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].

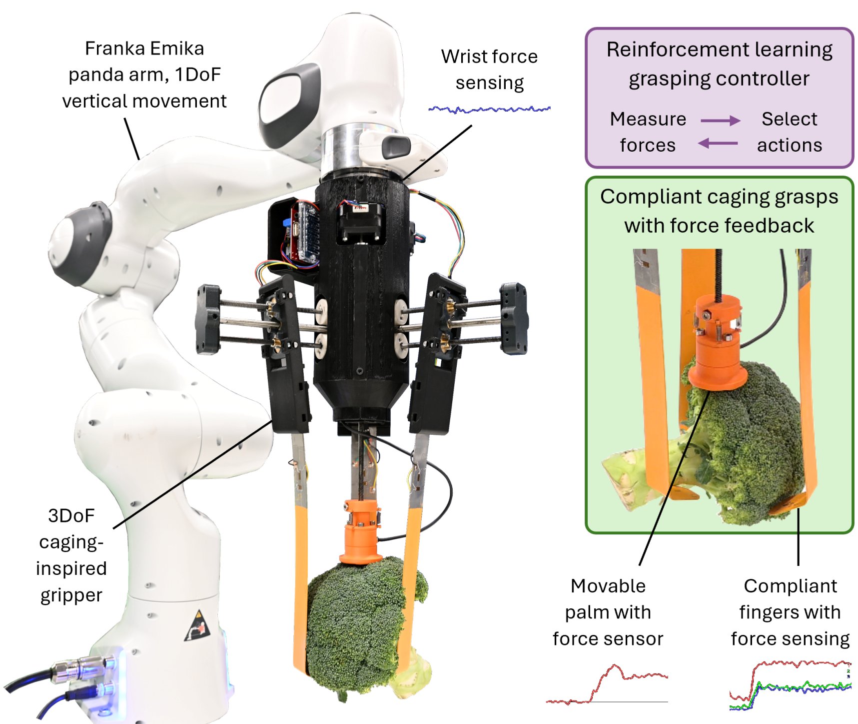

Figure 1: The developed novel grasping system, which combined a force feedback reinforcement learning grasping controller with a compliant caging gripper design. The new gripper is shown mounted on a robotic arm, having achieved a successful grasp of a broccoli. Key features, including the location of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

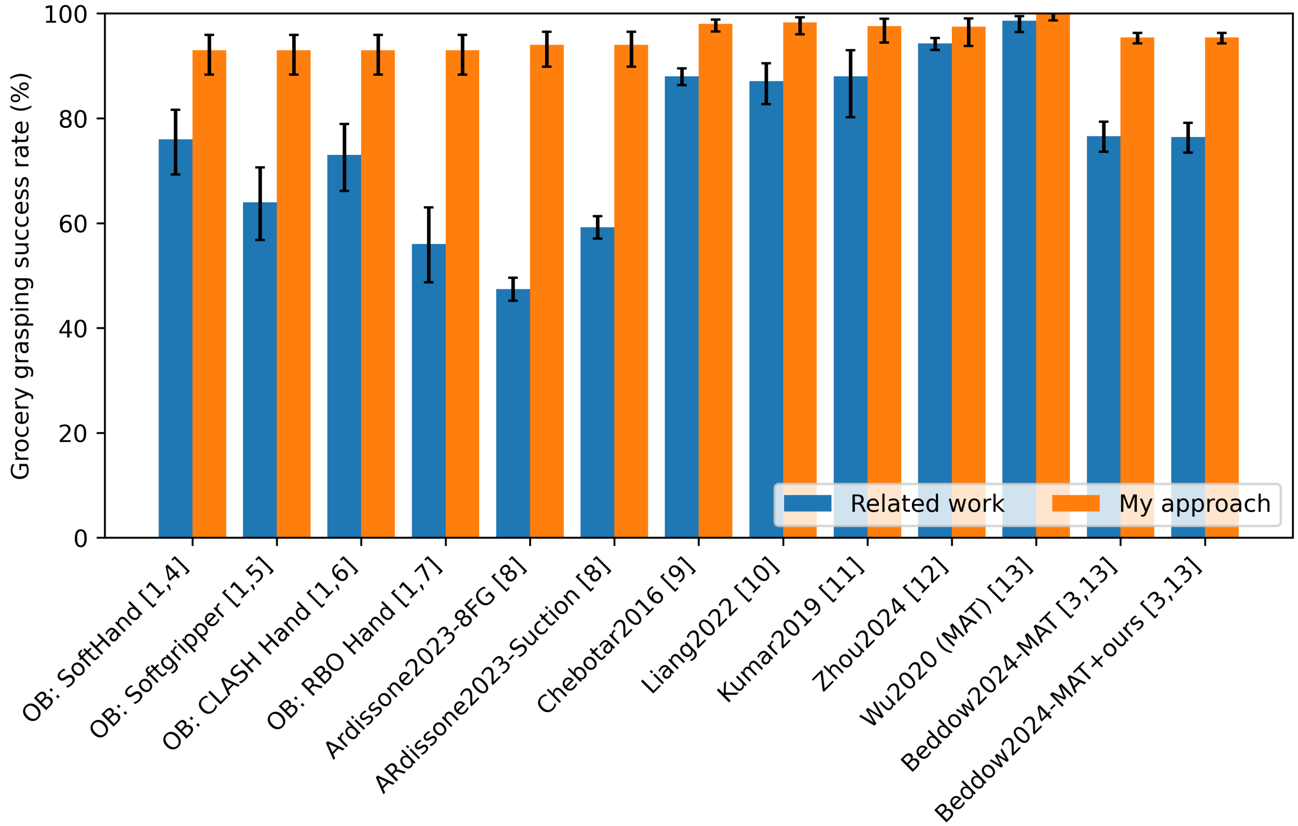

Figure 2: Comparing the grocery grasping performance of my gripper against related work, with the 95% confidence interval indicated atop each bar. See Table 1 for further detail on each entry. OB abbreviates Ocado Benchmark.

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] [1], [5] [1], [6] [1], [7]	Pisa/IIT SoftHand Pisa Softgripper DLR CLASH Hand RBO Gripper	5	Mango, net bag of limes, salad bag, cucumber, punnet of berries	76.0 64.0 73.0 56.0	**93.0**
[8] [8]	Soft (8 fingers) Suction (SGO65)	5	Limes, cucumber, apples bag, lemon net (tangerine net), berries box (raspberry punnet)	47.4 59.2	**94.0**
[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] [3], [13]	My gripper (MAT) My gripper (MAT+ours)	42	Real and YCB groceries, shown in Figure 3-b,c	76.6 76.4	**95.4**

(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.

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