Are Two Robots Better Than One?

An Investigation Into the Impact of Mass and Bumper Sensor Feedback Enabled PID on the Box Pushing Capabilities of One and Two Pololu 3Pi+ Robots

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***Abstract*—This paper explores the relationship between mass and the pushing ability of one and two robots. The pushing ability of the systems was quantified using a path deviation score, a cumulative measure of displacement of the centre of mass of the box from the intended straight path. A baseline experiment was conducted, measuring the performance of the one and two robot systems with PID speed control, pushing a box in a straight line. As the mass of the box increases, the pushing ability of both one and two robot systems increases. The integration of bumper sensor feedback improved the performance of the two robot system, however failed to improve the single robot. One robot was shown to outperform two robots at an absolute box mass of 185-225g across both tests. Bumper sensor reading was shown to be positively correlated with increased mass. There was no statistical correlation between pushing performance and frequency of trajectory correction as a result of bumper sensor readings, indicating no causal relationship between the two.**

I. Introduction

Automation of simple, repetitive tasks, is of increasing viability and utility within the modern world. In particular, systems that can transport objects along desired trajectories, in an efficient and dynamic manner, have a wide array of potential applications from hospitals to space [5]. At the core is the ability of a system to push a box along a straight line.

The mass of the box is a key environmental element of the system. A lighter box requires less force to move, resulting in a greater susceptibility to random error and deviation. Furthermore, a consideration of basic dynamics reveals that two, equidistant points of contact applying a force on a moving object will result in more stable motion compared to a single point of force. Two robots of equal strength are expected to perform better than a single robot at pushing a box.

Hypothesis I

The pushing performance of one and two robot systems will increase as mass increases, because the system has increased inertia and will be more stable. It is expected that two robots will have superior pushing performance than one, across the range of masses.

A. Sensing and Feedback

However, this speed based approach is simplistic: in the event of any slip or error, the system tends to failure. A robotic system's ability to react dynamically to its environment, in order to better perform tasks, is critical. The integration of environmental sensing allows dynamic system response, enabling fine-tuned control and correction. For example robot swarms rely on identical control systems, relying on environmental perception and predictable performance, rather than centralised control and cross communication, to facilitate simple, scalable and robust multi-robot systems [2].

The Pololu 3Pi+ robot, [1] is capable of detecting object contact, through bump sensors positioned at the front of the robot. Infra-red light is reflected off two flexible plastic bumpers; as the bumper is compressed the quantity of reflected light decreases [3]. However, sensing and feedback are non-perfect, vulnerable to the limitations of the sensor. For example, the material properties of the bumpers require sufficient force to enable physical detection.

A characterisation study of the sensors was performed, shown in Figure 1, confirming the expectation that the sensing ability is mass dependent. The slight decrease at 0° results from the overlap of sensors preventing complete compression.

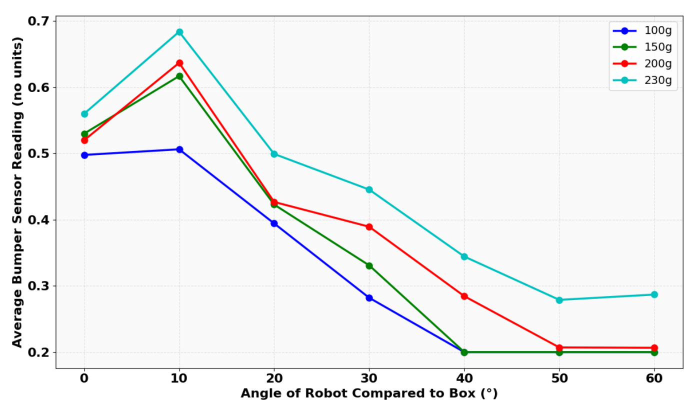

Fig. 1: Plot showing bumper sensor reading against angle of robot relative to the box, at various masses

Therefore a system that integrates bumper feedback will experience a larger signal, across a greater range of angles, for a larger mass. At 100g, the difference in detection between 0-10° is minimal, indicating a system would fail to detect smaller box deviations. A reading of 0.2 corresponds to no box detection, likely due to impact of background irradiance.

Hypothesis II

It is expected that the addition of bumper-sensor-feedback enabled PID control will improve the pushing ability of one and two robots, compared against their baseline performance, by enabling dynamic correction to system instability. This relationship is expected to hold across a range of masses.

Hypothesis III

The magnitude of the bumper sensor reading increases with mass. As the mass of the box increases, the system's pushing performance (whether one or two robots) is expected to increase, as a result of an increased frequency of trajectory correction due to the greater bumper sensor readings.

Pushing performance was quantified through use of a path deviation score, *PDS*, a measure of the displacement of the centre of mass (COM) of the box from the straight path. The mean magnitude of the bumper readings across each trial and frequency of path correction, across one and two robots, was also assessed.

II. Implementation

A. PID and Control Algorithm

An independent speed PID controller was implemented for each motor, the *baseline system*. This was then advanced, to incorporate feedback to create a bumper-sensor-feedback enabled PID controller, *BSF*, shown in Algorithm 1 below. The magnitude of the difference between bumper sensor readings was scaled by a factor of four and applied to the speed demand, to ensure sufficient sensitivity. Below a bumper difference of 0.1, the system assumes the box to be perpendicular to the robot. In this instance the robot operates PID control with equal demands of 5.5cm/s forward bias, resulting in straight forward travel.

An exponential moving average, Equation 1, was applied (as a noise filter) to the calibrated bumper readings to minimise jolting and erratic behaviour. The system updates every 50ms.

$$Reading_{filtered} = (0.1 Reading_{calibrated}) + (0.9 Reading_{lastFiltered}) \tag{1}$$

B. Data Recording

The robot was used to measure and store data throughout each trial, recorded every 150ms across a runtime of 15 seconds. Due to the finite storage memory on the robot, the resolution of the data was limited to two decimal places. However, this level was acceptable as the PID controller would not experience significant demand change for such minor deviation.

The incidence of data recorded was less than the frequency of PID update, primarily due to the balancing of storage limitations with the duration of trial needed to observe deviation. It is reasonable to assume that a robot travelling at (or less than) 5.5cm/s is unable to correct itself in less than 150ms, and thus make a change so quick that it would be undetected in the recorded data. Despite the PID updates occurring at three times the frequency of data collection, resolution of data is assumed to be sufficient to log trends.

Python's open computer vision [4] was used to track the trajectory of the centre of mass of the box, identified with a fixed coloured marker. Various example paths, along with corresponding PDSs are shown in Figure 2. Each trial was filmed from a fixed vertical and horizontal position to enable comparison across recordings.

Algorithm 1 Box-Chasing Controller

Input: Calibrated Bumper Readings
Output: Motor PWM values

$base_{demand} \leftarrow 5.5cm/s$
initialise PID controllers
while $experimentRunning$ **do**
  $l_{raw} \leftarrow readLeftBumperRaw()$
  $r_{raw} \leftarrow readRightBumperRaw()$

  $RB_{filtered} \leftarrow noiseFilter(l_{raw})$
  $LB_{filtered} \leftarrow noiseFilter(r_{raw})$

  $diff \leftarrow RB_{filtered} - LB_{filtered}$ ▷ [-1,+1] range
  if $|diff| < 0.1$ **then**
    $diff \leftarrow 0$
  end if

  $left_{demand} \leftarrow base_{demand} + (base_{demand} \times diff \times 4)$
  $right_{demand} \leftarrow base_{demand} - (base_{demand} \times diff \times 4)$

  $L_{PWM} \leftarrow PID.update_{left}(left_{demand})$
  $R_{PWM} \leftarrow PID.update_{right}(right_{demand})$
  $motors.setPWM(L_{PWM}, R_{PWM})$
end while

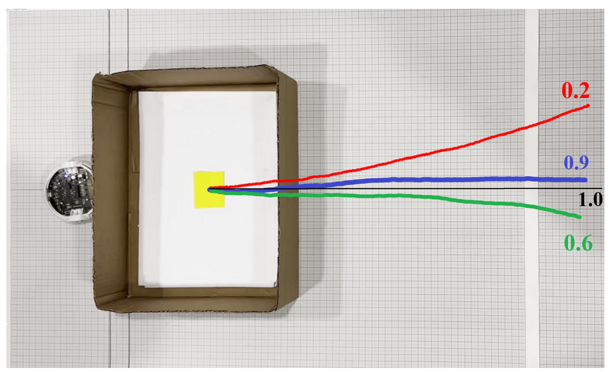

Fig. 2: Image showing recorded box trajectories, tracked using Python's computer vision, along with corresponding PDS

C. Calibration Procedure

At the beginning of each trial, the bumper sensors were calibrated, to detect minimum and maximum readings in order to establish a normalised scaled using Equation 2. The calibration routine consisted of three simultaneous compressions of both bumpers, each a second duration, from the same position on each bumper. Calibration was performed whilst in contact with the floor to account for any impact light of reflection from surface on the infra-red reading. The same individual performed the calibration across all trials.

$$Reading_{calibrated} = \frac{(Reading_{current} - minimum)}{range} \tag{2}$$

As previously highlighted, when the robot experiences pressure completely normal across both centres, the maximum compression of a single bumper is not achieved, as the two overlap. Whilst the bumper sensors can be fully compressed individually, this will not occur within the experiment, as the box is a uniform area of contact. Compressing each bumper individually during calibration would artificially increase the range, making the system less sensitive.

III. Methodology

A. Set Up and Procedure

Two experiments were run, using the same set up and procedure: the baseline (no bumper feedback) and feedback enabled (implementation of BSF using Algorithm 1).

The trial consists a calibration stage, a positioning stage and a pushing stage. Two sheets of A1 graph paper were used to create a smooth planar surface. Following calibration, the robots were normal to the box, 3cm away, to allow the PID to stabilise and the system to gain momentum prior to collision with the box. The single robot was positioned along the centreline of the box, the two robots were placed equidistant from the edge and centre. Initial position lines for the robot and box were drawn. The set up for one robot is shown in Figure 2.

For the various trials, the mass was increased and distributed uniformly across the box, through use of multiple sheets of A4 paper. The mass was increased to less than 10g of the maximum moveable mass (determined through an initial investigation), to prevent motor damage. Each trial was repeated five times. Incidences of slip induced failure (total loss of contact with the box) were found to occur only twice in 130 trials and therefore ignored.

B. Variables

1) Independent Variables: The experiment has two independent variables: the mass of the box and the number of robots. The absolute masses pushed by each robot system are shown in Table I

Number of Robots	Mass of Box Pushed (g)
1	100, 150, 200, 230
2	100, 150, 200, 250, 300, 350, 400, 450, 500

TABLE I: Mass of box pushed for each number of robots

2) Dependent Variables: For each trial, the path of the centre of mass of the box, the magnitude of the bumper sensor readings and the robot's PID demand were recorded.

3) Control Variables: The same cardboard box was used for all testing, dimensions 33x16x30cm, pushed on the same surface, to prevent impact of varying friction on both the robots and the box. Crucially the box was wide enough to enable two robots to push without collision in the event of minor slip and correction. All tests were performed in the same room with identical artificial lighting, as the robot is sensitive to ambient infra-red. Each trial was run for 15 seconds, with initial investigation finding this a sufficient time to for system settling and impact observations. The robots were positioned at a fixed distance perpendicular to the box (3cm), to enable momentum gathering and identical angle prior to box collision.

The same robot(s) were used for each trial. In the instance of two robots, the positioning (i.e the ”right” and ”left” robot) were kept identical, to minimise the impact of manufacturing differences.

C. Metrics

The purpose of the metrics is to enable quantifying and comparison of straight line pushing capability, as well as provide insight into causal mechanism, specifically determining whether the variation in performance is a result of mass-dependent sensing ability.

1) Path Deviation Score: The path deviation score, *PDS*, provides a cumulative measure of ”straightness of path”, where one is ideal performance.

The *relative deviation* from a straight path is measure for each observed point via computer vision, measuring how far its y-value diverges from a fixed baseline (the initial y-value). The deviation is normalised by the baseline, yielding a scale-independent ratio, essentially quantifying deviation as a percentage, to allow direct comparison across trials:

$$\textit{relative deviation} = \frac{|y - \text{baseline}|}{|\text{baseline}|} \tag{3}$$

An average is created across trials. An exponential decay function is applied to the average, to generate the PDS, ranging from 0 to 1, using Equation 4:

$$\textit{PDS} = \exp(-\alpha \cdot \textit{relative deviation}_{\textit{mean}}) \tag{4}$$

where α is a sensitivity constant, of value 10, controlling how rapidly the metric r decreases as deviations increase. This enabled greater clarity and resolution when plotting.

The path deviation score, PDS, normalises all values across a range of 0-1, critically regardless of the total distance pushed, allowing comparison across all trials. This score can be visualised in Figure 2. The direction of deviation is irrelevant, however in the event of a system bias (eg a tendency to deviate left) this would not be conveyed. This metric also enables filtering of random/small disruptions, for example due to camera shake.

2) Mass per Robot: The relative mass of the box is found by dividing the absolute mass of the box by the number of robots pushing it. This is to enable easier comparison across experiments and trials.

3) Average Bumper Sensor Reading: The magnitude of the calibrated bumper sensor readings from each time stamp are averaged across a single trial. The left and right sensor readings are averaged to produce one singular bumper sensor reading for each time stamp, with this value then averaged across all time stamps of the trial, producing one average bumper sensor reading per robot per mass.

4) Frequency of Correction: The frequency of correction is extracted from the raw PID demand data, by identifying when the left and right wheels felt a change in PID, which would only occur when the difference between left and right bumper sensor readings was greater than the threshold value (0.1). The frequency per trial was averaged for each mass. It simply a unit-less measure of the number of corrections per trial, to provide insight into the correcting and dynamic ability of the systems, and enable direct comparison due to the controlled time duration of all trials (15 seconds).

IV. RESULTS

A. Baseline Experiment - No Bumper Sensing

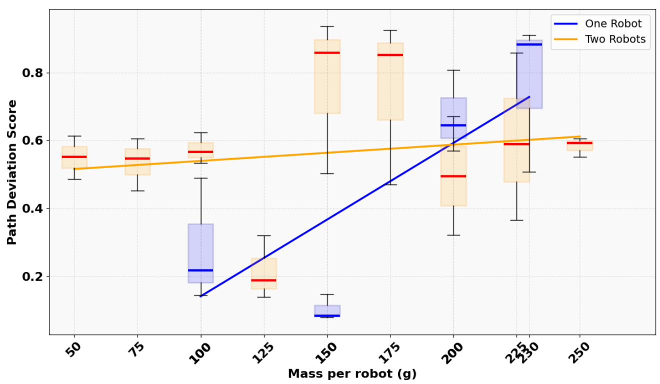

Fig. 3: Plot showing the path deviation score of the box pushed, across a range of masses, for one and two robots

A shown above in Figure 3 the pushing performance increases with mass for both one and two robot systems.

One robot shows a four-fold increase in pushing ability across the range of masses, with an R^2 value of 0.671. The outlying data shown at 150g per robot could be due to systematic slip occurring between the box and robot bumper, or non-perfect incident collision angle resulting in an erroneous trajectory. Whilst this was attempted to be controlled for, a more precise determiner of "erroneous collision" beyond initial observation would enable greater insight. More repeats would be needed for further validation.

Two robots shows a weak trend between path deviation and increase in mass; overall a 20% increase in median performance of the system improves, with an R^2 value of 0.042. Ultimately mass appears to play a less significant role in performance with the two robot system.

In general, the two robot system performs better across the overall range of masses, with a complete average performance of 0.56 vs 0.46 for one robot. However specifically, at an absolute mass of 200g, the one robot system performs better than the 2 robot system, with a median PDS score of 0.65 vs 0.56 respectively. Furthermore, for a relative mass (i.e. mass per robot) of 200g and more, the single robot outperforms the two robot system.

B. Feedback Enabled - BSF

For one robot, there remains a strong correlation between mass and performance. The bumper feedback appears to dampen the impact of mass seen in Figure 4, with the gradient decreasing from 0.004 to 0.0015. However, the large range seen at 230g per robot undermines the certainty of this trend, indicating more trials are required. Indeed, in general for one robot, the BSF system experiences greater variation in performance at each mass.

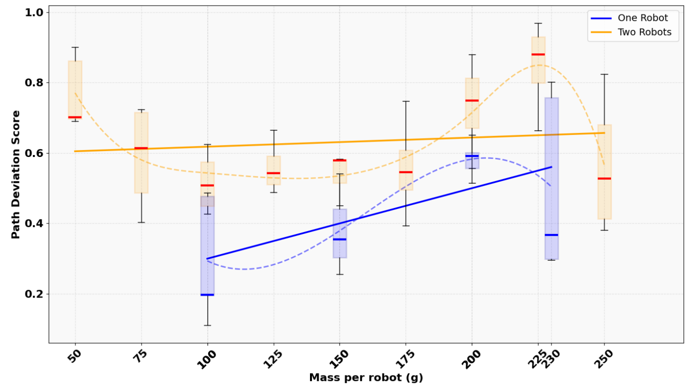

Fig. 4: Plot showing the path deviation score of the box pushed, across a range of masses, for one and two robots

The two robot system remains superior at all relative masses, showing a small increase in performance with mass. This is most noticeable across the range 100 to 225g per robot, but the data at the extremities undermines the strength of the assertion that performance improves with mass. It would be worth investigating the performance of one robot across the range 50-100g, to determine whether the upward trend at the lowest masses holds across both systems. As this initial downward curve is not experienced within Figure 3, it suggests that the BSF is the causal mechanism. The mean performance of two robots across all masses is also greater (0.64) compared to the baseline system.

As before, one robot outperforms two at an absolute mass of 200g. This is better illustrated in Figure 5. A cubic and linear line of fit, of R^2 value 0.9 and 0.6 respectively, were found. The cubic, with the greater correlation, was used to predicted the range of absolute masses one robot would outperform two: 185-225g. This is an almost identical range compared with the baseline system, where one robot is expected to be superior from an absolute mass of 185g-230g. More trials at a narrower mass increments would test this prediction.

In Figures 4 and 5, the system as a whole is highly variable across all masses, as shown by the large range and standard deviations. Both one and two robot systems experience a decrease in straight line pushing capacity at the maximum end of their movable mass (230g and 500g respectively). This could be due to the larger mass (and therefore greater inertia of the box) being less responsive to attempted corrections but not completed by the robot. However, this decrease in performance at the maximum mass is not observed within the baseline system and both show a large variance at the upper extremity, indicating further repeats would be worthwhile.

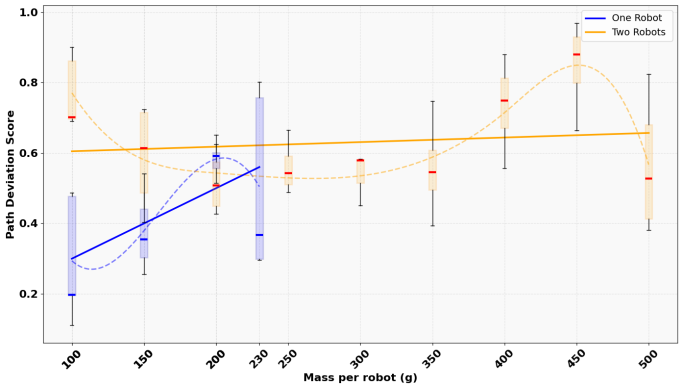

Fig. 5: Plot showing the path deviation against absolute box mass, for one and two robots

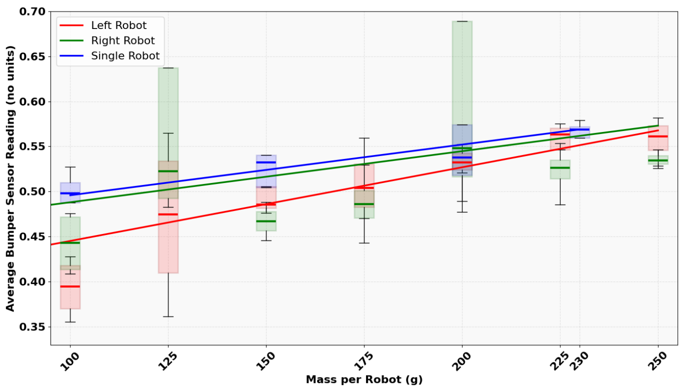

Fig. 6: Average bumper sensor readings against mass per robot

C. Bumper Sensor Reading & Correction Frequency - BSF

A random error, resulting in increased bumper sensor magnitude during non-contact was encountered, rendering the two robot, 300g box trial void and was excluded from the data. This was assumed to be a calibration error. As a result only four data points were plotted for magnitude and frequency.

Figure 6 shows that the average bumper sensor reading increases with mass for all systems. For one robot, this is strongly positively correlated with its overall performance shown in Figure 4, which can be quantified using an R^2 statistical test, producing a value of 0.88. However two robots shows no correlation between bumper sensor readings and performance, hence exhibiting a R^2 value of -0.08 and 0.03 for the left and right robots respectively.

It could be expected that the average bumper reading (per relative mass) is consistent across all robots, irrespective of number within the system, but this is not the case. The average bumper magnitude experienced between the pair of robots is less than the magnitude experienced by the single robot system. There may be some relation between the overall reduced bumper reading and the observation that a two robot system could move a greater normalised mass. This may be a feature of moments, as the pair or robots are pushing from a position further from the centre of mass, impacting the vertical force component felt.

At all masses (for a two robot system) there is a difference between median bumper magnitude between the right and left robots, although it appears random whether the larger magnitude for a given mass is experienced by the right or left robot. Given that a greater mass produces a greater bumper reading (as shown in Figure 1), this both implies that weight is not evenly distributed across the robots and that it is variable which robot provides greater pushing contribution, for each trial. This is likely resulting in dynamic instability. There appears no clear pattern relating difference in median bumper magnitude between the two robots, for a given mass, and the straight line pushing performance. This is surprising, as it could be expected that a system with less evenly distributed mass performs worse. However, the use of averages could obscure insight, as direct comparison between trials is prevented and remains an area for further investigation.

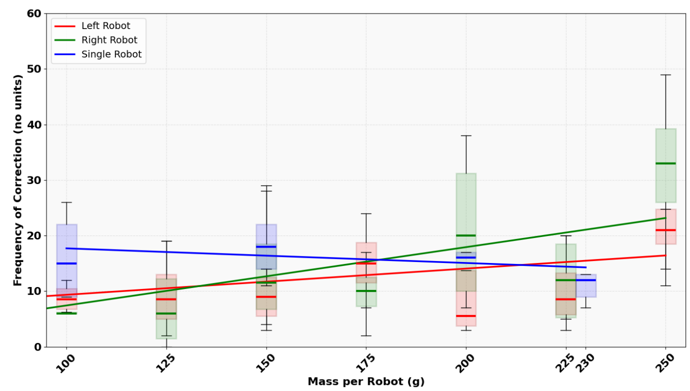

Fig. 7: Correction frequency against mass per robot

For one robot, there is minimal variation in median correction frequency across all masses (albeit a slight downward trend is observed), and minimal correlation between pushing performance and correction frequency. This holds with the suggestion that mass is the dominant factor for pushing performance with a single robot.

For the two robot system, both robots show an upward trend between frequency of correction and mass per robot, but no correlation was found between frequency and box pushing performance. At the lowest mass, both the frequency and average bumper sensor are low, yet correspond to a strong performance in box push (median PDS value of 0.72). Given that the average bumper magnitude is greater than the ”no sensing” value of 0.2 exhibited in Figure 1, it is assumed the robots sense the box throughout the trial. Therefore, it is most likely that the trajectory of the box path was straight and stable, hence the two robots did not need to correct, reinforcing the idea that a two point system enables greater stability.

V. Discussion

Hypothesis I

The pushing performance of one and two robot systems will increase as mass increases, because the system has reduced inertia and will be more stable. It is expected that two robots will have superior pushing performance than one, across the range of masses.

In general, the pushing performance of the baseline system, quantified by the PDS, increases with mass across both one and two robot systems. For the majority of normalised masses (relative to the number of robots), two robots are better than one. However, as at certain absolute masses (185-230g) and relative masses (200-230g per robot), a single robot pushed a box along a straighter trajectory. Therefore, hypothesis one does not hold in all cases.

Hypothesis II

It is expected that the addition of bumper sensor feedback enabled PID control will improve the pushing ability of one and two robots, compared against their baseline performance, by enabling dynamic correction to system instability. This relationship is expected to hold across a range of masses.

The addition of BSF fails to improve single robot performance. The large variation in all data points suggests more trials are necessary to draw a confident conclusion, however it appears to damp the impact increasing mass has on improving the single robot systems performance. However, for a two robot system, the pushing performance experiences an overall increase, most obvious within the range 125-225g per robot.

Across the range of masses shown, the pushing ability of one robot is superior to two robots at 200g. However, assuming sufficient accuracy of the trend lines, it is expected that for 185-225g, one robot will be better than two. Hypothesis two, therefore, is rejected.

Hypothesis III

The magnitude of the bumper sensor reading increases with mass. As the mass of the box increases, the system's pushing performance (whether one or two robots) is expected to increase, as a result of an increased frequency of trajectory correction due to the greater bumper sensor readings.

The pushing performance of a single robot improves as mass increases and, as expected, there is a strong correlation between the increase in bumper sensor magnitude and pushing performance. However, there is minimal variation in frequency of all trials, showing no correlation with box pushing ability. For two robots, there is a positive correlative relationship between correction frequency, bumper sensor readings.

On reflection, the third hypothesis assumes a causal relationship between box pushing ability and frequency of correction, yet, there is no evidence of causation for the implemented system. If the box is solely pushing along an ideal path, there is no deviation to detect and therefore no correction necessary, an idea supported by the performance of the two robots at 100g per robot. Frequency of correction is not a determiner of robot pushing performance and is not dependent upon the magnitude of the bumper reading. Ultimately hypothesis three must be rejected across both systems.

The role of mass, and subsequent effect on moments and force experienced by the system, is fundamental. Interestingly, the mass, in combination with the baseline PID system, may already behave as a feedback loop. When mass is unevenly distributed across the robot, one wheel will experience greater opposition to movement, causing a greater difference between the demand and current speed. Power is then increased, essentially causing a corrective mechanism, the effects of which will increase as the mass increases. Additionally, the forward bias of both the baseline and BSF algorithms implemented has a significant effect within the two robot system. In the instance that a significant portion of mass is distributed to one robot, it may lack the pushing force required to correct deviations despite detecting them, as its partner continues onward, leading to system failure. Therefore, alternative feedback-enabled partnership algorithms should be explored to enhance performance of two robot systems. Finally, addition of higher traction wheels, or rough surfaced bumpers would likely improve performance by reducing slip at points of contact.

VI. Conclusion

To conclude, this paper has investigated the relationship between mass and pushing performance of one and two robot systems, and the role of bumper sensor feedback enabled PID control. It was shown that, as expected, pushing performance for both systems increases with mass. However, at an absolute mass of 185-230g, a single robot performed better than two. This unexpected trend continued to hold even with the introduction of BSF, despite improving the overall performance of the two robot system.

It has also been shown that the sensory perception of a box is mass dependent, as expected. The implemented dynamic environmental feedback, when designed to produce greater pushing capacity, enables correction during error or slip. However, there is no causal relationship demonstrated between the magnitude of bumper sensor reading, frequency of a path correction and pushing performance.

Whilst, in general, a two robot system performs better than one, this is not always true. Appropriate characterisation of system capabilities, such as demonstrated here, enables the deployment of maximally efficient and reliable systems.

VII. Future Work

The dynamics of heterogenous control with sensory feedback requires further investigation. Further detailed investigation into the exact dynamics of the two robot system will enable more specialised and cooperative algorithms, informed by the information gleaned from a single robot pushing performance. Implementation of identical algorithms within a larger team (or swarm) remains a broad area for further investigation. More trials across 180-230g would increase certainty in the result that one robot with bumper feedback is superior to two across this range.

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