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A Hybrid Quantum-Classical Algorithm for Robust Fitting

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Robust fitting via consensus maximisation

Outliers exist in computer vision

Transformation?

Figure 1 : Feature point matches containing outliers (red lines).

Least square is sensitive to outliers

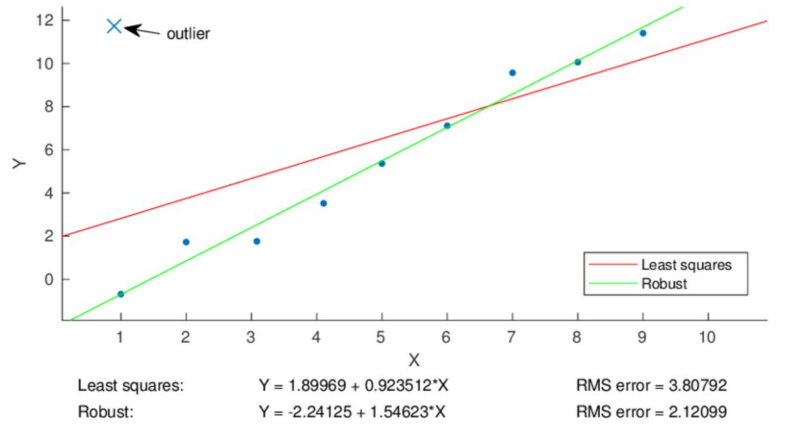
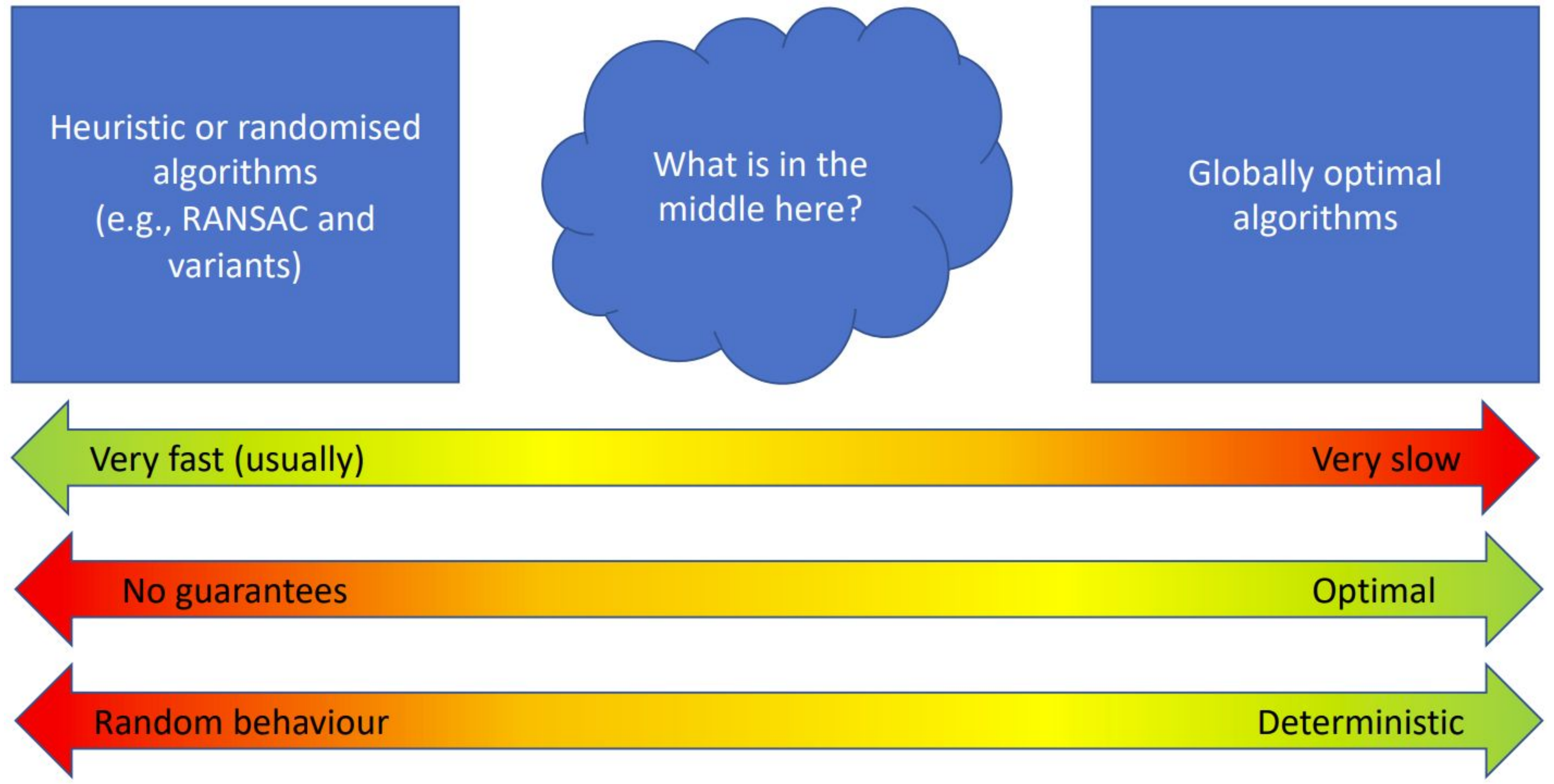


Figure 2 : Sensitivity of least squares to outliers.

Objective: make model fitting robust (insensitive) to outliers

Research gap in consensus maximisation

Theoretical results on classical computers [1]



Motivation

1. Investigate a new type of computer
2. Address the random behaviour

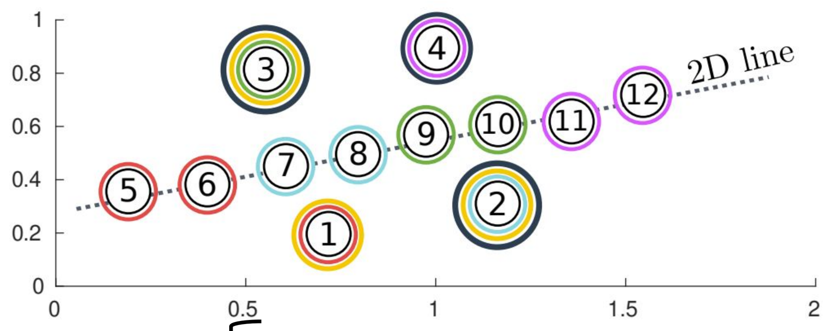
Contributions

→ A *hybrid quantum-classical algorithm*

→ An *error bound* $|\mathcal{I}^*| - |\tilde{\mathcal{I}}| \leq \rho$

Maximise consensus as minimise vertex cover

2D data space



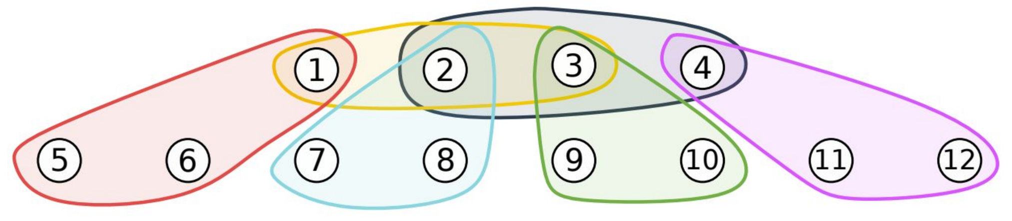
Infeasible bases: {1, 5, ({3, 9, 10} {1, 2, 3} {4, 11, 12} {2, 7, 8} {2, 3, 4}

Outlier set $\{1,2,3,4\}$

Consensus set $\{5,6,7,8,9,10,11,12\}$

⟺

Hypergraph space



Hyperedges: {1, 5, ({3, 9, 10} {1, 2, 3} {4, 11, 12} {2, 7, 8} {2, 3, 4}

Vertex cover $\{1,2,3,4\}$

Independent set $\{5,6,7,8,9,10,11,12\}$

Maximum consensus set ⟺ **Maximum independent set**

⇕

Minimum outlier set ⟺ **Minimum vertex cover**

Hybrid quantum-classical robust fitting

Hypergraph vertex cover as 0-1 ILP

$$I(A) = \min_{\mathbf{z} \in \{0,1\}^N} \|\mathbf{z}\|_1 \quad s.t \quad \mathbf{A}^T\mathbf{z} \geq 1_M,$$

where $z_i = 1$ implies vertex $i \in$ vertex cover

can be solved by quantum annealer

Hypergraph vertex cover as QUBO

$$Q_\lambda(A) = \min_{\mathbf{v} \in \{0,1\}^{N+\delta' M}} [\mathbf{v}^T \quad 1](\mathbf{J} + \lambda \mathbf{H}_A^T \mathbf{H}_A)[\mathbf{v}^T \quad 1]^T$$

where, $\mathbf{v} = [\mathbf{z}^T \quad \mathbf{t}_{(1)}^T \quad \dots \quad \mathbf{t}_{(M)}^T]$

Relaxation

$$LP(A) = \min_{\mathbf{z} \in [0,1]^N} \|\mathbf{z}\|_1 \quad s.t \quad \mathbf{A}^T\mathbf{z} \geq 1_M,$$

Hybrid quantum-classical robust fitting

1. $A \leftarrow$ Sample new hyperedge
2. Decay penalty λ
3. Solve $Q_\lambda(A)$ with *quantum annealing*
4. If $\mathcal{I} \leftarrow \mathcal{V} \backslash C_{\mathbf{z}}$ is a consensus set
5. If $\|\mathbf{z}\|_1 < \|\mathbf{z}_{\text{best}}\|_1$, then
6. $\mathbf{z}_{\text{best}} \leftarrow \mathbf{z}$ and $\mathcal{I}_{\text{best}} \leftarrow \mathcal{I}$
7. Repeat step 1

Error bound

$$|\mathcal{I}^*| - |\mathcal{I}_{\text{best}}| \leq \|\mathbf{z}_{\text{best}}\|_1 - LP(A)$$

Current best solution

Relaxation

Experiments

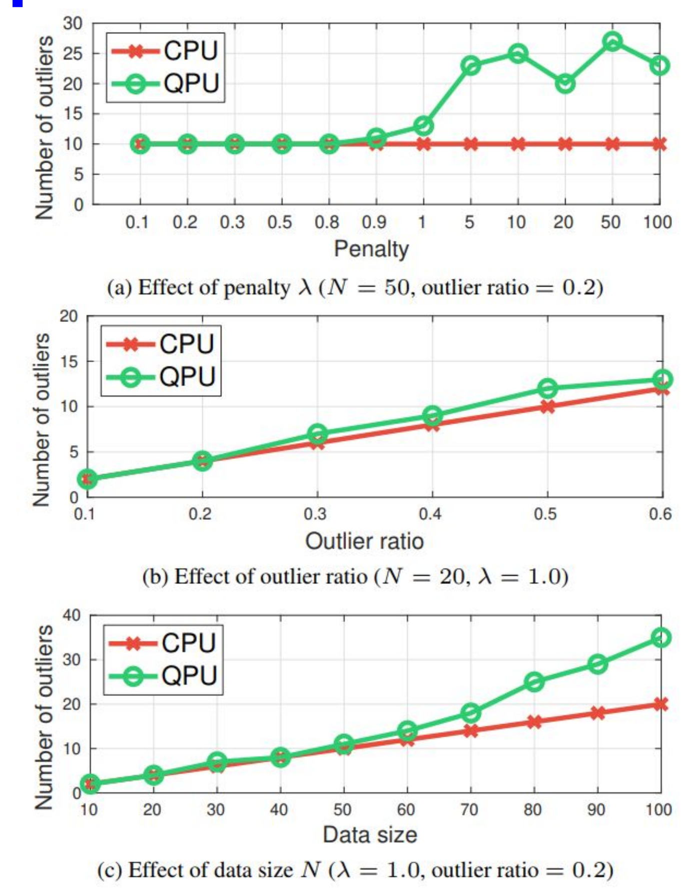


Figure 3. Comparison between CPU and QPU in solving QUBO

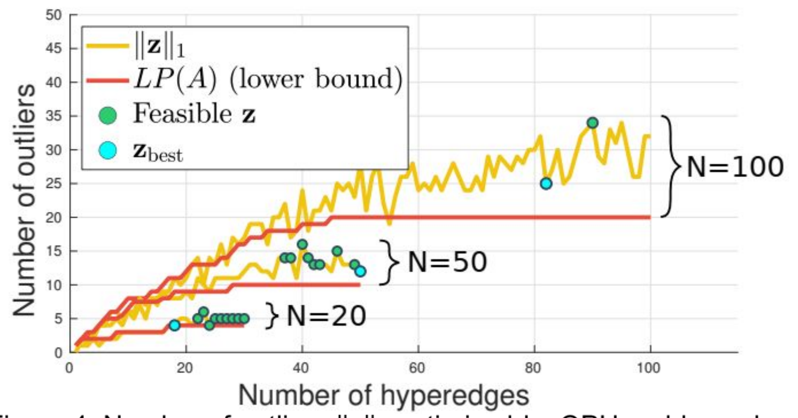


Figure 4. Number of outliers $\|\mathbf{z}\|_1$ optimised by QPU and lower bound $LP(A)$, plotted across the iterations of the proposed algorithm

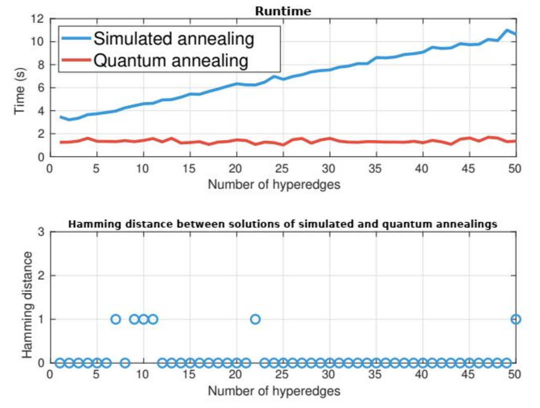


Figure 5. Comparison between quantum annealing (on D-Wave Advantage) and simulated annealing (on classical computer)

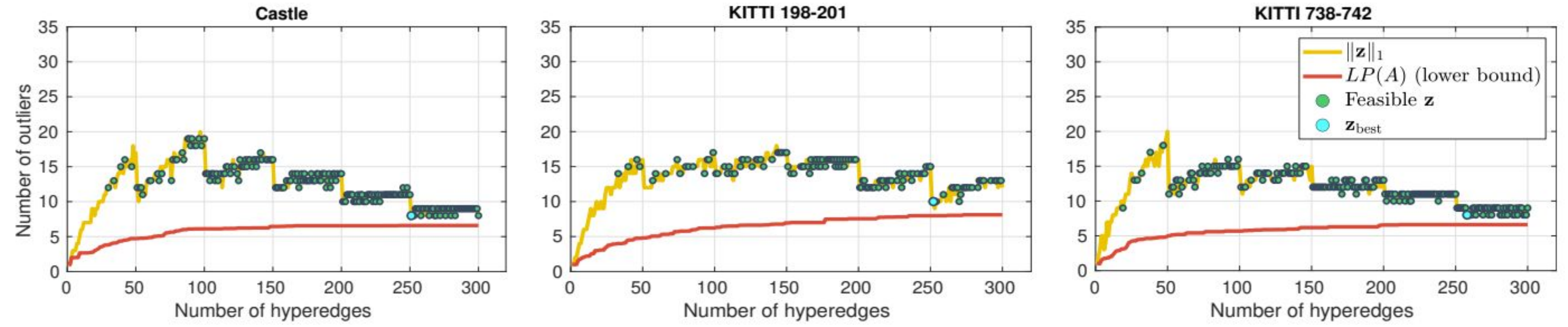


Figure 5. . Fundamental matrix estimation, where number of outliers $\|\mathbf{z}\|_1$ and lower bound $LP(A)$

Method		RS [36]	LRS [21]	FLRS [47]	EP [45]	IBCO [15]	QRF [20]	Alg. 1-E	Alg. 1-F
Castle	$\lvert\mathcal{I}\rvert$ (Error bound)	74 (−)	74 (−)	74 (−)	70 (−)	76 (−)	73 (−)	72 (8.17)	76 (1.41)
$N = 84$	Time (s)	0.20	0.11	0.20	0.25	0.34	199.48	18.07	1998.87
Valbonne	$\lvert\mathcal{I}\rvert$ (Error bound)	34 (−)	36 (−)	36 (−)	33 (−)	38 (−)	29 (−)	36 (6.00)	36 (4.00)
$N = 45$	Time (s)	0.21	0.20	0.31	0.34	0.44	110.30	6.71	1915.82
Zoom	$\lvert\mathcal{I}\rvert$ (Error bound)	90 (−)	91 (−)	91 (−)	92 (−)	95 (−)	89 (−)	93 (9.91)	94 (3.64)
$N = 108$	Time (s)	0.31	0.29	0.14	0.21	0.35	257.03	92.35	2109.13
KITTI 104-108	$\lvert\mathcal{I}\rvert$ (Error bound)	309 (−)	313 (−)	312 (−)	318 (−)	321 (−)	256 (−)	320 (9.91)	324 (2.30)
$N = 337$	Time (s)	0.04	0.04	0.07	0.28	0.39	799.33	137.26	2408.04
KITTI 198-201	$\lvert\mathcal{I}\rvert$ (Error bound)	306 (−)	308 (−)	307 (−)	308 (−)	312 (−)	309 (−)	308 (10.00)	312 (1.89)
$N = 322$	Time (s)	0.05	0.13	0.07	0.23	0.42	774.06	36.15	2350.39
KITTI 738-742	$\lvert\mathcal{I}\rvert$ (Error bound)	481 (−)	483 (−)	483 (−)	491 (−)	492 (−)	447 (−)	492 (5.88)	493 (1.39)
$N = 501$	Time (s)	0.05	0.18	0.23	0.53	0.61	1160.12	22.46	2506.04

Figure 5. Fundamental matrix estimation. Only our algorithm amongst all methods returns error bounds

Conclusions

- A hybrid quantum-classical algorithm for consensus maximisation
- The algorithm is terminated with an error bound

Paper Code

References

[1] Tat-Jun Chin, Zhipeng Cai, and Frank Neumann. “Robust fitting in computer vision: Easy or hard?.” ECCV 2018.