Calibrating Mixed Reality for Scalable Multi-Robot Experiments

Robotics Track

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ABSTRACT

When testing multi-robot teams, researchers are often forced to make a choice: test on real robots (where fidelity is high, but the number of actual robots is low) or test in simulation (where fidelity is low, but the number of robots can be large). This problem is acute for robots with sophisticated sensing and planning systems, where the cost of the robots rises in concert with their need for more realistic environments. We propose a mixed-reality testing framework in which real robots interact with virtual counterparts, allowing a large number of robots to interact in the environment with high fidelity. However, this creates a new problem: the simulated robots must behave like their real teammates. We consider the problem of calibrating the parameters of virtual robots so that the results of a mixed-reality experiment are representative of the performance of a real robotic team. In particular, we use virtual robots to elicit behaviors from physical robots in order to empirically measure their kino-dynamic characteristics.

KEYWORDS

Mixed Reality, Multi-Robot Experiments, Calibration

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1 INTRODUCTION

The development of robotic teams that can interact in the world hinges on the evaluation of the algorithms. However, researchers face choosing between experimenting with physical robots or simulated robots, which has important implications on the type and value of results produced by multi-agent team research [5].

Having a full-scale team of robots yields high-fidelity results. For results to have high-fidelity we mean that the outcome of the experiment closely relates to what will happen in the real-world. As robots leave the lab and go into the world, they need sophisticated sensors to handle the complexities of the environment, which leads to higher cost and maintenance. Real multi-robot teams are available when sufficient money and manpower exist [11–13], but it is often prohibitive to evaluate multi-agent team algorithms in the real-world.

The alternative to a robotic team is simulation, which can accommodate large number of agents while providing a safe mechanism for testing algorithms. The physics engines in simulators have improved over the last decade which, define the behavior of objects in a simulated world [3, 9]. Simulations often produce results that are low-fidelity when object models do not have the necessary detail.

We use a skid-steer robot and consequently, we will focus on system identifications for a skid-steer model. In Yu et al. [17] the authors model a skid-steer-wheeled vehicle and perform experimental verification of their model that uses a large number of parameters, ie: mass, coefficient of friction, rolling resistance, and many more. We propose a simplified model, instead of a full model, that allows us to perform a real-time calibration before a series of experiments is executed.

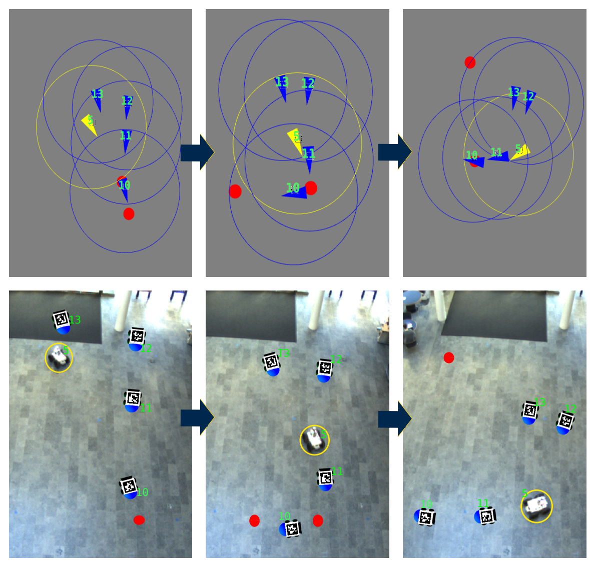

Figure 1: Calibrated Mixed Reality used for experimenting with follow the leader behavior. Top Row: Robot 10 is the leader in the simulated world. Bottom Row: Simulated agents are projected into the real world, Robot 10 is the leader. The red dots in the top and bottom images are waypoints for Robot 10 to follow.

In Honig et al., [6], mixed reality is defined as a world where in real time physical and virtual objects are able to interact and be dynamically aware of one another. They go on to describe a variety of benefits for mixed reality including, the use of larger testing spaces, increased safety, and scalability. Additionally, Chen et al. [4] propose mixed reality as a development platform for engineers to test interactions between robots and objects in the physical world.

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In this work we will focus on the scaliblity of mixed reality by proposing Calibrated Mixed Reality (CMR) as a way to experiment with large numbers of robots.

To have confidence in our results from CMR, we need a high fidelity representation of how a robot drives in the world. Using real-world data we perform a calibration to determine the values of key parameters of the virtual robots' model. This allows us to capture the kino-dynamic characteristics from the real robot to have our simulated robot perform similarly to its real counterpart. Other research areas have considered simulator calibration including embedded computer models [10], computer architecture models [2], airplane models[15], pedestrian tracking [8], and autonomous vehicles [1, 7] to name a few. Additionally, using data from the real world and adding it to mixed reality was explored in Quinlan et al., [14] with autonomous vehicles' crossing an intersection. Our calibration process happens in real-time as an initialization step for running experiments with CMR on any uniform 2D flat terrain. This allows experiments with CMR to go out of the lab and into real-world spaces to evaluate multi-robot team performance.

2 METHOD

Our mixed reality experiments are composed of $n \in \mathbb{N}$ agents, and must have the following: at least one physical robot, r_R, at least one simulated robot, r_S, a simulated world, $\mathcal{W}_S$, and a real environment, $\mathcal{W}_R$. We assume that $\mathcal{W}_S$ and $\mathcal{W}_R$ are free of obstacles, consists of one terrain, and are on a flat 2D plane. All agents, r_R and r_S, must be aware of interactions that occur in both $\mathcal{W}_R$ and $\mathcal{W}_S$. Interactions between agents consist of moving in accordance with the state of the world and in the pursuit of an overall goal. Our agents in CMR make observations about the world using global knowledge of the world, which is maintained by the simulator.

Each agent is composed of the following state vector:

$$r_R = r_S = \begin{bmatrix} x & y & \theta & \psi_L & \psi_R & \dot{\omega_L} & \dot{\omega_R} \end{bmatrix},$$

where ψ_L and ψ_R are the left and right wheel velocities and $\dot{\omega_L}$ and $\dot{\omega_R}$ are the angular accelerations of the left and right wheels. This general representation of a robot's state in the world is the key to mixed reality.

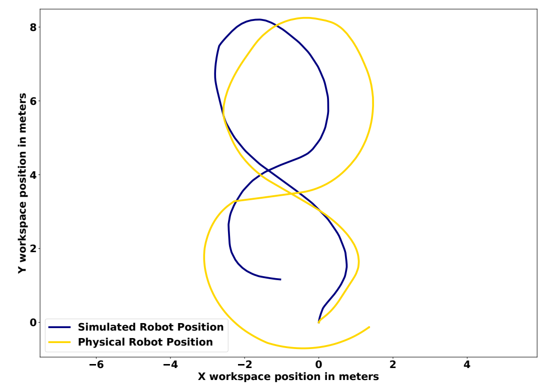
To calibrate our model we compute the kino-dynamics of r_R, such that we can inform our model of r_S to behave like r_R. We use a motor model which simplifies down to the following:

$$\dot{\omega_i} = \frac{K_2}{K_3}\mathcal{V}_i - K_1\frac{K_2}{K_3}\psi_i, \tag{1}$$

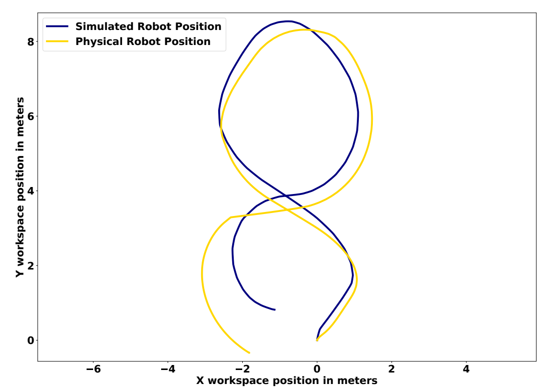
where $\frac{K_2}{K_3}$ and K_1 are physical constants and other modeled values from the robot driving, and $\mathcal{V}_i$ is the commanded current to the motor. Calibration starts at the same initial point for r_R and r_S. We perform numerical integration to solve for $\frac{K_2}{K_3}$, K_1, and b (the base width of the robot). We perform a grid search over the course of a calibration path, to find the best parameters to minimize the Euclidean distance between r_R and r_S at every time step.

3 RESULTS

Our mixed reality simulator was custom-built for CMR. We did this to maximize support for mixed reality and to ensure the right level of fidelity for our robot model. The physical robots that we used



(a) The path that a real robot (yellow) and simulated robot (blue) take without calibration.



(b) The path that a real robot (yellow) and simulated robot (blue) take with calibration applied to the model.

Figure 2: The calibration pattern performed to find our unknown parameters is a figure-eight to capture both left and right driving characteristics.

are four-wheeled robots that follow a skid-steer drive model. They have a Thinkpad T480, Velodyne VLP-16, and KVH Fiber Optic Gyroscope on board.

We execute a figure-eight pattern for our calibration. This allows us to see both the left and right driving characteristics when we do our calibration calculations. Results for before and after calibration while driving a figure-eight pattern are seen in Figure 2a and 2b.

4 CONCLUSIONS

Calibrated mixed reality is a solution for testing multi-agent team algorithms. Calibration found from real-world data and numerical integration allows simulated agents to perform realistically, relative to a real robot.

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REFERENCES

[1] J. Asamer, H. J. van Zuylen, and B. Heilmann. 2013. Calibrating car-following parameters for snowy road conditions in the microscopic traffic simulator VISSIM. *IET Intelligent Transport Systems* 7, 1 (March 2013), 114–121. https://doi.org/10.1049/iet-its.2011.0193

[2] M. Asri, A. Pedram, L. K. John, and A. Gerstlauer. 2016. Simulator calibration for accelerator-rich architecture studies. In *2016 International Conference on Embedded Computer Systems: Architectures, Modeling and Simulation (SAMOS)*. 88–95. https://doi.org/10.1109/SAMOS.2016.7818335

[3] S. Balakirsky. 2006. Usarsim: Providing a framework for multi-robot performance evaluation. In *In: Proceedings of PerMIS*. 98–102.

[4] I. Y. H. Chen, B. MacDonald, and B. Wunsche. 2009. Mixed reality simulation for mobile robots. In *2009 IEEE International Conference on Robotics and Automation*. 232–237. https://doi.org/10.1109/ROBOT.2009.5152325

[5] S. Dawson, B. Wellman, and M. Anderson. 2010. The effect of multiple robots on simulation accuracy. In *ICRA Workshop on The Role of Experiments in Robotics Research*.

[6] W. HÃűnig, C. Milanes, L. Scaria, T. Phan, M. Bolas, and N. Ayanian. 2015. Mixed reality for robotics. In *2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. 5382–5387. https://doi.org/10.1109/IROS.2015.7354138

[7] L. Jia, M. Lu, and J. Wang. 2011. Using real-world data to calibrate a driving simulator measuring lateral driving behaviour. *IET Intelligent Transport Systems* 5, 1 (March 2011), 21–31. https://doi.org/10.1049/iet-its.2009.0094

[8] Sujeong Kim, Stephen J. Guy, Wenxi Liu, David Wilkie, Rynson W.H. Lau, Ming C. Lin, and Dinesh Manocha. 2015. BRVO: Predicting pedestrian trajectories using velocity-space reasoning. *The International Journal of Robotics Research* 34, 2 (2015), 201–217. https://doi.org/10.1177/0278364914555543 arXiv:https://doi.org/10.1177/0278364914555543

[9] N. Koenig and A. Howard. 2004. Design and use paradigms for Gazebo, an open-source multi-robot simulator. In *2004 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) (IEEE Cat. No.04CH37566)*, Vol. 3. 2149–2154 vol.3. https://doi.org/10.1109/IROS.2004.1389727

[10] M. Lattuada and F. Ferrandi. 2010. Fine grain analysis of simulators accuracy for calibrating performance models. In *Proceedings of 2010 21st IEEE International Symposium on Rapid System Protyping*. 1–7. https://doi.org/10.1109/RSP.2010.5656414

[11] Francesco Mondada, Michael Bonani, Xavier Raemy, James Pugh, Christopher Cianci, Adam Klaptocz, Stephane Magnenat, Jean-Christophe Zufferey, Dario Floreano, and Alcherio Martinoli. 2009. The e-puck, a robot designed for education in engineering. In *Proceedings of the 9th conference on autonomous robot systems and competitions*, Vol. 1. IPCB: Instituto Politécnico de Castelo Branco, 59–65.

[12] Edwin Olson, Johannes Strom, Rob Goeddel, Ryan Morton, Pradeep Ranganathan, and Andrew Richardson. 2013. Exploration and Mapping with Autonomous Robot Teams. *Commun. ACM* 56, 3 (March 2013), 62–70. https://doi.org/10.1145/2428556.2428574

[13] J. A. Preiss, W. Honig, G. S. Sukhatme, and N. Ayanian. 2017. Crazyswarm: A large nano-quadcopter swarm. In *2017 IEEE International Conference on Robotics and Automation (ICRA)*. 3299–3304. https://doi.org/10.1109/ICRA.2017.7989376

[14] M. Quinlan, Tsz-Chiu Au, J. Zhu, N. Stiurca, and P. Stone. 2010. Bringing simulation to life: A mixed reality autonomous intersection. In *2010 IEEE/RSJ International Conference on Intelligent Robots and Systems*. 6083–6088. https://doi.org/10.1109/IROS.2010.5651993

[15] W. R. Scott, W. B. Powell, and H. P. SimÃčo. 2010. Calibrating simulation models using the knowledge gradient with continuous parameters. In *Proceedings of the 2010 Winter Simulation Conference*. 1099–1109. https://doi.org/10.1109/WSC.2010.5679082

[16] Tianmiao Wang, Yao Wu, Jianhong Liang, Chenhao Han, Jiao Chen, and Qiteng Zhao. 2015. Analysis and Experimental Kinematics of a Skid-Steering Wheeled Robot Based on a Laser Scanner Sensor. *Sensors* 15, 5 (2015), 9681–9702. https://doi.org/10.3390/s150509681

[17] W. Yu, O. Chuy, E. G. Collins, and P. Hollis. 2009. Dynamic modeling of a skid-steered wheeled vehicle with experimental verification. In *2009 IEEE/RSJ International Conference on Intelligent Robots and Systems*. 4212–4219. https://doi.org/10.1109/IROS.2009.5354381