Not lightweight, requiring GPU resource Weak generalization ability

3. Existing solutions

Two main categories 2. Traditional: Maximum clique based methods are dominating

Prior: Inliers are compatible with each other

- First construct a compatibility graph
- ② Find the maximum clique



(1)

2



Still sensitive to heavy outliers

 C_6

C7

4. Our insight

Loosen the maximum clique constraint

- We do not have a "perfect" compatibility metric
- Inliers are not "perfect" inliers, they not always form the maximum clique
- Mine more local consensus information in the graph



Compatible?



Inliers also suffer errors

5. Our contributions

 A novel 6-DoF pose hypothesis representation: Maximal Cliques (MAC)

A novel correspondence-based 3D registration method based on MAC

Surprisingly effective: 1) SOTA in registration recall and accuracy;
 2) Friendly to deep learned methods (MAC is a booster for learned ones)



Figure 2. **Pipeline of MAC**. **1.** Construct a graph for the initial correspondence set. **2.** Select a set of maximal cliques from the graph as the consistent sets. **3.** Generate and evaluate the hypotheses according to the consistent sets. **4.** Select the best hypothesis to perform 3D registration.

MAC is technically very simple, which performs hypothesis generation & verification (like RANSAC) in a graph space



Figure 2. **Pipeline of MAC**. **1.** Construct a graph for the initial correspondence set. **2.** Select a set of maximal cliques from the graph as the consistent sets. **3.** Generate and evaluate the hypotheses according to the consistent sets. **4.** Select the best hypothesis to perform 3D registration.

Step 1: Graph construction

- 1) Node: correspondences
- 2) Edge: compatible correspondences, measure with a compatibility metric

Motivation: The graph space can more accurately depict the affinity relationship between correspondences than the Euclidean space



Figure 2. **Pipeline of MAC**. **1.** Construct a graph for the initial correspondence set. **2.** Select a set of maximal cliques from the graph as the consistent sets. **3.** Generate and evaluate the hypotheses according to the consistent sets. **4.** Select the best hypothesis to perform 3D registration.

Step 2: Search maximal cliques

- 1) Quick search with a *igraph* C++ library
- 2) Node-guided selection: i) there are too many MACs in a graph (>10,000);
 ii) representative MACs are selected based on node-guided selection, i.e.,
 the 'best' MAC associated with a node is kept for that node



Figure 2. **Pipeline of MAC**. **1.** Construct a graph for the initial correspondence set. **2.** Select a set of maximal cliques from the graph as the consistent sets. **3.** Generate and evaluate the hypotheses according to the consistent sets. **4.** Select the best hypothesis to perform 3D registration.

Step 3: Hypotheses generation & evaluation

- 1) Hypotheses generation: Each MAC generates one hypothesis with SVD
- 2) Hypotheses evaluation: metrics in RASNAC, such as inlier count, MAE, MSE, are employed to find the best hypothesis

1. U3M dataset: an object-scale dataset





Figure 3. Registration performance of tested point cloud registration methods on U3M.

2. 3DMatch/3DLoMatch dataset: an indoor scene dataset

		FPFH			FCGF	
	RR(%)	RE(°)	TE(cm)	RR(%)	RE(°)	TE(cm)
i) Traditional						
SM [20]	55.88	2.94	8.15	86.57	2.29	7.07
FGR [45]	40.91	4.96	10.25	78.93	2.90	8.41
RANSAC-1M [13]	64.20	4.05	11.35	88.42	3.05	9.42
RANSAC-4M [13]	66.10	3.95	11.03	91.44	2.69	8.38
GC-RANSAC [5]	67.65	2.33	6.87	92.05	2.33	7.11
TEASER++ [36]	75.48	2.48	7.31	85.77	2.73	8.66
CG-SAC [30]	78.00	2.40	6.89	87.52	2.42	7.66
SC^2 -PCR [8]	<u>83.73</u>	<u>2.18</u>	6.70	<u>93.16</u>	<u>2.09</u>	<u>6.51</u>
ii) Deep learned						
3DRegNet [27]	26.31	3.75	9.60	77.76	2.74	8.13
DGR [9]	32.84	2.45	7.53	88.85	2.28	7.02
DHVR [19]	67.10	2.78	7.84	91.93	2.25	7.08
PointDSC [3]	72.95	<u>2.18</u>	<u>6.45</u>	91.87	2.10	6.54
MAC	84.10	1.96	6.18	93.72	1.89	6.03

Table 1. Registration results on 3DMatch dataset.

		FPFH			FCGF	
	RR(%)	RE(°)	TE(cm)	RR(%)	RE(°)	TE(cm)
i) Traditional						
RANSAC-1M [13]	0.67	10.27	15.06	9.77	7.01	14.87
RANSAC-4M [13]	0.45	10.39	20.03	10.44	6.91	15.14
TEASER++ [36]	35.15	4.38	10.96	46.76	4.12	12.89
SC^2 -PCR [8]	<u>38.57</u>	<u>4.03</u>	10.31	<u>58.73</u>	<u>3.80</u>	10.44
ii) Deep learned						
DGR [9]	19.88	5.07	13.53	43.80	4.17	10.82
PointDSC [3]	20.38	4.04	<u>10.25</u>	56.20	3.87	10.48
MAC	40.88	3.66	9.45	59.85	3.50	9.75

Table 2. Registration results on 3DLoMatch dataset.

2. 3DMatch/3DLoMatch dataset: MAC can boost deep –learned methods.

# Samplas		3DN	Iatch RI	R(%)			3DLo	Match R	R(%)	
# Samples	5000	2500	1000	500	250	5000	2500	1000	500	250
FCGF [10]	85.1	84.7	83.3	81.6	71.4	40.1	41.7	38.2	35.4	26.8
SpinNet [1]	88.6	86.6	85.5	83.5	70.2	59.8	54.9	48.3	39.8	26.8
Predator [18]	89.0	89.9	90.6	88.5	86.6	59.8	61.2	62.4	60.8	58.1
CoFiNet [43]	89.3	88.9	88.4	87.4	87.0	67.5	66.2	64.2	63.1	61.0
GeoTransformer [29]	92.0	91.8	91.8	91.4	91.2	75.0	74.8	74.2	74.1	73.5
ECCELMAC	91.3	92.2	91.6	90.4	85.6	57.2	56.0	52.6	42.4	32.1
I'COI'+MAC	6.2↑	$7.5\uparrow$	8.3↑	$8.8\uparrow$	$14.2\uparrow$	17.1↑	14.3↑	$14.4\uparrow$	$7.0\uparrow$	5.3↑
SpinNat MAC	95.3	95.1	93.3	91.4	81.2	72.8	69.9	59.2	54.8	32.1
Spinnet+WAC	6.7↑	$8.5\uparrow$	$7.8\uparrow$	7.9↑	$11.0\uparrow$	13.0↑	15.0↑	$10.9\uparrow$	15.0↑	5.3↑
Produce MAC	94.6	94.4	94.0	93.5	92.3	70.9	70.4	69.8	67.2	64.1
FIEdator+MAC	5.6	$4.5\uparrow$	$3.4\uparrow$	$5.0\uparrow$	$5.7\uparrow$	11.1↑	$9.2\uparrow$	7.4↑	6.4↑	$6.0\uparrow$
	94.1	94.4	94.5	93.8	92.7	71.6	71.5	70.6	69.2	68.1
Corniet+MAC	4.8↑	$5.5\uparrow$	$6.1\uparrow$	$6.4\uparrow$	$5.7\uparrow$	4.1↑	5.3↑	6.4↑	6.1↑	$7.1\uparrow$
Gao Transformar MAC	95.7	95.7	95.2	95.3	94.6	78.9	78.7	78.2	77.7	76.6
Geomansionner+MAC	3.7↑	3.9↑	$3.4\uparrow$	3.9↑	3.4↑	3.9↑	3.9↑	$4.0\uparrow$	3.6↑	3.1↑

Table 3. Performance boosting for deep-learned methods when combined with MAC.

3. KITTI dataset: an outdoor scene dataset

		FPFH			FCGF	
	RR(%)	RE(°)	TE(cm)	RR(%)	RE(°)	TE(cm)
i) Traditional						
FGR [45]	5.23	0.86	43.84	89.54	0.46	25.72
TEASER++ [36]	91.17	1.03	17.98	94.96	0.38	13.69
RANSAC [13]	74.41	1.55	30.20	80.36	0.73	26.79
CG-SAC [30]	74.23	0.73	14.02	83.24	0.56	22.96
SC^2 -PCR [8]	<u>99.28</u>	<u>0.39</u>	8.68	97.84	0.33	20.58
ii) Deep learned						
DGR [9]	77.12	1.64	33.10	96.90	<u>0.34</u>	21.70
PointDSC [3]	<u>98.92</u>	0.38	8.35	97.84	0.33	20.32
MAC	99.46	0.40	8.46	97.84	0.34	19.34

Table 4. Registration results on KITTI dataset.



7. Experiments-analysis exp.

1. The quality of MAC hypotheses

	3DN	/latch			3DLc	Match	
RANS	SAC	MA	мС	RAN	SAC	MA	AC
FCGF	FPFH	FCGF	FPFH	FCGF	FPFH	FCGF	FPFH
10.45	0.76	61.94	50.67	1.25	0.05	30.47	12.22
20.76	1.50	119.20	89.27	2.52	0.09	55.57	17.59
51.74	3.68	269.06	162.41	6.21	0.21	109.32	23.32
103.65	7.39	456.18	217.32	12.43	0.41	156.11	26.02
208.24	14.90	669.32	254.13	24.80	0.81	202.12	29.31
	RANS FCGF 10.45 20.76 51.74 103.65 208.24	3DNRANSACFCGFFPFH10.450.7620.761.5051.743.68103.657.39208.2414.90	3DMatch RANSAC MAA FCGF FPFH FCGF 10.45 0.76 61.94 20.76 1.50 119.20 51.74 3.68 269.06 103.65 7.39 456.18 208.24 14.90 669.32	3DWatch RANSAC MAC FCGF FPFH FCGF FPFH 10.45 0.76 61.94 50.67 20.76 1.50 119.20 89.27 51.74 3.68 269.06 162.41 103.65 7.39 456.18 217.32 208.24 14.90 669.32 254.13	3DMatch RANSAC MAC RAN FCGF FPFH FCGF FPFH FCGF 10.45 0.76 61.94 50.67 1.25 20.76 1.50 119.20 89.27 2.522 51.74 3.68 269.06 162.41 6.21 103.65 7.39 456.18 217.32 12.43 208.24 14.90 669.32 254.13 24.80	$\begin{array}{ c c c c c c c c c c c c c c c c c c c$	$\begin{array}{ c c c c c c c c c c c c c c c c c c c$

Table 6. Comparison of the number of correct hypotheses generated by MAC and RANSAC on 3DMatch and 3DLoMatch.

7. Experiments-analysis exp.

2. The upper bound of MAC

	3DMatch	3DLoMatch
	RR (%)	RR (%)
MAC-1	98.46	91.24
MAC-5	97.10	83.32
MAC-10	96.43	77.93
MAC-20	94.70	70.47
MAC-50	91.13	56.37
MAC-origin	93.72	59.85

Table 7. Registration recall on 3DMatch with FCGF setting based on judging MAC's hypotheses. MAC-n: a point cloud pair is considered alignable if at least n hypotheses are correct.

Comparison with current SOTA: <u>98.46%/91.24%</u> vs ~94%/58%

7. Experiments-analysis exp.

3. Efficiency analysis

# Corr.	250	500	1000	2500	5000
PointDSC	32.24 ± 0.81	$78.38 {\pm} 0.89$	240.46 ± 2.18	1401.97 ± 12.24	5504.11±10.32
TEASER++	$6.40{\pm}1.88$	$6.68{\pm}0.66$	$16.74{\pm}1.21$	$104.24 {\pm} 0.53$	$484.93 {\pm} 1.87$
SC^2 -PCR	19.34 ± 0.63	63.23 ± 0.55	215.98 ± 1.24	1282.73 ± 4.05	5210.17 ± 8.30
MAC	$7.32{\pm}0.55$	$23.32{\pm}0.38$	56.45 ± 1.41	282.67±7.83	3259.38±12.66

Table 4. Comparisons on average time consumption (ms).

# Corr.	250	500	1000	2500	5000
PointDSC	3531.46	3538.26	3582.57	3634.22	3736.10
TEASER++	1631.92	1634.77	2029.22	2266.84	2484.83
SC^2 -PCR	448.01	453.18	508.40	621.27	690.22
MAC	15.59	17.43	23.49	52.79	150.86

Table 5. Comparisons on average memory consumption (MB).

8. Conclusion

1. MAC's advantages

Simple

- Technically simple
- A few parameters
- Learning-free

Effective

- SOTA performance
- Light-weight
- Robust to outliers

General

- Cross-dataset 1st
- Booster for learning
- Various scenarios

8. Conclusion

- 2. MAC's limitations & future work
- MAC can generate high-quality hypotheses, but may still fail to find them
- A better hypothesis evaluation metric is desired

	3DMatch	3DLoMatch
	RR(%)	RR(%)
MAC-1	98.46	91.24
MAC-5	97.10	83.32
MAC-10	96.43	77.93
MAC-20	94.70	70.47
MAC-50	91.13	56.37
MAC-origin	93.72	59.85

Table 7. Registration recall on 3DMatch with FCGF setting based on judging MAC's hypotheses. MAC-n: a point cloud pair is considered alignable if at least n hypotheses are correct.

Final Remark

Handcrafted methods can be great again.

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Github: https://github.com/zhangxy0517/3D-Registration-with-Maximal-Cliques **Contact**: 2426988253@mail.nwpu.edu.cn; jqyang@nwpu.edu.cn