Evidence for State of the Art Performance

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This brief document summarises the comparison of my reinforcement learning grasping method, shown in Figure 1, against related work. The same set of comparisons are shown visually in Figure 2, and in detail in Table 1. The comparison includes performance on the low clutter scenarios from the Ocado gorcery bin picking benchmark [1] (first four entries) and single object grocery grasping performance against the most related works, most frequently using the YCB benchmark grocery objects [2] (remaining entries). The objects my method was tested on are shown in Figure 3. Please refer to the Transactions on Mechatronics paper for further information about my method [3].

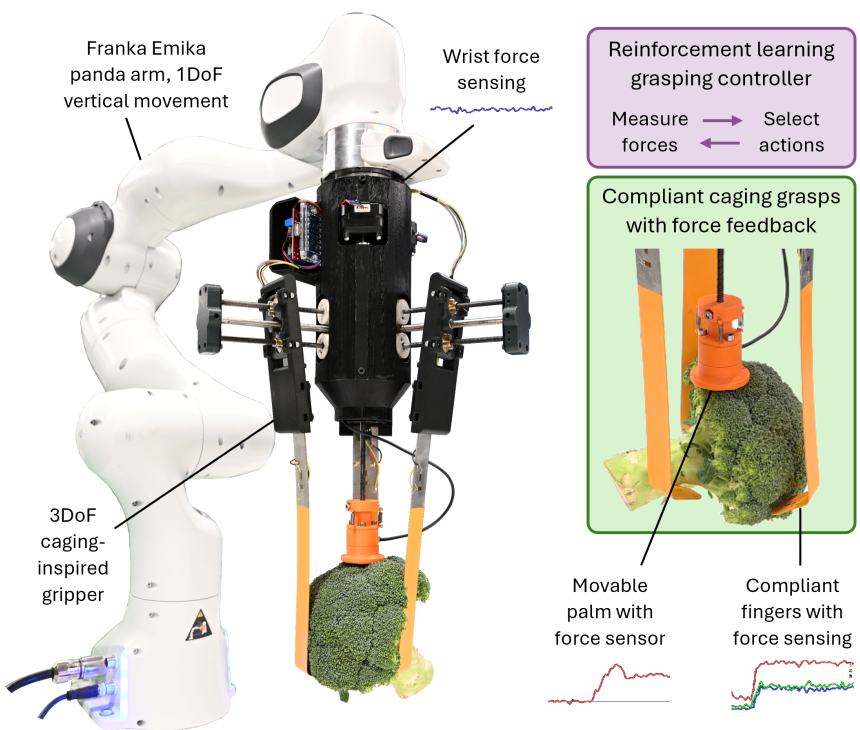

Figure 1: The developed novel grasping system, which combined a force feedback reinforcement learning grasping controller with a compliant caging gripper design. The new gripper is shown mounted on a robotic arm, having achieved a successful grasp of a broccoli. Key features, including the location of force sensing, and the degrees of freedom (DoF) of the grasp, are indicated.

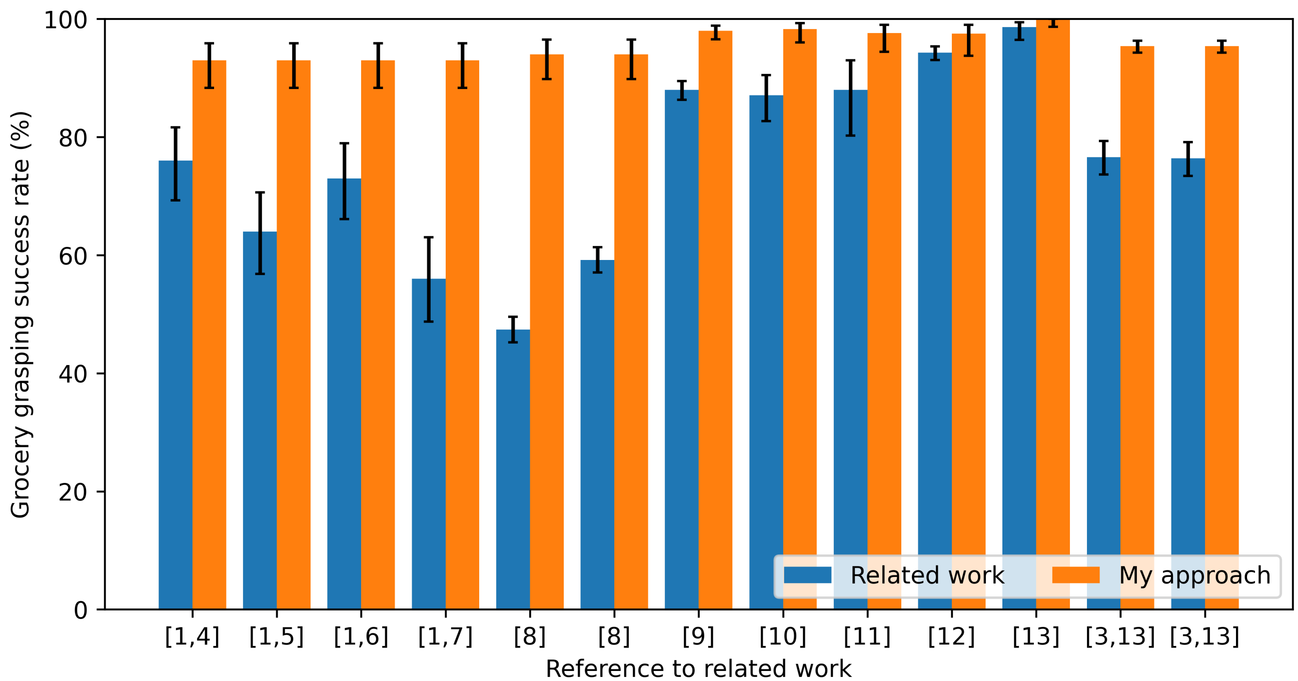

Figure 2: Comparing the grocery grasping performance of my gripper against related work, with the 95% confidence interval indicated atop each bar. See Table 1 for further detail on each entry.

Table 1: Comparing the grasping performance of my gripper with related work on the same or equivalent (shown in brackets) objects. Experiment procedures were similar, being single object grasping with limited object initial position error, but not identical. For the top four rows (Ocado benchmark [1]), the bin clearance rate is used as a proxy for success rate (SR), and grasping occurred in low clutter. Bold indicates a statistically significant improvement over the test objects (see Section 1).

Reference	Gripper used with their method	No. objects	Test objects	Their SR %	My SR %
[1], [4]	Pisa/IIT SoftHand	5	Mango, net bag of limes, salad bag, cucumber, punnet of berries	76.0	**93.0**
[1], [5]	Pisa Softgripper			64.0	
[1], [6]	DLR CLASH Hand			73.0	
[1], [7]	RBO Gripper			56.0	
[8]	Soft (8 fingers)	5	Limes, cucumber, apples bag, lemon net (tangerine net), berries box (raspberry punnet)	47.4	**94.0**
[8]	Suction (SGO65)			59.2	
[9]	Barrett hand	4	Cube, sphere, two cuboids (elementary object set Figure 3-a)	88.0	**98.0**
[10]	Shadow hand	7	YCB groceries: maxwell house, domino box, soup, mustard bottle, pringles can, cheezeit box, spam tin	87.1	**98.3**
[11]	Allegro hand	5	YCB groceries: domino box, soup, mustard bottle, cheezeit box, spam tin	88.0	**97.6**
[12]	DH Robotics AG95	4	Apple, banana, orange (YCB orange), pocky box (YCB chocolate jello box)	94.3	97.5
[13] (MAT)	Barrett hand	7	YCB groceries: pringles can, cheezeit box, soup tin, spam tin, maxwell house, chocolate jello box, mustard bottle	98.6	**100.0**
[3], [13]	My gripper (MAT)	42	Real and YCB groceries, shown in Figure 3-b,c	76.6	**95.4**
[3], [13]	My gripper (MAT+ours)			76.4	

(a) 30 elementary objects, success rate = 98.0% [3]

(b) The 18 YCB grocery items [2], success rate = 95.8% [14]

(c) 24 real grocery items, success rate = 95.8% [3]

Figure 3: Object sets used for experiments, labelled with the grasp success rate achieved on that set using my method, and also with mass distributions indicating object masses throughout each set. Objects shown in grasping orientation.

1 Statistical Significance

Many authors do not report statistical significance for grasp success rate. Wu et al. [13] estimated success rate standard deviations over the object set and then defined statistical significance as occurred when two controllers success rates varied by more than one times the larger standard deviation. Mahler et al. [15] and Liu et al. [16] used the standard error of the mean success rate per object, at the 95% confidence level. Morrison et al. [17] reported using the 95% confidence interval, but did not provide exact details of its calculation. Usage of the 95% confidence interval is considered the most rigorous and justified approach.

Grasping can be considered a Bernoulli random variable, with binary success or failure of grasps, and with a probability given by the grasp success rate. This means that the 95% confidence interval has to be approximated, since it is applied to a binomial distribution. The standard approximation for confidence intervals of a binomial distribution, sometimes termed the "Wald interval", involves using the normal distribution to approximate error. However, Brown et al. [18] argued this approach is severely flawed. This approach performs particularly poorly with low numbers of trials, n, and when the success probability, p, is close to 0 or 1, with problems such as overshoot (exceeding the bounds at 0 and 1), intervals converging to a singular value (which implies perfect knowledge of p), and high variation and error in the true coverage of the interval, depending on the number of samples, n, and the value of p. One example they provide is the interval coverage being only 91.1% with $p = 0.107$ and $n = 100$, whereas it changes to 95.2% with $p = 0.106$. They robustly recommend that the Wilson interval should be used instead.

The Wilson interval is an approximation for the confidence intervals of the binomial distribution. Let the standard normal interval half-width $z_\alpha = 1 - \alpha$, where α is the normal interval half-width corresponding to the desired confidence (e.g., $z_\alpha = 0.975$ for the 95% confidence interval). Then, using the estimated probability from n trials and k successes, of $\hat{p} = k/n$, the Wilson confidence intervals are:

$$p \in (w^-, w^+) = \frac{1}{1 + z_\alpha^2/n} \left(\hat{p} + \frac{z_\alpha^2}{2n} \pm \frac{z_\alpha}{2n} \sqrt{4n\hat{p}(1-\hat{p}) + z_\alpha^2} \right). \tag{1}$$

Therefore, a result was considered a statistically significant improvement compared to another if neither 95% confidence interval overlapped with the mean value of the other.

References

[1] H. Mnyusiwalla *et al.*, "A bin-picking benchmark for systematic evaluation of robotic pick-and-place systems," *IEEE Robotics and Automation Letters*, vol. 5, no. 2, pp. 1389–1396, 2020.

[2] B. Calli, A. Singh, A. Walsman, S. Srinivasa, P. Abbeel, and A. M. Dollar, "The YCB object and model set: Towards common benchmarks for manipulation research," in *2015 International Conference on Advanced Robotics (ICAR)*, 2015, pp. 510–517.

[3] L. Beddow, H. Wurdemann, and D. Kanoulas, "Reinforcement learning grasping with force feedback from modeling of compliant fingers," *IEEE/ASME Transactions on Mechatronics*, 2024, in press.

[4] M. G. Catalano, G. Grioli, E. Farnioli, A. Serio, C. Piazza, and A. Bicchi, "Adaptive synergies for the design and control of the Pisa/IIT SoftHand," *International Journal of Robotics Research*, vol. 33, no. 5, pp. 768–782, 2014.

[5] F. Angelini, C. Petrocelli, M. G. Catalano, M. Garabini, G. Grioli, and A. Bicchi, "SoftHandler: An integrated soft robotic system for handling heterogeneous objects," *IEEE Robotics and Automation Magazine*, vol. 27, no. 3, pp. 55–72, 2020.

[6] W. Friedl and M. A. Roa, "CLASH — a compliant sensorized hand for handling delicate objects," *Frontiers in Robotics and AI*, vol. 6, no. January, pp. 1–15, 2020.

[7] R. Deimel and O. Brock, "A novel type of compliant and underactuated robotic hand for dexterous grasping," *International Journal of Robotics Research*, vol. 35, no. 1-3, pp. 161–185, 2016.

[8] E. Ardissone, S. Ulrich, and A. Kirchheim, "Design and evaluation of an automatic decision system for gripper selection in order picking," *Logistics Journal: Proceedings*, vol. 2023, no. 1, 2023.

[9] Y. Chebotar, K. Hausman, O. Kroemer, G. S. Sukhatme, and S. Schaal, "Generalizing regrasping with supervised policy learning," in *2016 International Symposium on Experimental Robotics*. Springer, 2017, pp. 622–632.

[10] H. Liang, L. Cong, N. Hendrich, S. Li, F. Sun, and J. Zhang, "Multifingered grasping based on multimodal reinforcement learning," *IEEE Robotics and Automation Letters*, vol. 7, no. 2, pp. 1174–1181, 2022.

[11] V. Kumar, T. Hermans, D. Fox, S. Birchfield, and J. Tremblay, "Contextual reinforcement learning of visuo-tactile multi-fingered grasping policies," in *NeurIPS: Robot learning workshop*, 2019.

[12] Y. Zhou, Y. Jin, P. Lu, S. Jiang, Z. Wang, and B. He, "T-TD3: A reinforcement learning framework for stable grasping of deformable objects using tactile prior," *IEEE Transactions on Automation Science and Engineering*, pp. 1–15, 2024.

[13] B. Wu, I. Akinola, J. Varley, and P. K. Allen, "MAT: Multi-fingered adaptive tactile grasping via deep reinforcement learning," in *Proceedings of the Conference on Robot Learning*, ser. Proceedings of Machine Learning Research, L. P. Kaelbling, D. Kragic, and K. Sugiura, Eds., vol. 100. PMLR, 30 Oct–01 Nov 2020, pp. 142–161.

[14] L. Beddow, H. Wurdemann, and D. Kanoulas, "Evaluating a movable palm in caging inspired grasping using a reinforcement learning-based approach," in *2024 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2024, in press.

[15] J. Mahler *et al.*, "Learning ambidextrous robot grasping policies," *Science Robotics*, vol. 4, no. 26, 2019.

[16] F. Liu, F. Sun, B. Fang, X. Li, S. Sun, and H. Liu, "Hybrid robotic grasping with a soft multimodal gripper and a deep multistage learning scheme," *IEEE Transactions on Robotics*, vol. 39, no. 3, pp. 2379–2399, 2023.

[17] D. Morrison *et al.*, "Cartman: The low-cost cartesian manipulator that won the amazon robotics challenge," in *2018 IEEE International Conference on Robotics and Automation (ICRA)*, 2018, pp. 7757–7764.

[18] L. D. Brown, T. T. Cai, and A. DasGupta, "Interval estimation for a binomial proportion," *Statistical Science*, vol. 16, no. 2, pp. 101 – 133, 2001.