

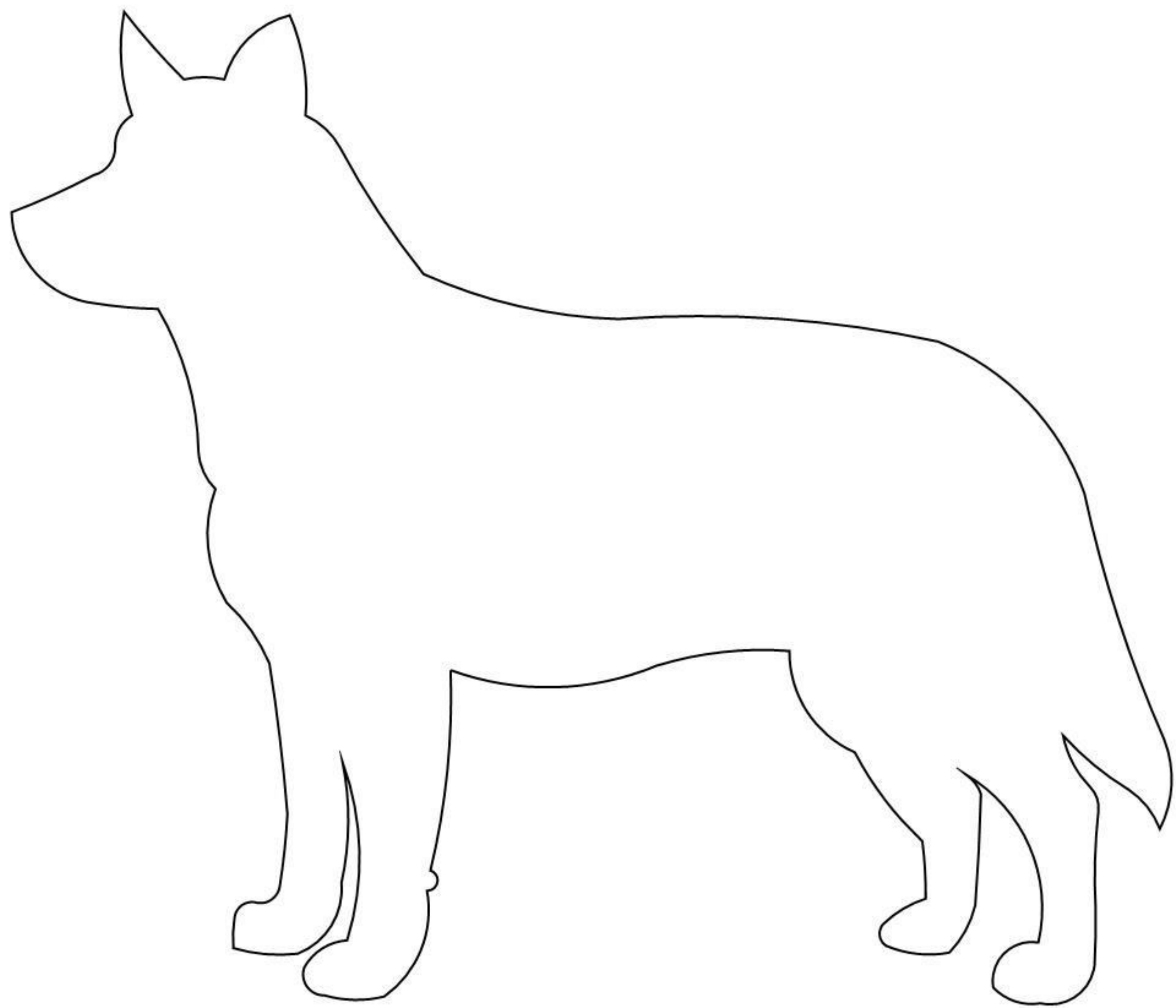
Fast Global Registration

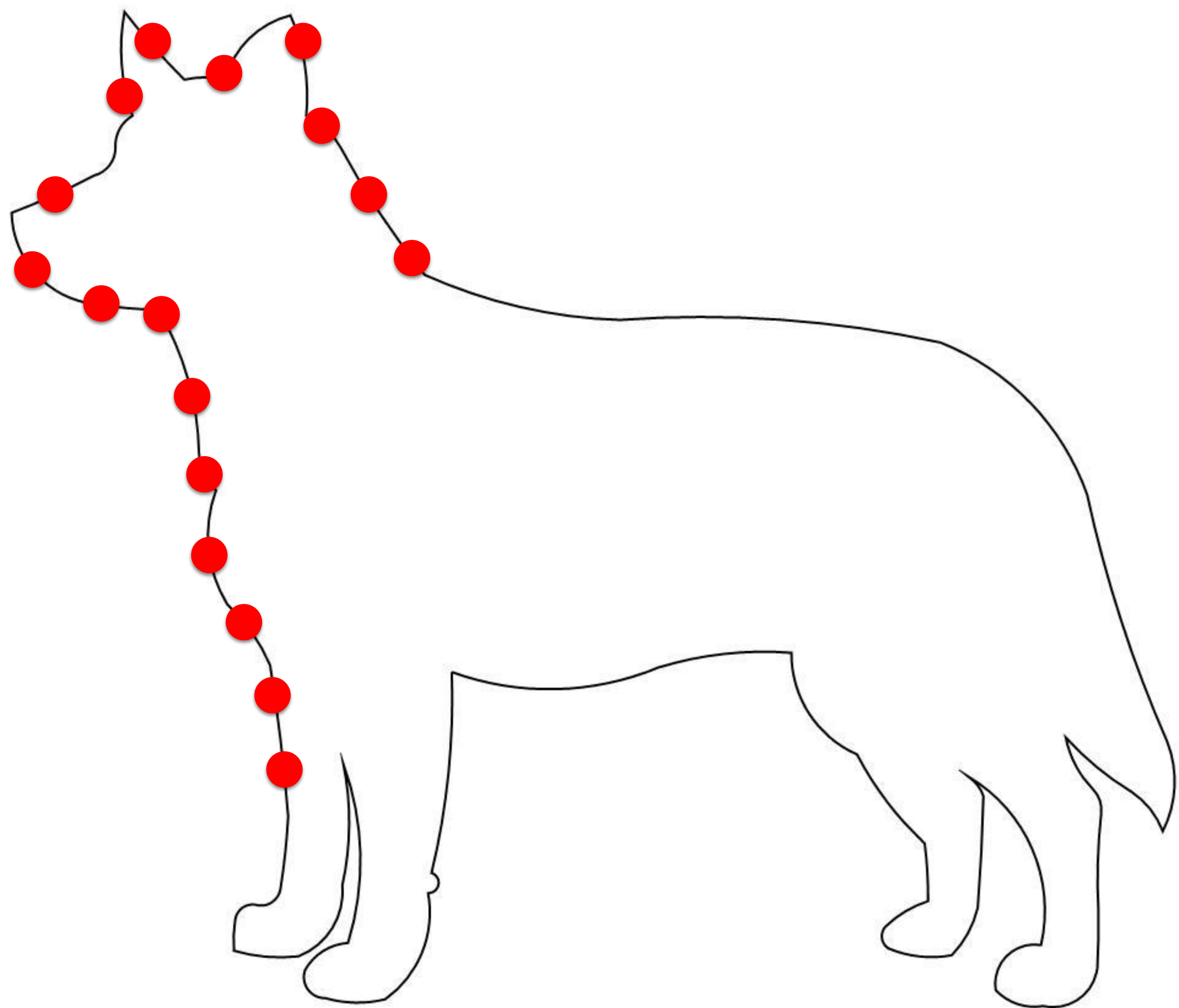
Qian-Yi Zhou

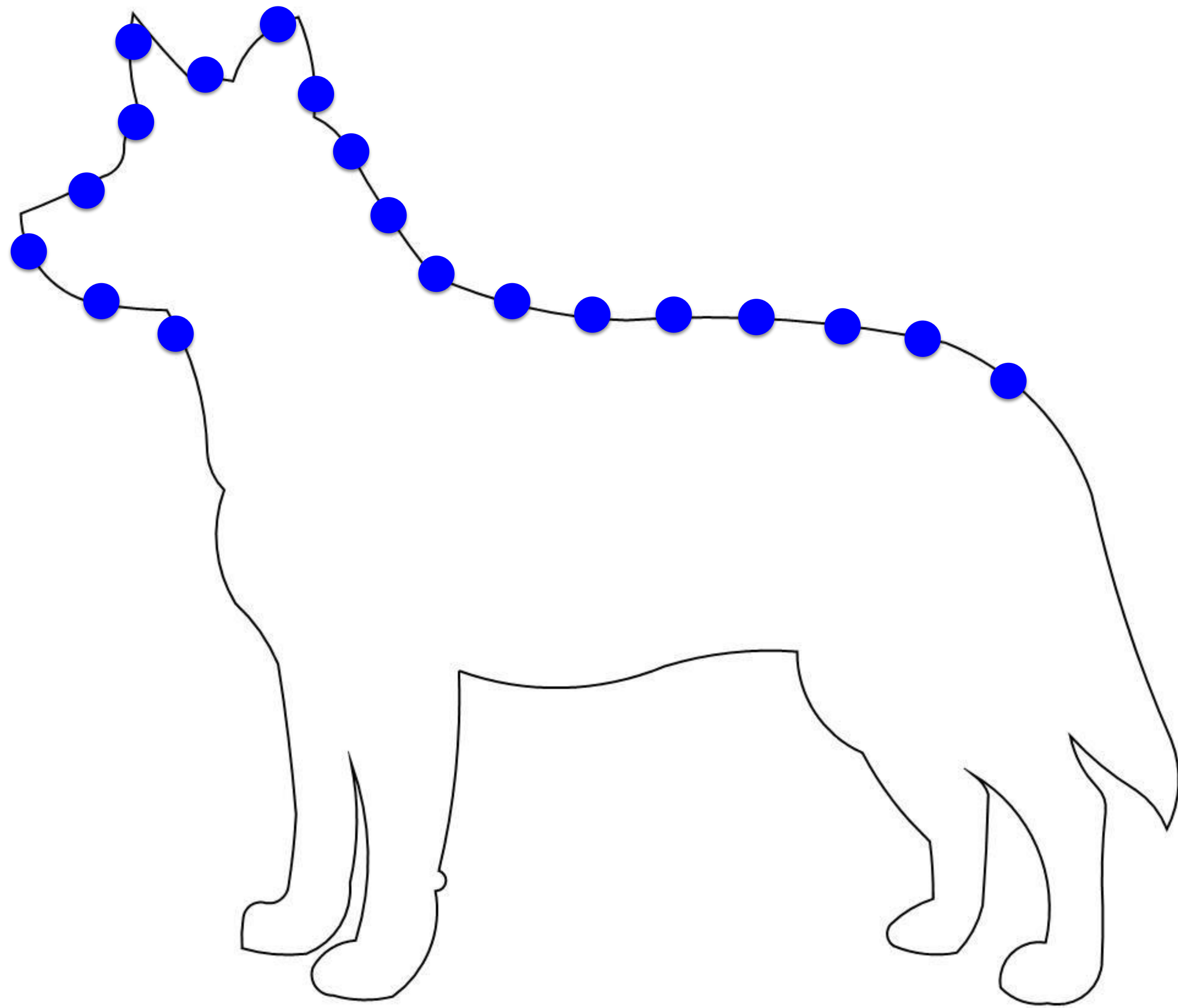
Jaesik Park

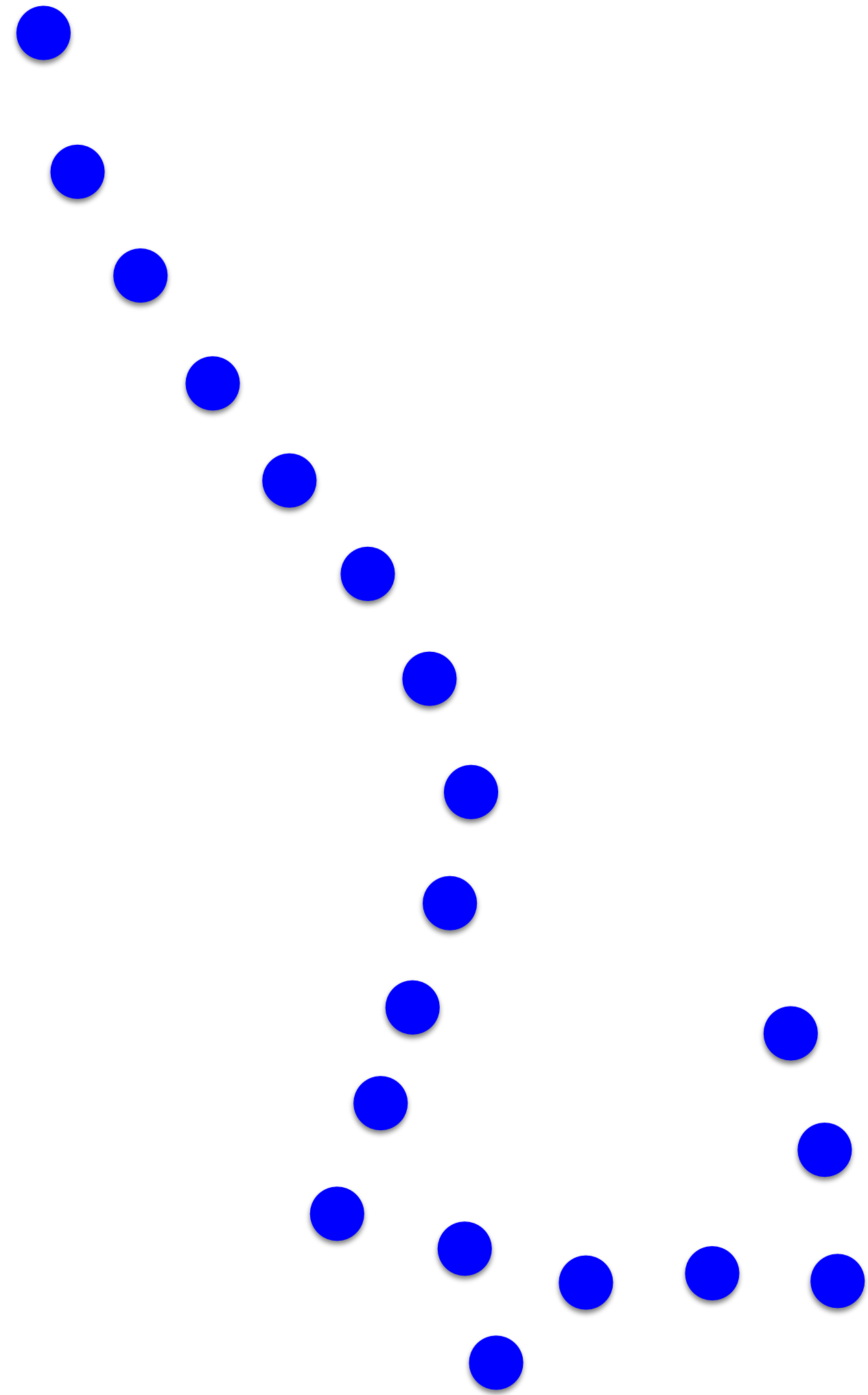
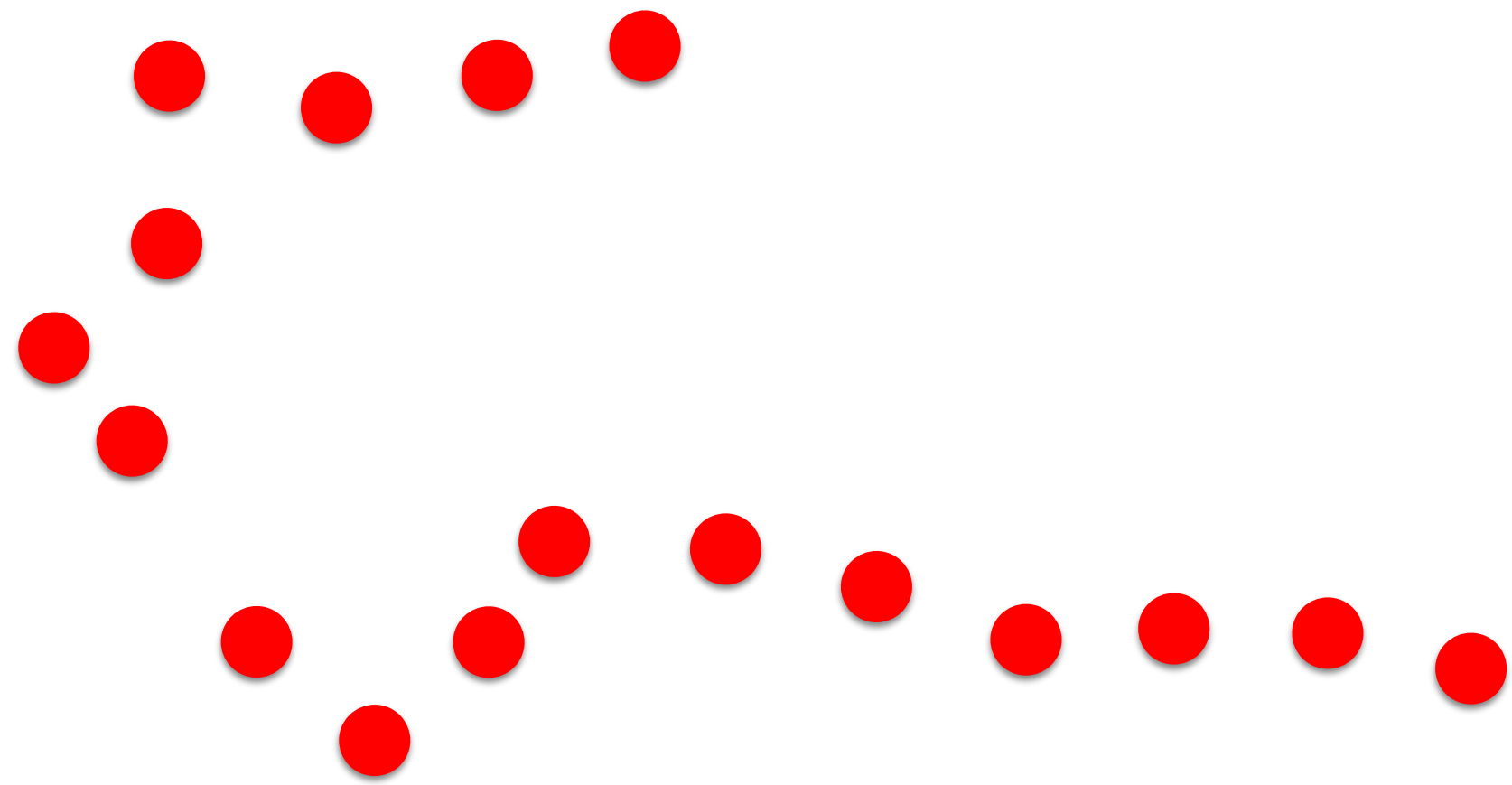
Vladlen Koltun

Intel Labs

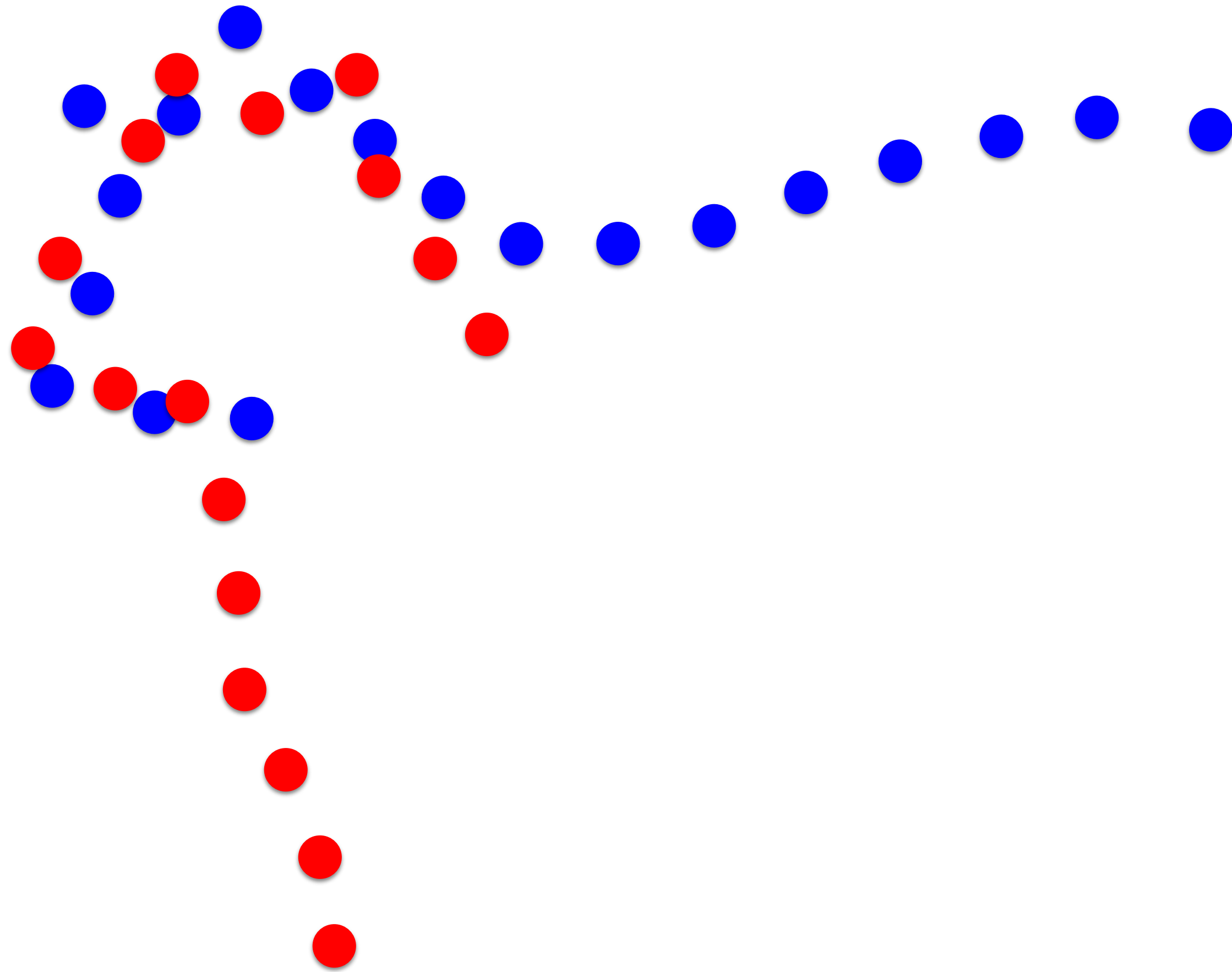




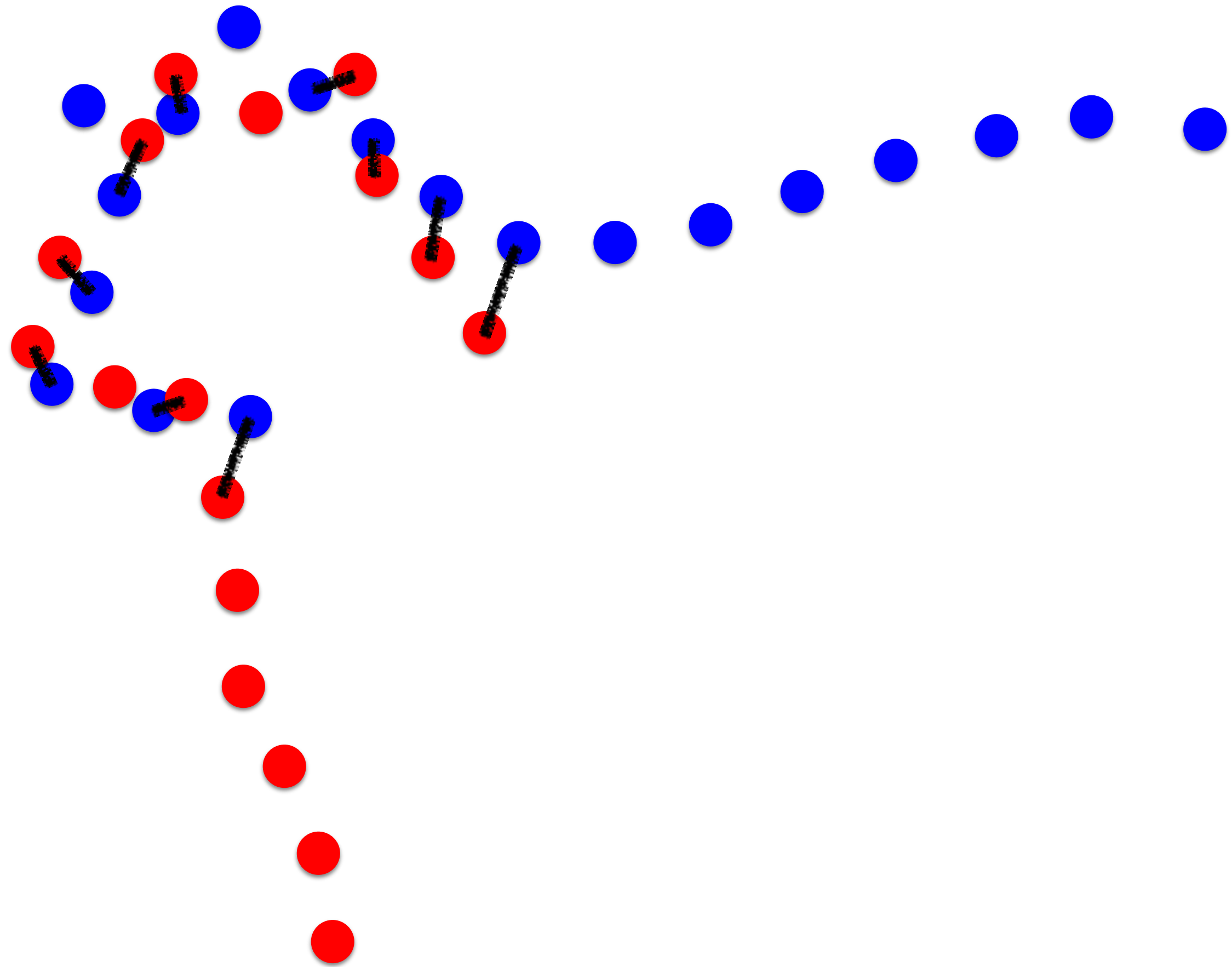




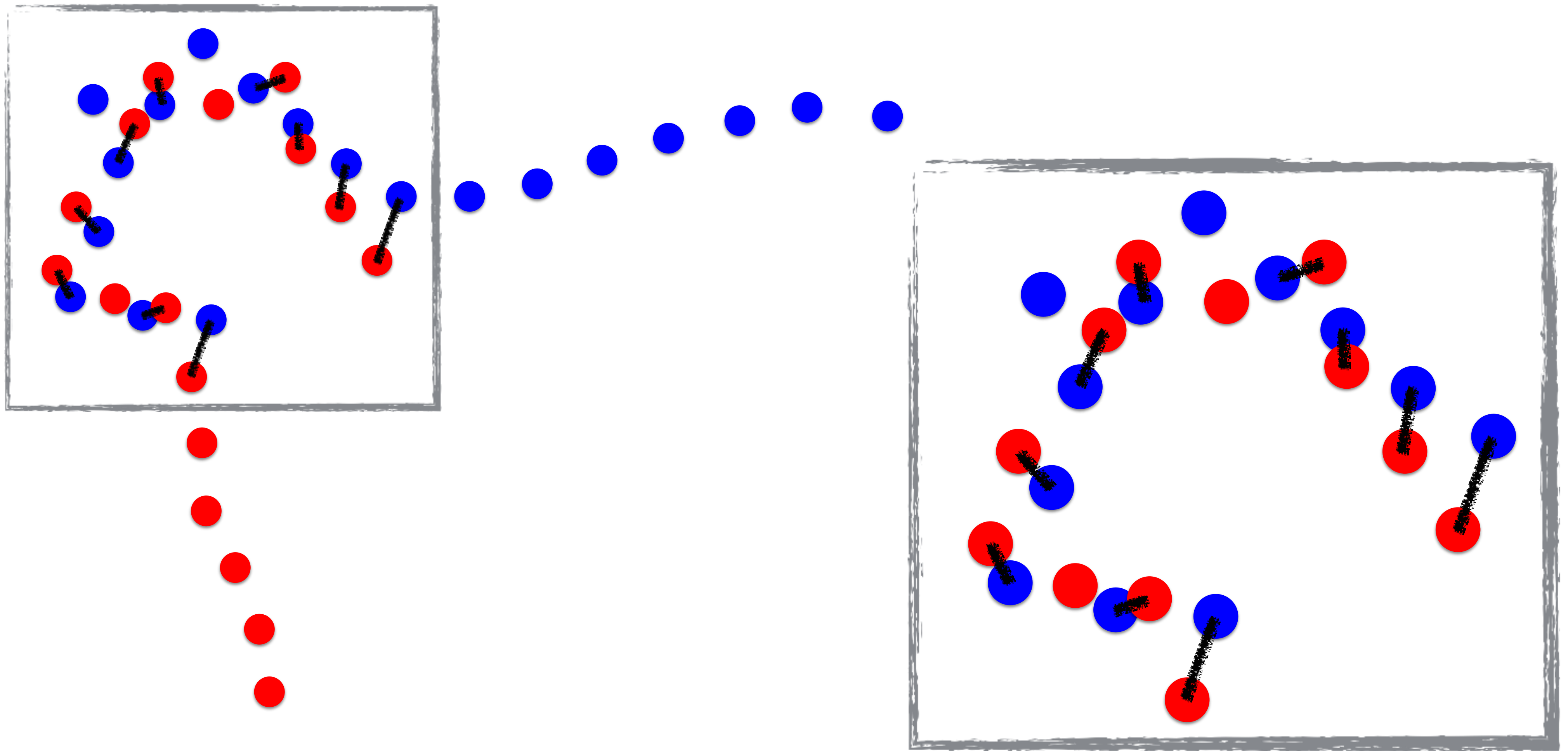
Iterative Closest Points



Iterative Closest Points

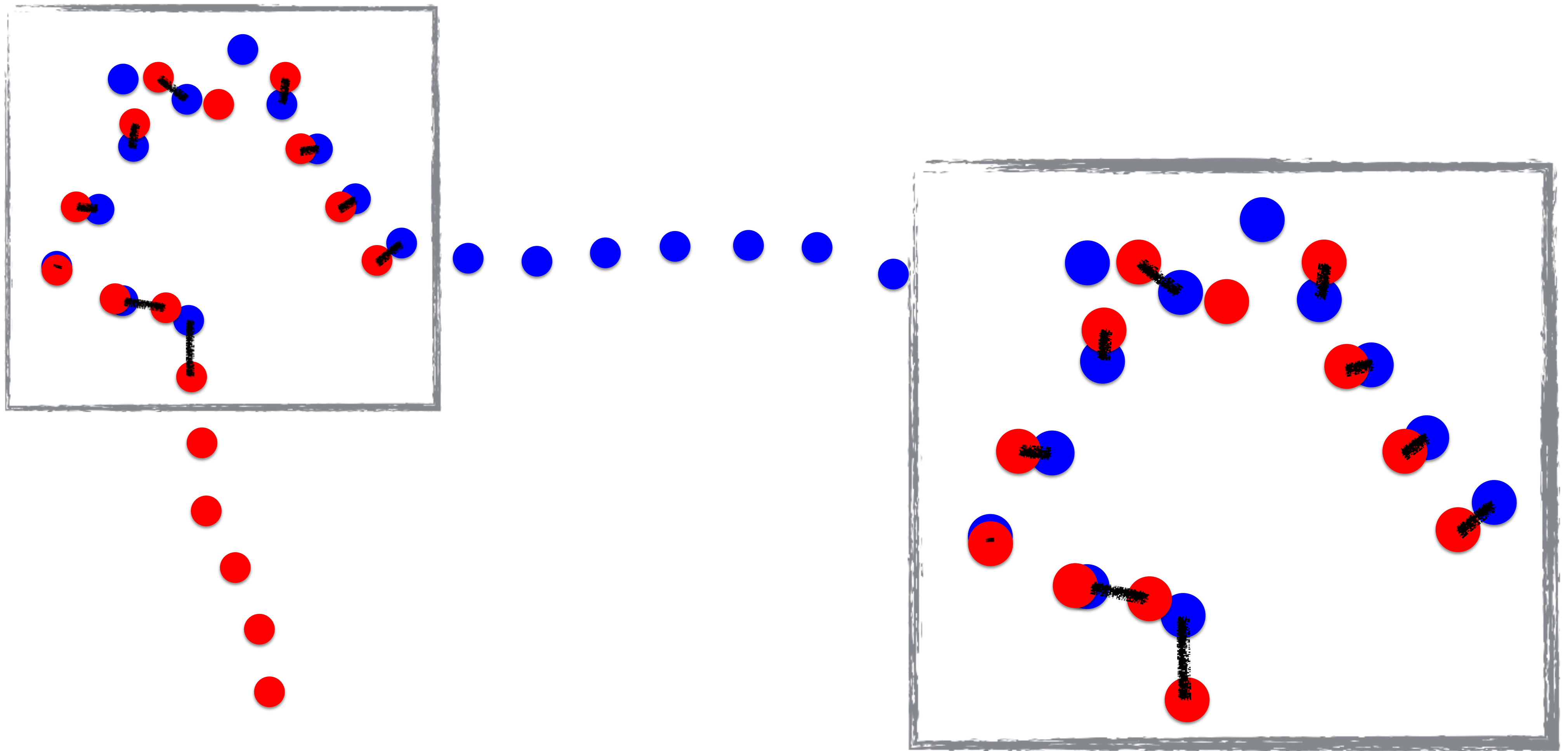


Iterative Closest Points



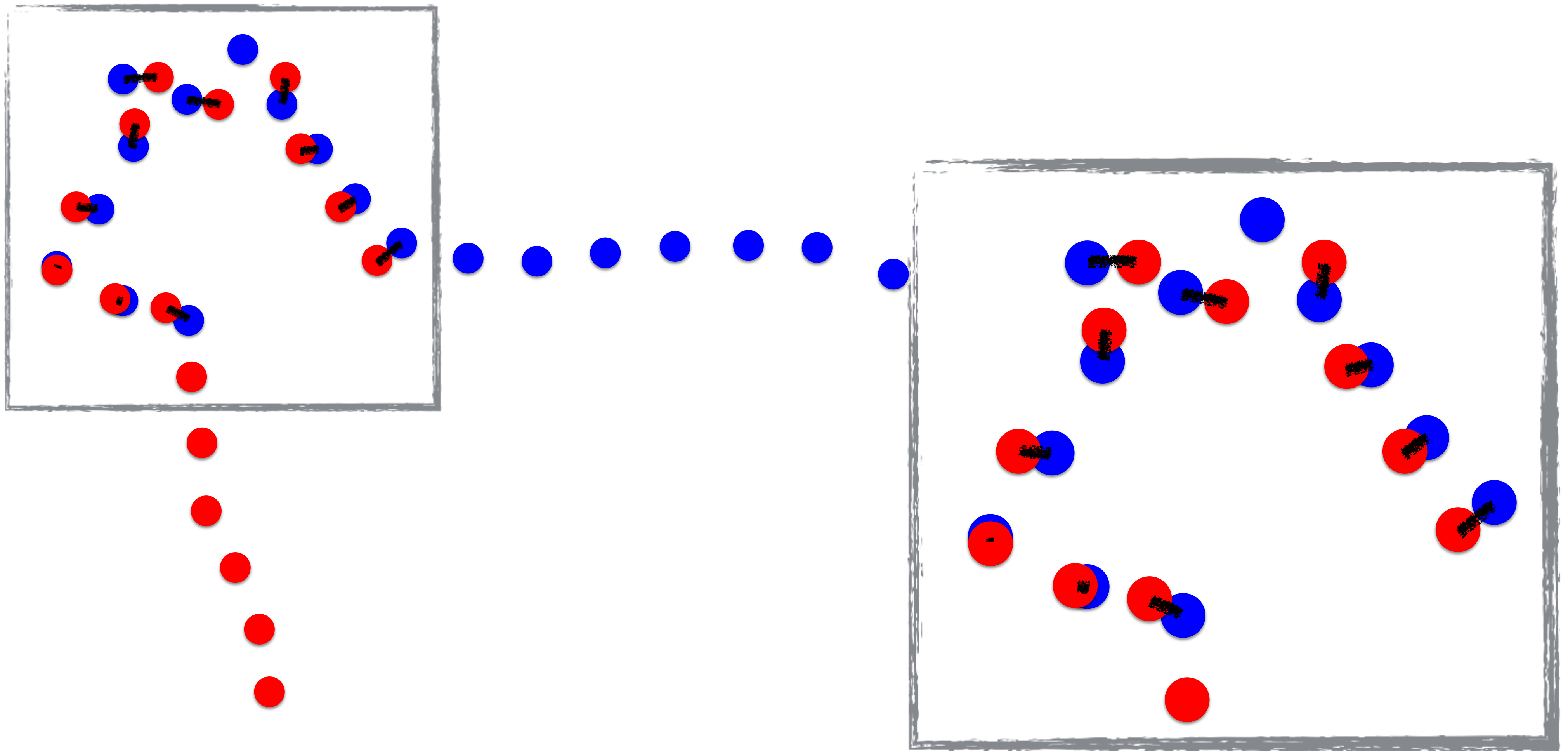
$$E(\mathbf{T}) = \sum_{(\mathbf{p}, \mathbf{q}) \in \mathcal{K}} \|\mathbf{p} - \mathbf{T}\mathbf{q}\|^2$$

Iterative Closest Points



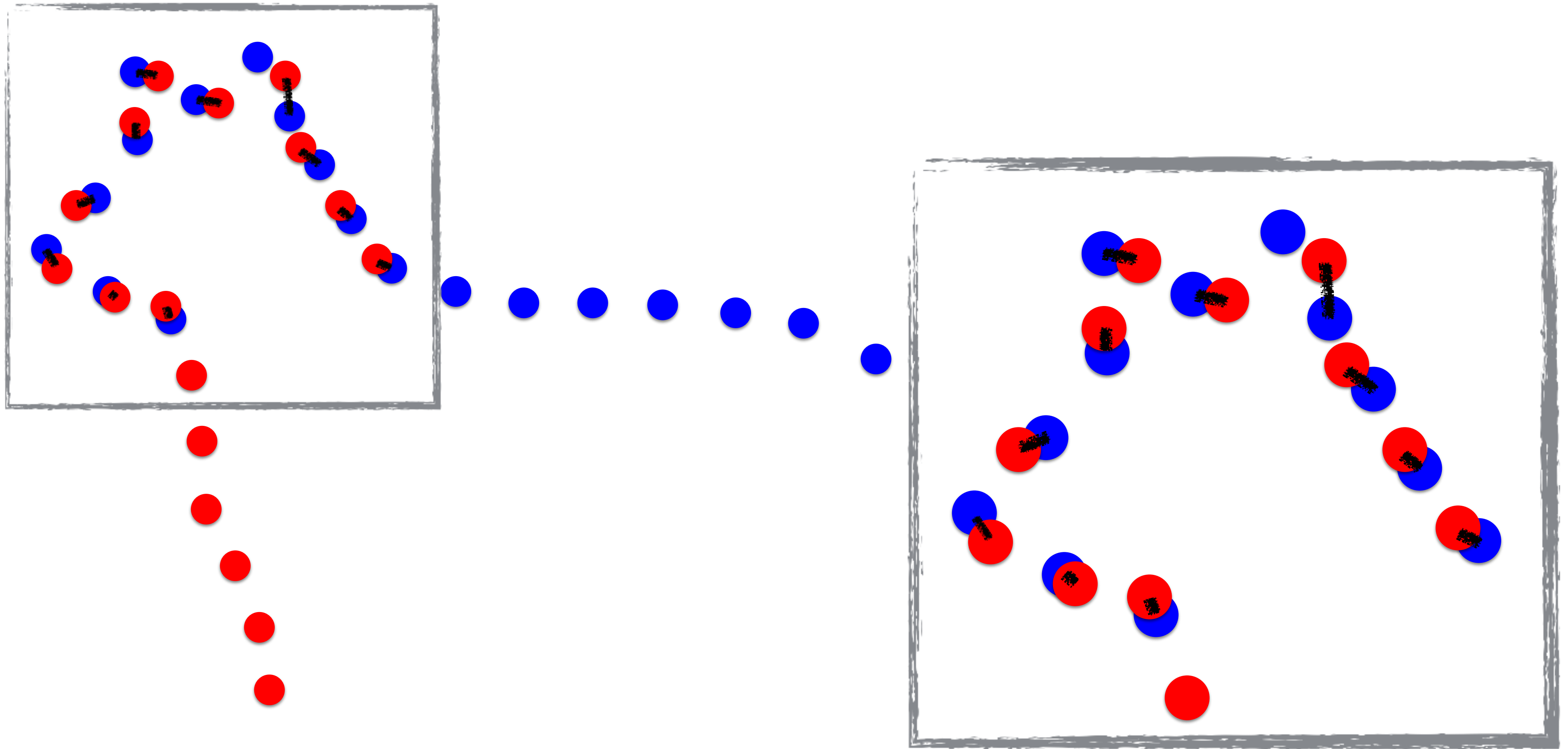
$$E(\mathbf{T}) = \sum_{(\mathbf{p}, \mathbf{q}) \in \mathcal{K}} \|\mathbf{p} - \mathbf{T}\mathbf{q}\|^2$$

Iterative Closest Points



$$E(\mathbf{T}) = \sum_{(\mathbf{p}, \mathbf{q}) \in \mathcal{K}} \|\mathbf{p} - \mathbf{T}\mathbf{q}\|^2$$

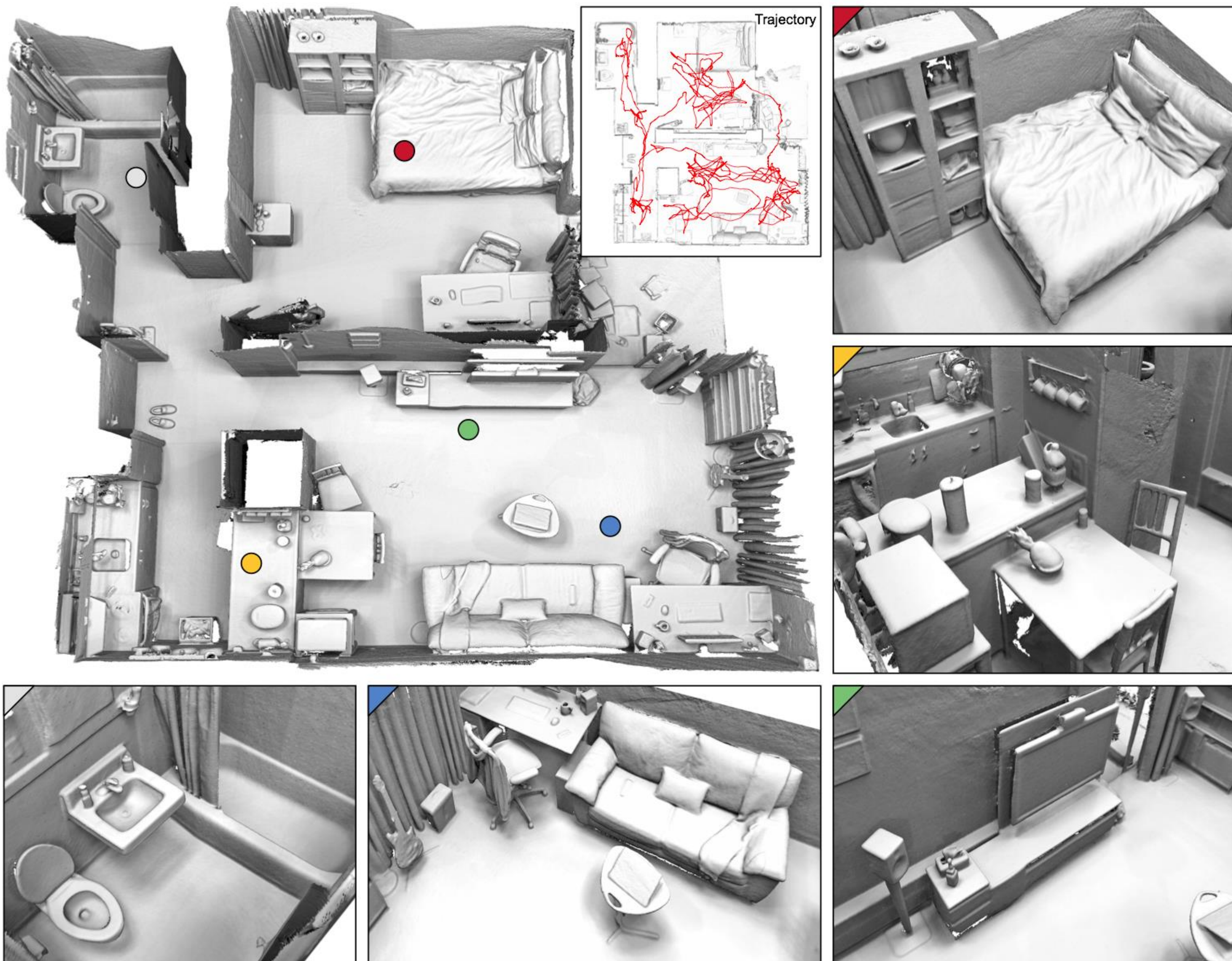
Iterative Closest Points



$$E(\mathbf{T}) = \sum_{(\mathbf{p}, \mathbf{q}) \in \mathcal{K}} \|\mathbf{p} - \mathbf{T}\mathbf{q}\|^2$$

Global Registration

- Stage 1: Coarse alignment
 - RANSAC or another sampling scheme
- Stage 2: Local refinement
 - ICP

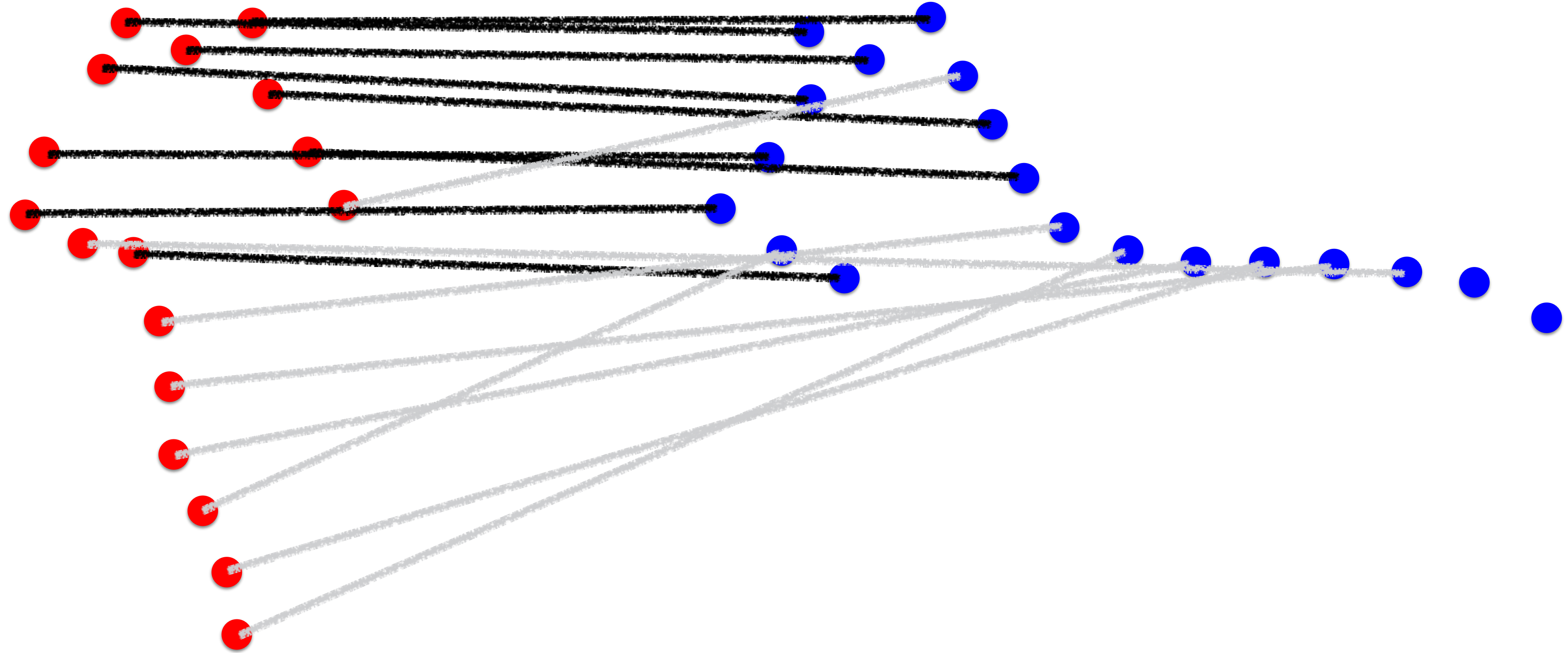


Choi, Zhou, K., CVPR 2015

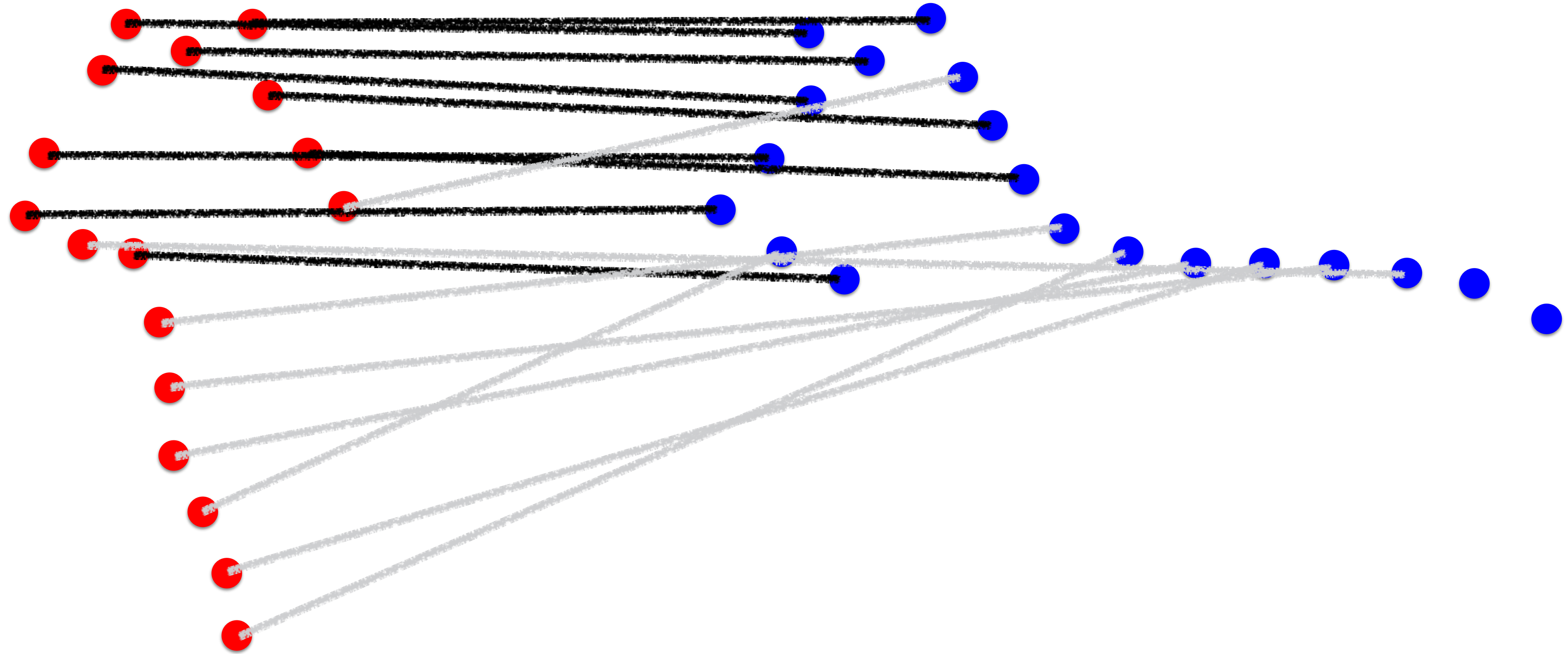
Issues

- Expensive: nearest-neighbor queries in the inner loop
- Inelegant: two stages instead of direct alignment

Fast Global Registration



Fast Global Registration

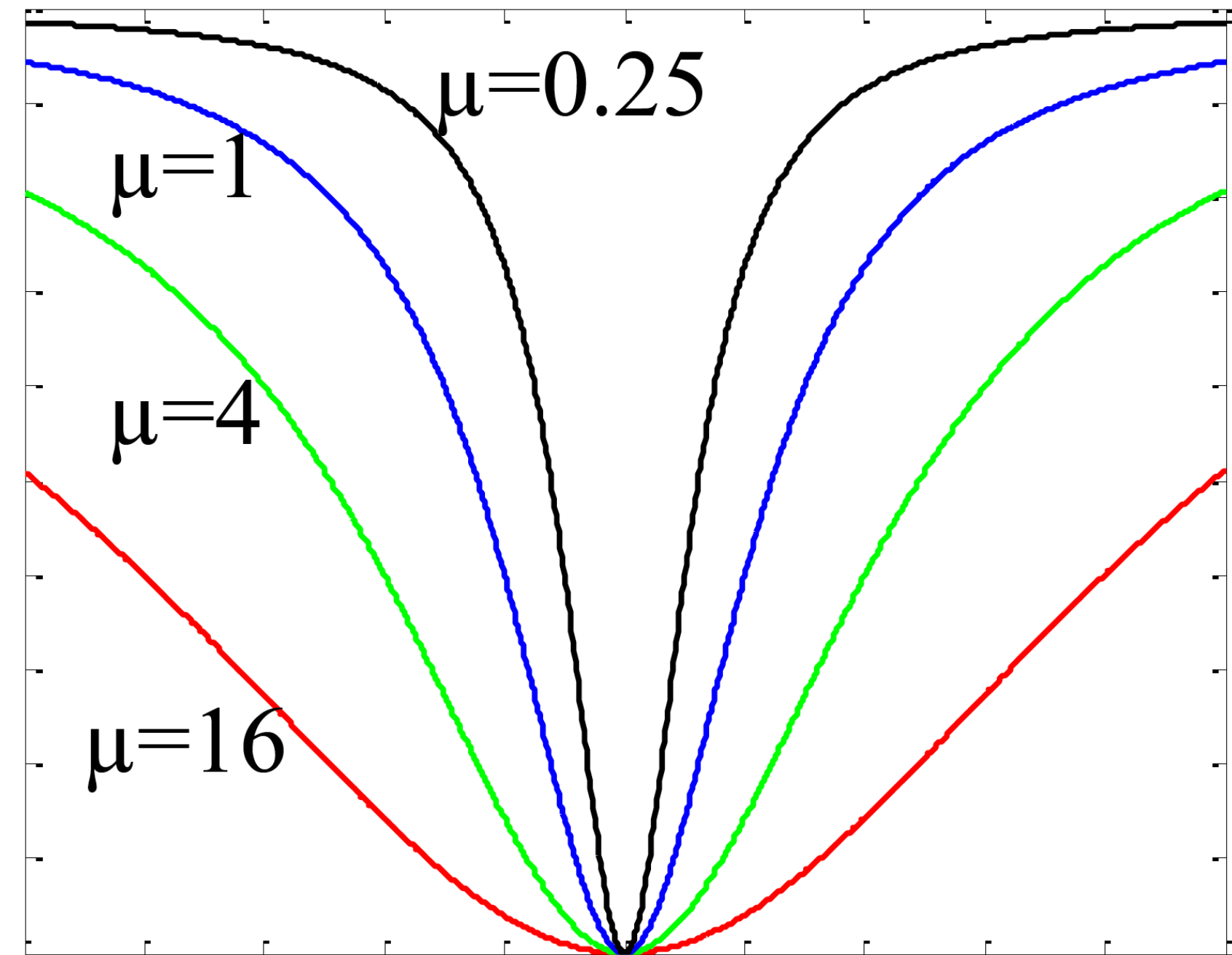


$$E(\mathbf{T}) = \sum_{(\mathbf{p}, \mathbf{q}) \in \mathcal{K}} \rho(\|\mathbf{p} - \mathbf{T}\mathbf{q}\|)$$

Objective

$$E(\mathbf{T}) = \sum_{(\mathbf{p}, \mathbf{q}) \in \mathcal{K}} \rho(\|\mathbf{p} - \mathbf{T}\mathbf{q}\|)$$

$$\rho(x) = \frac{x^2}{\mu + x^2}$$



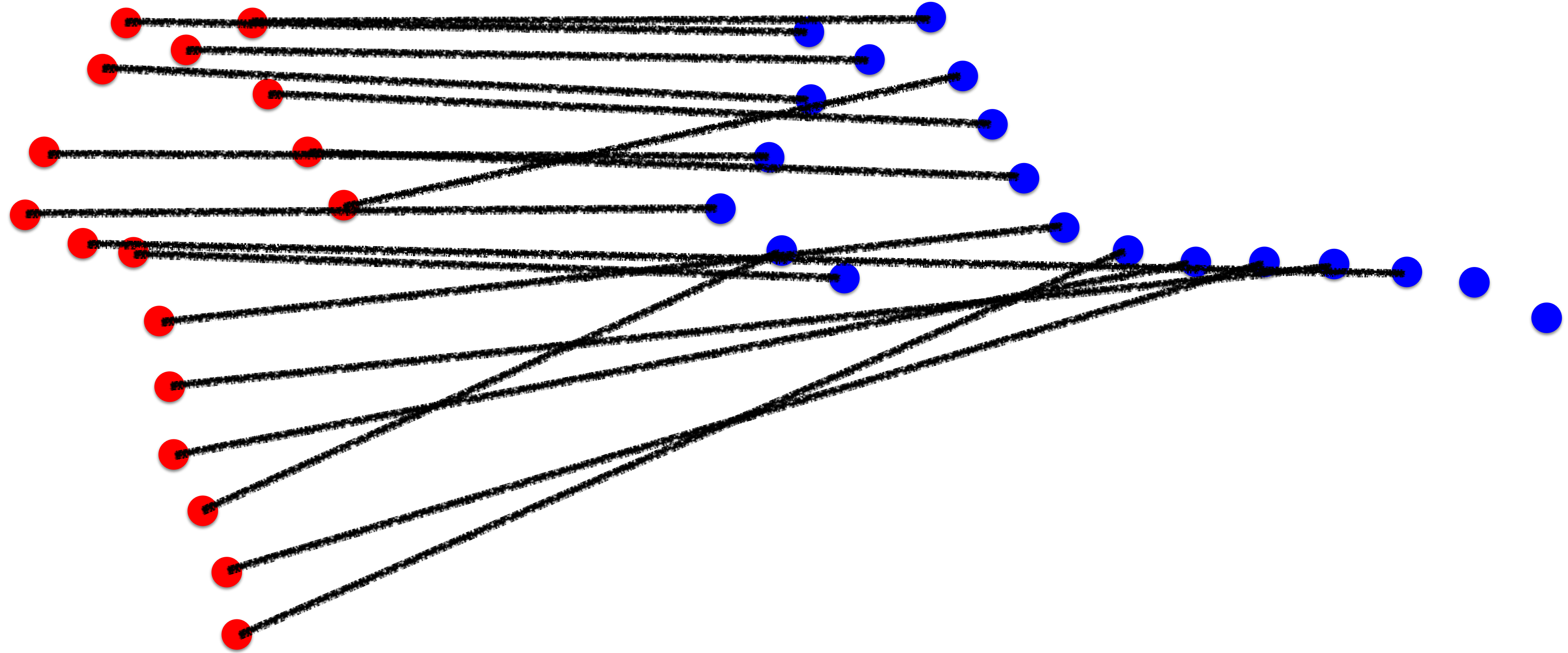
Optimization

$$E(\mathbf{T}) = \sum_{(\mathbf{p}, \mathbf{q}) \in \mathcal{K}} \rho(\|\mathbf{p} - \mathbf{T}\mathbf{q}\|)$$

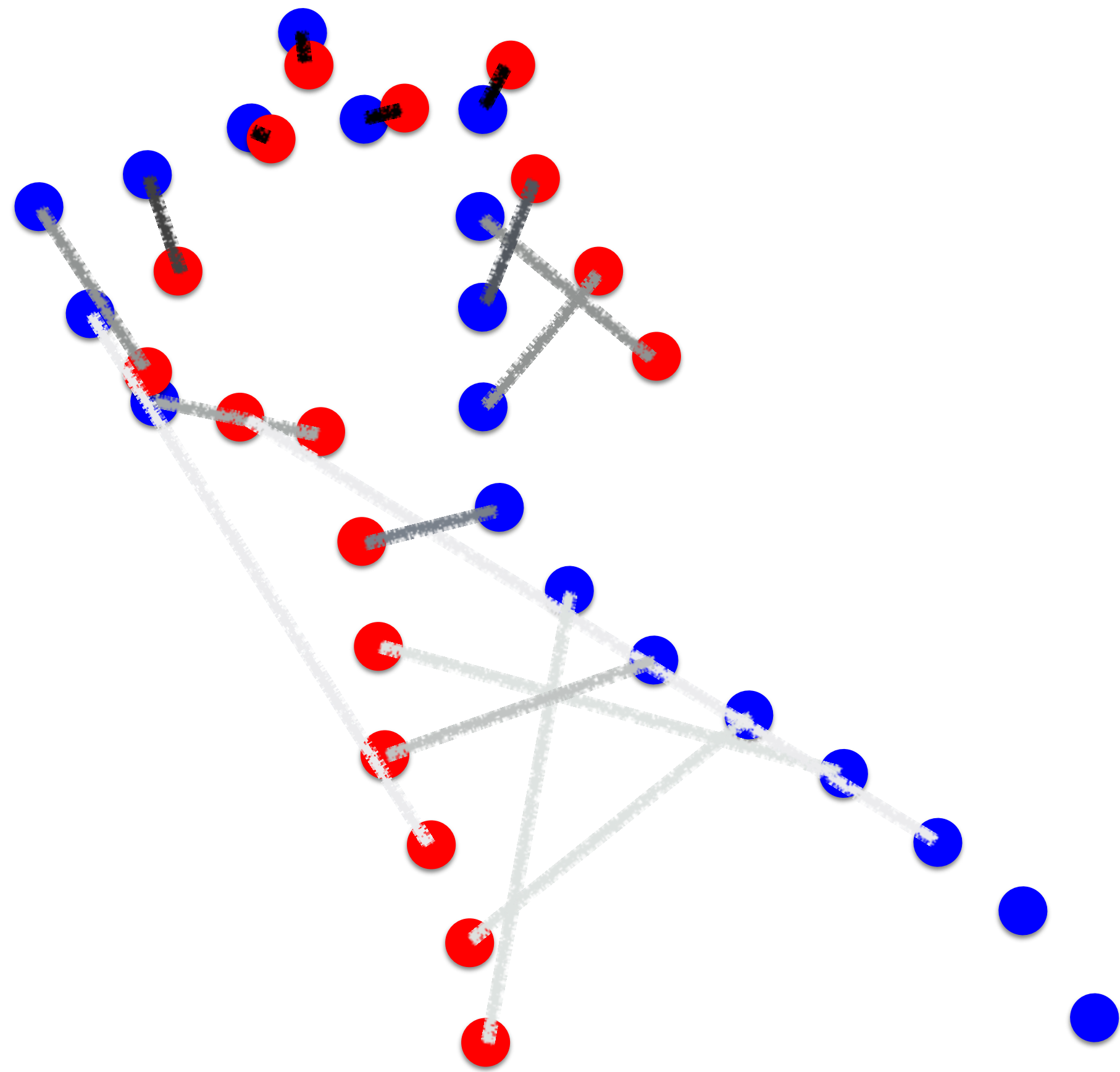
$$E(\mathbf{T}, \mathbb{L}) = \sum_{(\mathbf{p}, \mathbf{q}) \in \mathcal{K}} l_{\mathbf{p}, \mathbf{q}} \|\mathbf{p} - \mathbf{T}\mathbf{q}\|^2 + \sum_{(\mathbf{p}, \mathbf{q}) \in \mathcal{K}} \Psi(l_{\mathbf{p}, \mathbf{q}})$$

$$\Psi(l_{\mathbf{p}, \mathbf{q}}) = \mu(\sqrt{l_{\mathbf{p}, \mathbf{q}}} - 1)^2$$

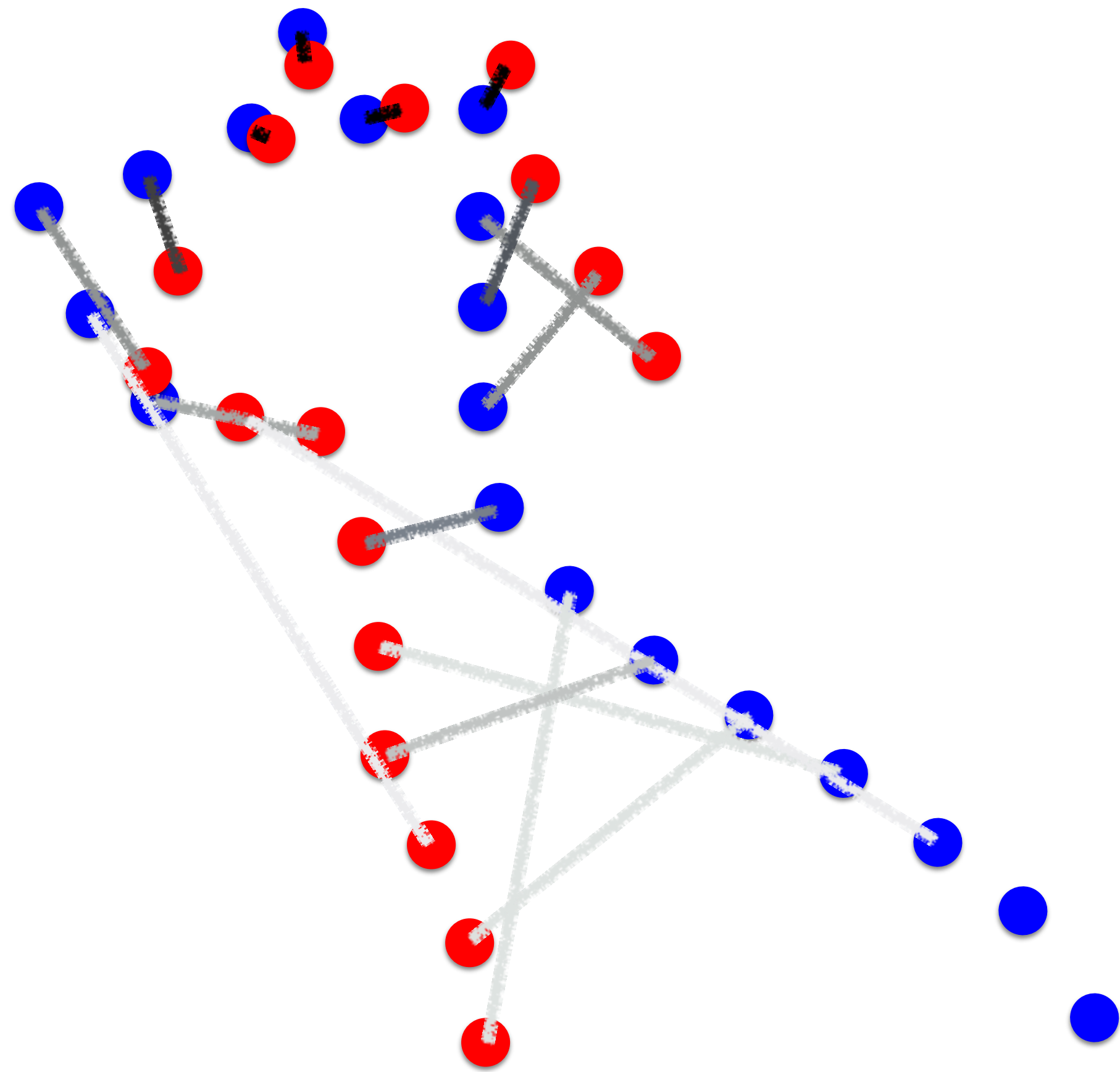
Fast Global Registration



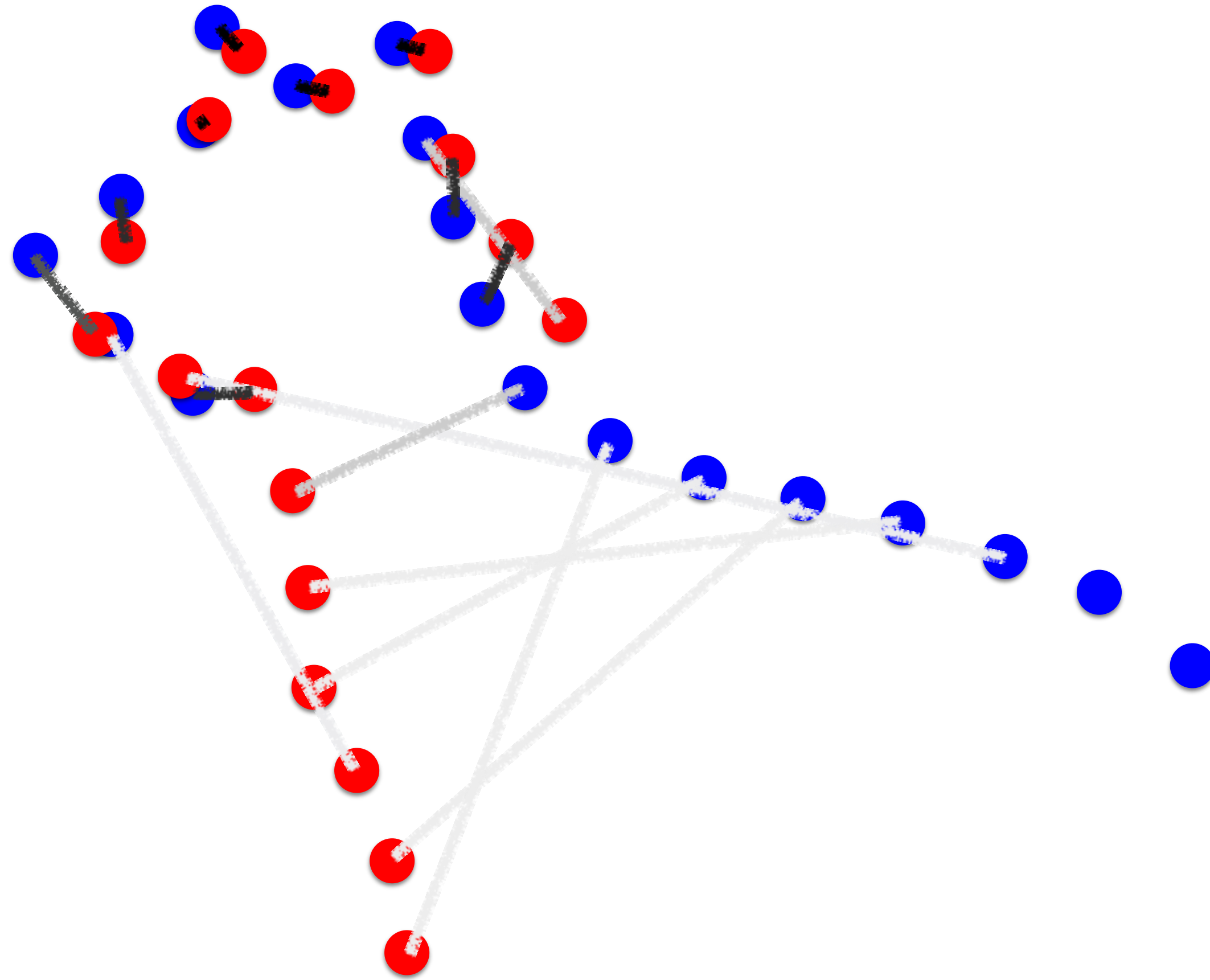
Fast Global Registration



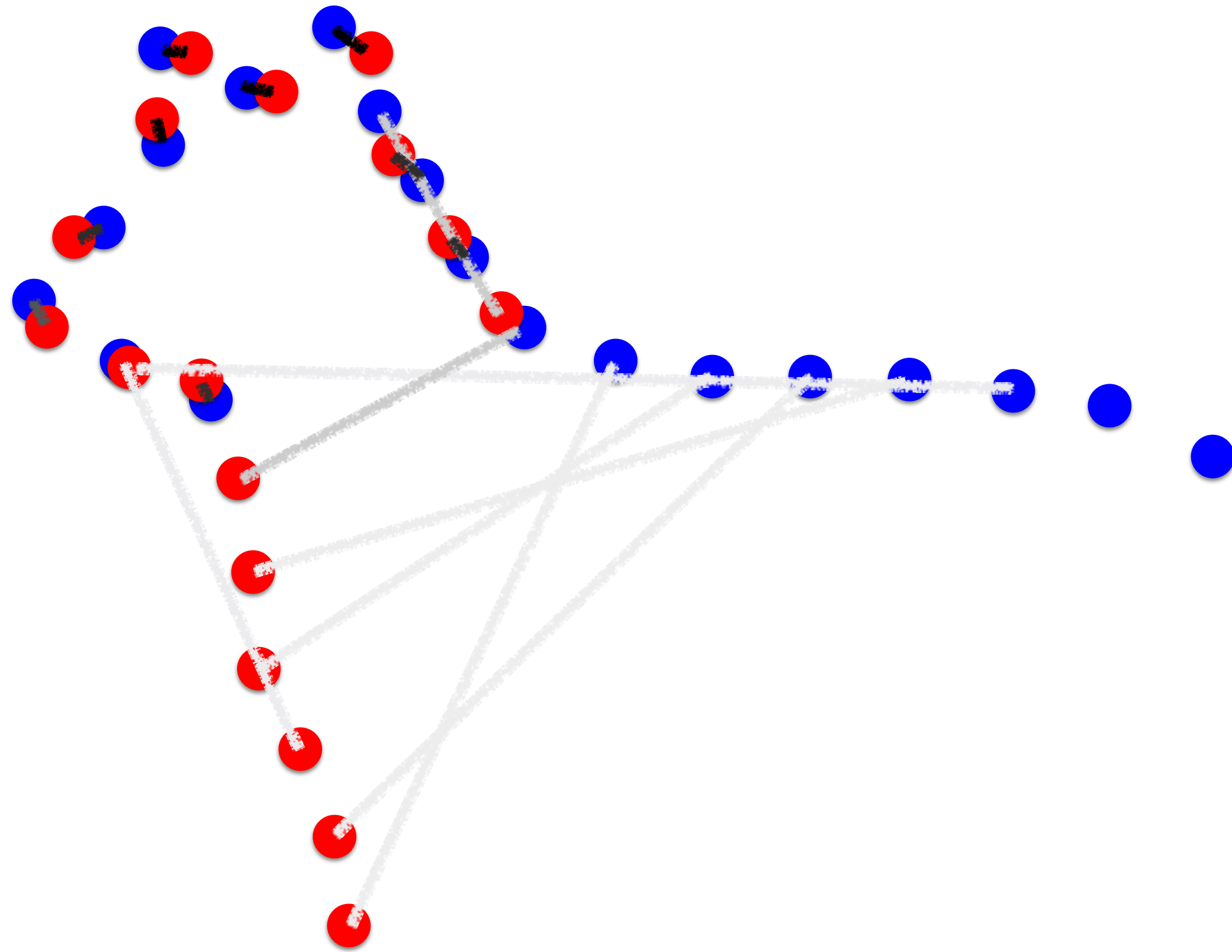
Fast Global Registration



Fast Global Registration



Fast Global Registration



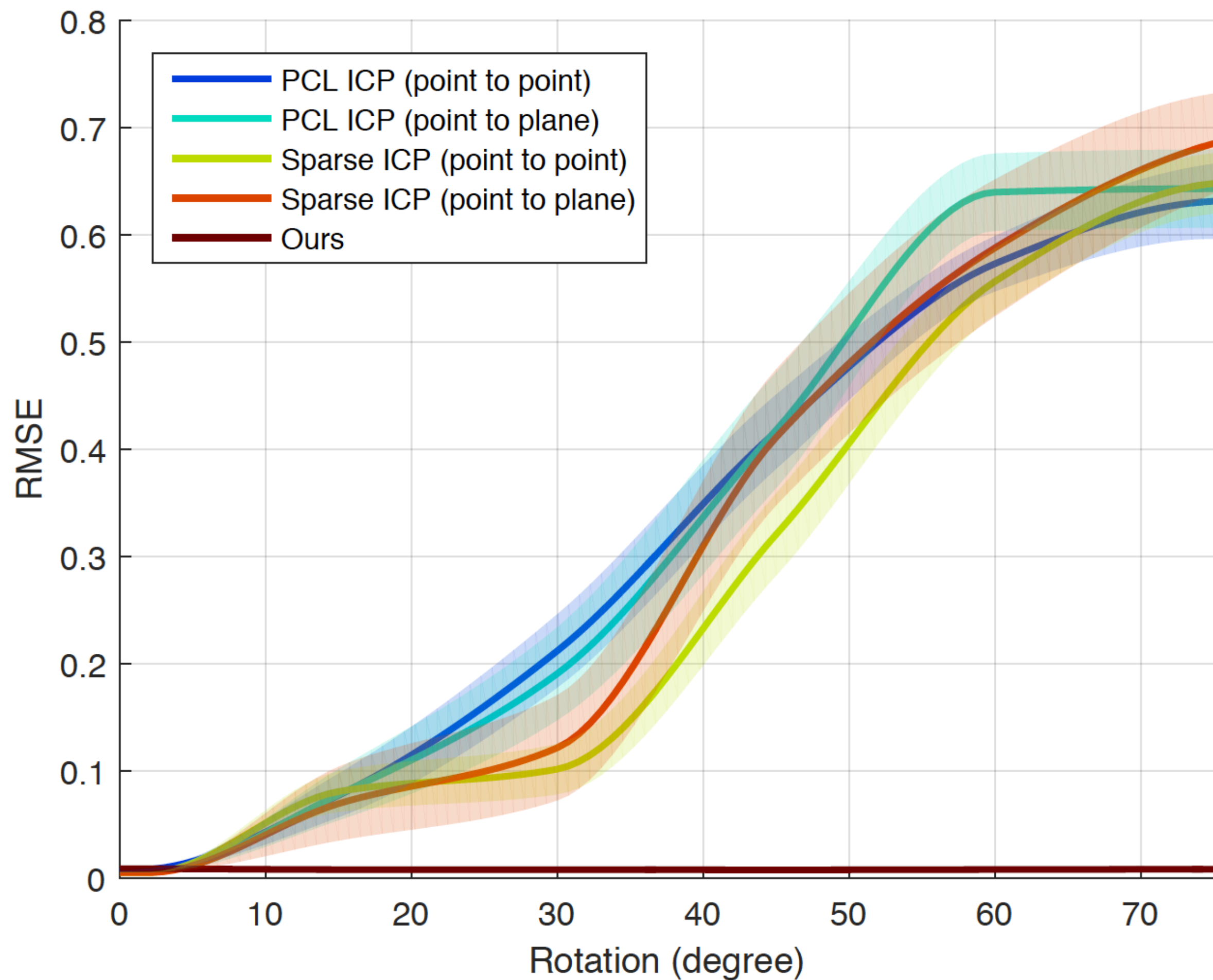
Results

	$\sigma = 0$		$\sigma = 0.0025$		$\sigma = 0.005$	
	Average RMSE	Maximal RMSE	Average RMSE	Maximal RMSE	Average RMSE	Maximal RMSE
GoICP [42]	0.029	0.130	0.032	0.133	0.037	0.127
GoICP-Trimming [42]	0.035	0.473	0.039	0.475	0.044	0.478
Super 4PCS [26]	0.012	0.019	0.014	0.029	0.017	0.095
OpenCV [8]	0.009	0.013	0.018	0.212	0.032	0.242
PCL [34, 19]	0.003	0.005	0.009	0.061	0.111	0.414
CZK [7]	0.003	0.005	0.008	0.022	0.035	0.274
Our approach	0.003	0.005	0.006	0.011	0.008	0.017

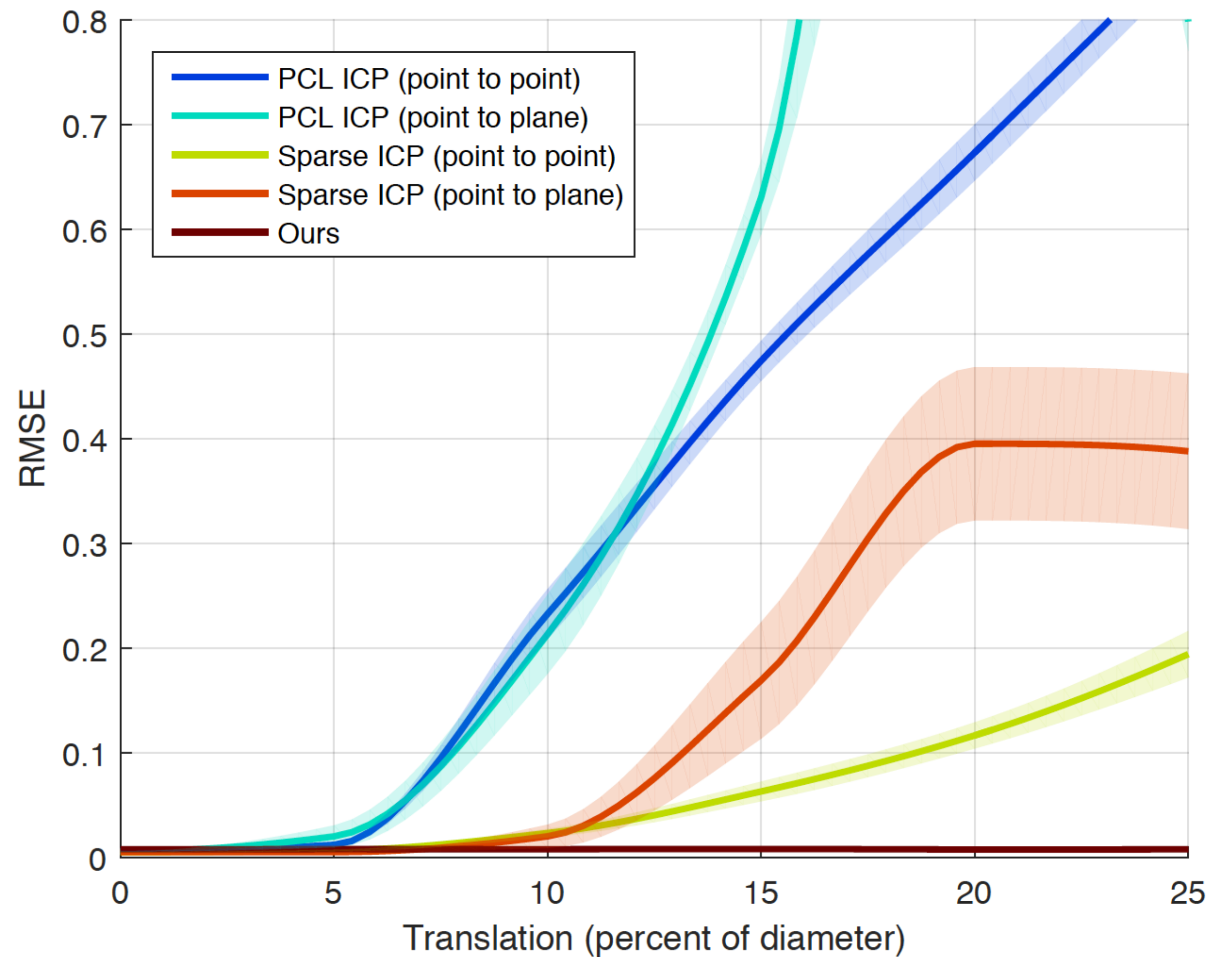
With noisy data, the average RMSE of our approach is more than 2 times lower than the best prior approach. Maximal RMSE is 5.6 times lower.

	Average # of points	GoICP [42]	GoICP-Trimming [42]	OpenCV [8]	Super 4PCS [26]	PCL [34, 19]	CZK [7]	Our approach
Bimba	9,416	19.3	19.4	41.0	311.4	18.2	12.8	0.13
Children	11,148	21.0	19.2	136.3	238.2	4.8	6.6	0.20
Dragon	11,232	94.1	38.4	57.7	483.7	8.6	11.9	0.23
Angel	12,072	21.0	20.4	80.9	171.5	8.7	11.3	0.26
Bunny	13,357	74.7	72.4	12.3	283.8	55.6	12.7	0.28
Average	11,445	46.0	34.0	65.6	297.7	19.2	11.1	0.22

Our algorithm is 50 times faster than the fastest prior global registration method.



(a) Rotation perturbation



(b) Translation perturbation

Our algorithm matches the accuracy achieved by the local algorithms when they are initialized near the ground-truth pose, but does not require an initialization.

	Average # of points	PCL ICP point-to-point	PCL ICP point-to-plane	Sparse ICP point-to-point [5]	Sparse ICP point-to-plane [5]	Our approach
Bimba	9,416	0.73	0.31	3.1	11.8	0.13
Children	11,148	0.75	0.46	3.9	15.0	0.20
Dragon	11,232	0.99	0.47	3.6	13.8	0.23
Angel	12,072	0.81	1.01	4.9	18.5	0.26
Bunny	13,357	2.10	1.70	9.2	10.3	0.28
Average	11,445	1.08	0.79	4.9	13.9	0.22

Our global algorithm is 2.8 times faster than a state-of-the-art implementation of ICP.

Summary

- Fast algorithm for global registration of partially overlapping 3D surfaces
- More than an order of magnitude faster than prior global registration algorithms and much more robust to noise
- Matches the accuracy of well-initialized local refinement algorithms such as ICP, without requiring an initialization and at lower computational cost

Thank you