Robotics & Intelligent Systems Expo (RISEx 2025), Nov. 13-14, 2025, Edmonton, Canada

Empirical Analysis of Visual Servoing Complexity Across Different DOF Robots via the Global LLS Method

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INTRODUCTION

Despite the long-standing development of uncalibrated visual servoing (VS) [1], there is little research exploring how the complexity of the VS task varies across robots with different degrees of freedom (DOF). To analyse this, we generate a globally valid visual-motor model of the VS function using the Local Least Squares (LLS) method [2], where the Jacobian is estimated by fitting a hyperplane to the k-nearest datapoints from previous robot trajectories. We examine the number of data points, *N*, required to construct a global model for robots with 2, 3, 6 and 7 DOF to compare complexity of the VS task across different systems.

MATERIALS AND METHODS

We generate the global LLS model with *N* datapoints within joint configurations appropriate for a pick-and-place task for a 2 DOF arm, 3 DOF arm, the 6 DOF Kinova Jaco robot, and the 7 DOF Kinova Gen3 robot. We assign q as a joint configuration and K as the number of neighbours to use in the LLS calculation. The LLS estimate of the Jacobian is

$$J_i^{LLS}(q,K) = \underset{J\in\mathbb{R}^n}{\arg\min} \sum_{r=1}^{t}\sum_{s=1}^{t}\left(\Delta x_i^{[r,s]} - J\Delta q^{[r,s]}\right) \times I\left(q(r) \in \{q^{(1,t)},\dots,q^{(K,t)}\}\right) \times I\left(q(s) \in \{q^{(1,t)},\dots,q^{(K,t)}\}\right)$$

During acquisition of the LLS model, we measure the estimation error between $J^{LLS}(q,K)$ and the true Jacobian:

$$\mathrm{JacEstimationError}(q,K) = \frac{\| J(q) - J^{LSS}(q,K) \|_F}{\| J(q) \|_F}$$

The LLS model is then employed in VS to compare the feasibility and number of data points needed between robots. For a VS trial we use dampened Gauss-Newton updates $q_{i+1} = q_i - \alpha J^{LLS}(q_i, K)e_i$ as our control method to converge from a random initial joint position to a random goal feature y_{goal}, where α=0.1 dampens each update, K=80 [2] is the number of nearest neighbour datapoints to use in the LLS calculation, and $e_i = y_{goal} - y_i$. The total error of a trial is measured at each update *i:*

$$\mathrm{VisualServoingError} = \frac{\sum_{i=0}^{n} \| y_{goal} - y_i \|}{\| y_{goal} - y_0 \|} - 1$$

RESULTS AND DISCUSSION

Results show that the higher DOF robots perform very well for visual servoing, despite poor Jacobian estimates calculated from the LLS model. Between the systems, the Jacobian estimation error increases only linearly as DOF increases despite the exponential growth in possible joint configurations, and estimation improvement generally stagnates as *N* increases. We observe that as *N* grows, all confidence intervals shrink. Despite having the largest Jacobian estimation error for all *N*, the Kinova Gen3 achieves progressively stronger VS performance as *N* grows, outperforming the other robots. This is likely due to the 7 DOF joint redundancy (where DOF > dim(task space)), which increases the number of joint solutions and potentially reduces the necessity for accurate Jacobian estimates.

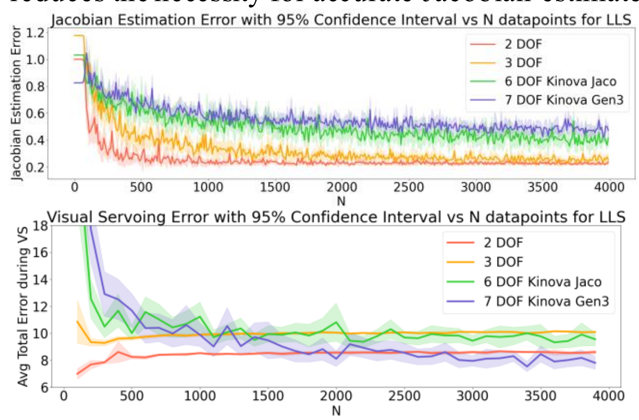

Fig 1 *Average visual servoing performance across 100 runs per robot converges similarly for all robots, despite differences in Jacobian estimation.*

CONCLUSIONS

The VS function is analytically more complicated for higher DOF; yet we observe that it is not necessarily more difficult to perform in practice. We highlight the robustness of Gauss-Newton VS in higher-DOF robots to inaccurate Jacobian estimates, and the performance benefits of joint redundancy. Robust VS via the global LLS method can be achieved with a surprisingly similar and low number of a few thousand datapoints between different DOF robots; motivating further research in creating even smaller global models, thus lowering the cost of data collection and enabling faster or real-time deployment of visual servoing in new environments.

REFERENCES

[1] Chaumette F et al. Visual servo control, Part I: Basic approaches, IEEE Robotics and Automation Magazine **13**: 82-90, 2006.
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