Robust Multi-Model Fitting Using Density and Preference Analysis

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Motivation

- The number of structures in data is not known a priori. Scale of noise is also unknown and changes across multiple structures.

- Density is an important cue for distinguishing between inliers and outliers of a particular structure.

- Previously proposed preference based methods solely rely on residual based rank ordering.

Contributions

- Combine consensus and preference paradigms.

- Define *residual density* to leverage consensus maximization.

- Compute residual density based point preferences for model hypothesis selection and inlier scale estimation.

- Devise a greedy model selection algorithm and point-model assignment based on residual density drop.

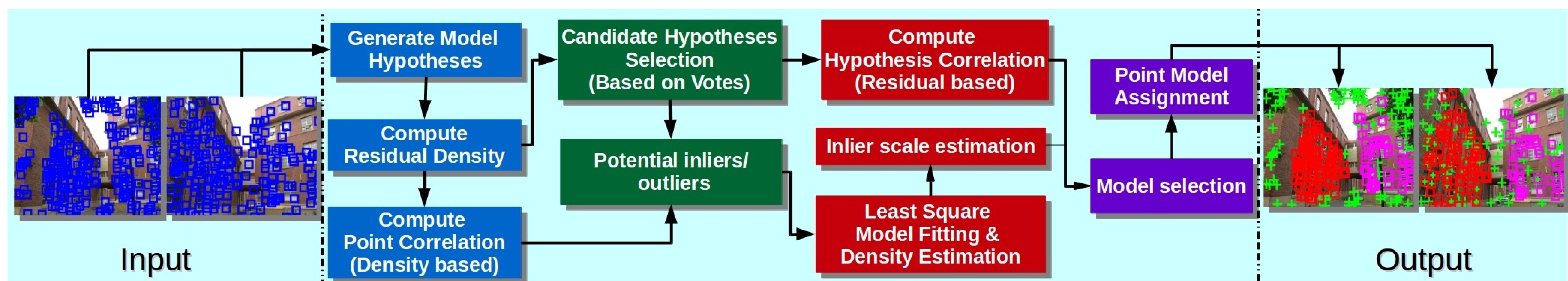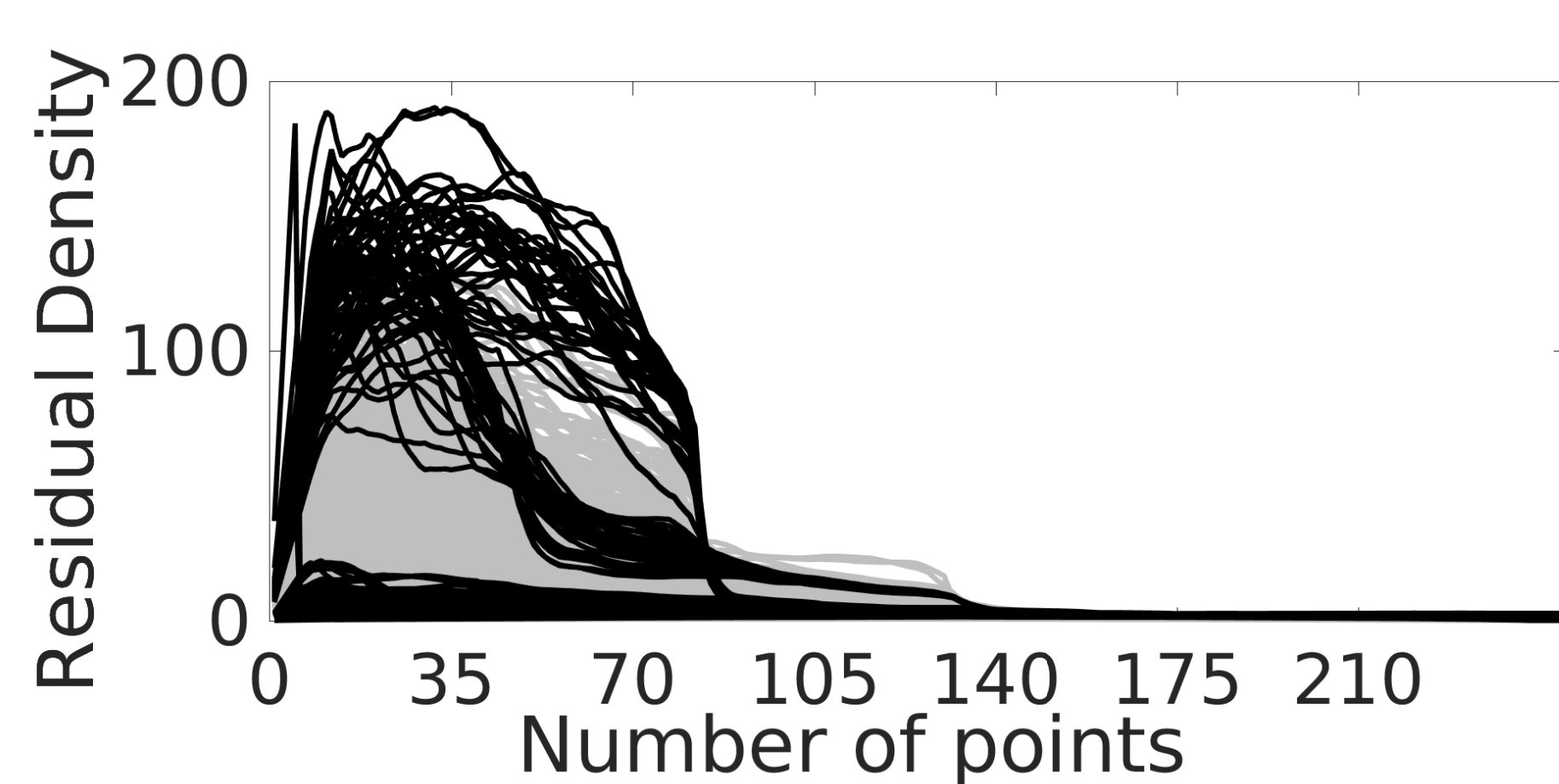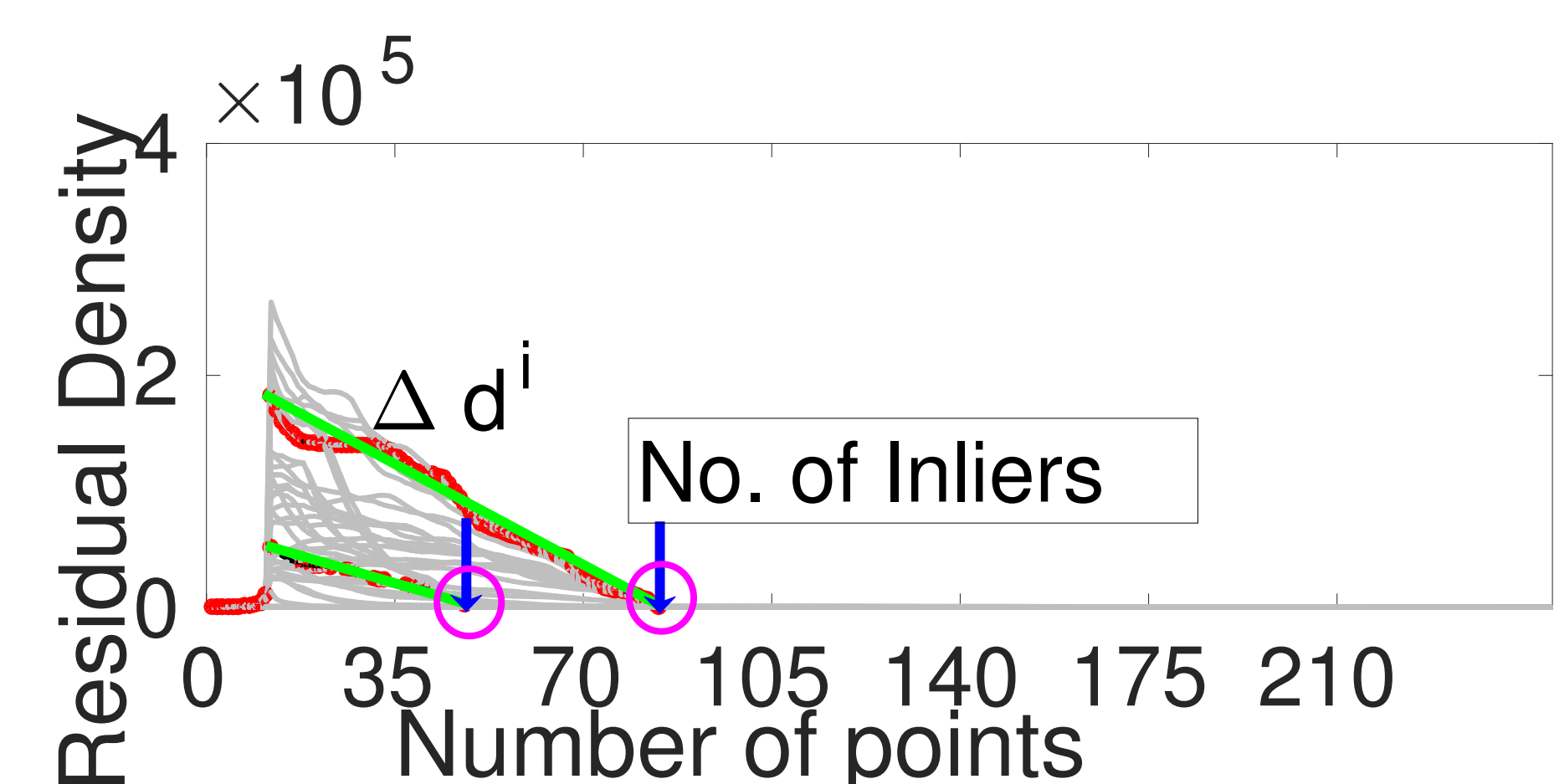## Density Preference Analysis (DPA)

Figure 1: Density Preference Analysis (Block Diagram)

(a) Candidate Hypotheses

(b) Potential Inliers/Outliers

(c) Inlier Scale Estimation

Figure 2: Intermediate Steps

Results- Qualitative

| Ground truth | RPA[3] | T-Link[2] | RCMSA[4] | DPA |

(a) (b) CA=58.79 (c) CA=40.86 (d) CA=16.02 (e) CA=86.20

(f) (g) CA=76.28 (h) CA=83.67 (i) CA=82.33 (j) CA=97.67

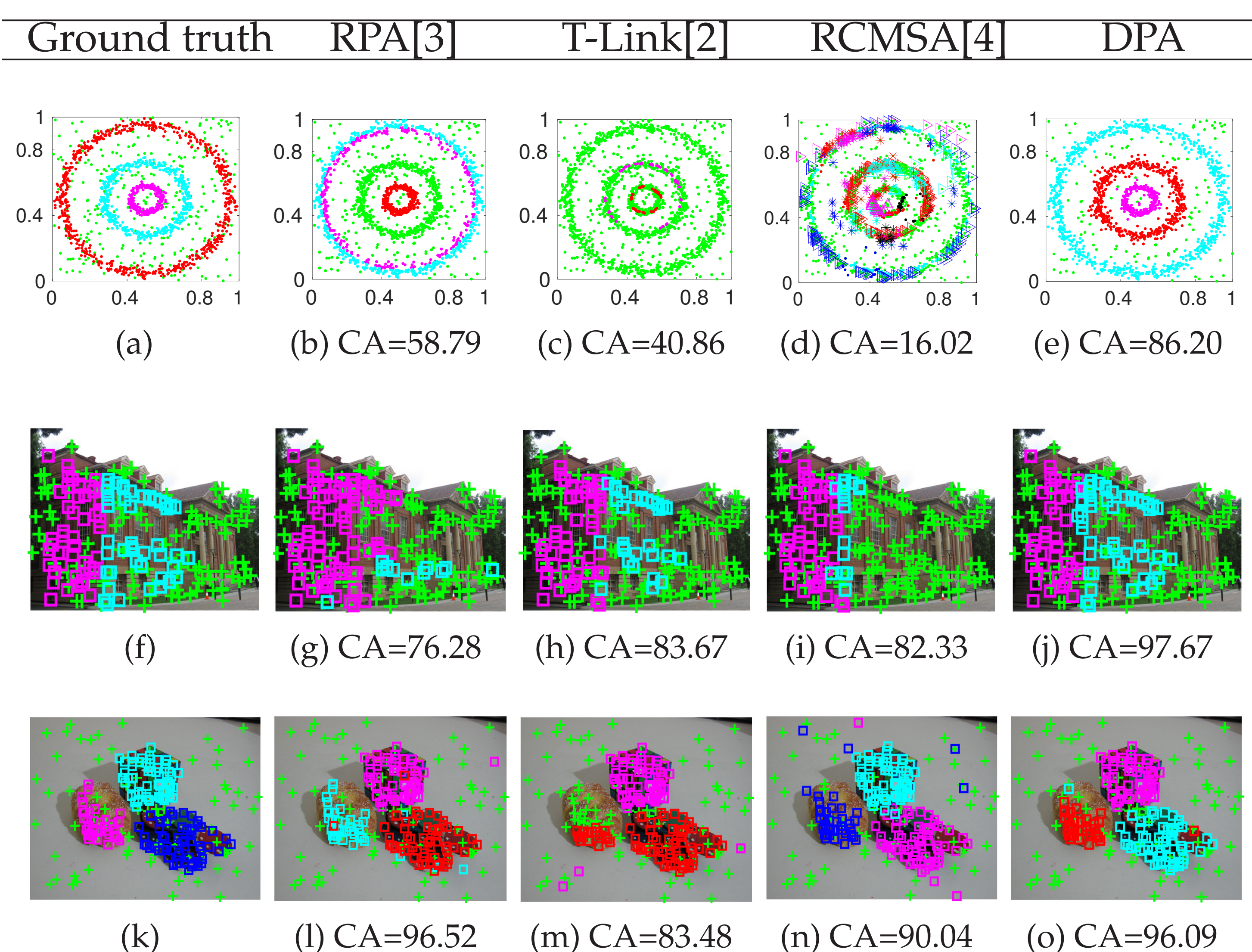(k) (l) CA=96.52 (m) CA=83.48 (n) CA=90.04 (o) CA=96.09

Figure 3: **Row-1** Three Concentric Circles, **Row-2** Planar Segmentation (*library*), **Row-3** Motion Segmentation (*breadcubechips*). CA= Classification Accuracy(%). Point membership is color coded. Outliers in green.

Results- Quantitative

Table 1: AdelaideRMF[1] Dataset. Classification Accuracy (%) and T-Time Taken (sec)

		RPA	T	T-Link	T	RCMSA	T	DPA	T
Planar Segmentation	mean	80.50	967.23	68.99	492.48	78.55	5.31	90.90	37.68
	std	13.51	2174.70	9.92	1347.1	9.54	4.14	8.10	39.19
	median	79.16	247.19	70.72	81.33	77.38	3.39	95.21	30.06
Motion Segmentation	mean	94.47	39.25	81.65	12.81	84.99	4.62	90.64	50.34
	std	3.55	13.21	11.36	5.44	6.16	2.20	4.86	34.03
	median	95.95	38.75	82.57	11.69	83.71	3.83	90.95	46.78

Conclusions

- We show that combing density information with preference analysis improves the multi-model fitting process.

- DPA can handle structures with different scales efficiently.

References

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