

The Cambridge RoboMaster: An Agile Multi-Robot Research Platform

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Abstract. Compact robotic platforms with powerful compute and actuation capabilities are key enablers for practical, real-world deployments of multi-agent research. This article introduces a tightly integrated hardware, control, and simulation software stack on a fleet of holonomic ground robot platforms designed with this motivation. Our robots, a fleet of customised DJI Robomaster S1 vehicles, offer a balance between small robots that do not possess sufficient compute or actuation capabilities and larger robots that are unsuitable for indoor multi-robot tests. They run a modular ROS2-based optimal estimation and control stack for full onboard autonomy, contain ad-hoc peer-to-peer communication infrastructure, and can zero-shot run multi-agent reinforcement learning (MARL) policies trained in our vectorized multi-agent simulation framework. We present an in-depth review of other platforms currently available, showcase new experimental validation of our system’s capabilities, and introduce case studies that highlight the versatility and reliability of our system as a testbed for a wide range of research demonstrations. Our system as well as supplementary material is available online.¹

1 Introduction

Multi-agent robotics research necessitates robotic platforms that can be used as deployment testbeds for rapid development and evaluations [32, 16, 52, 6, 41, 8, 34, 38, 54, 43, 50, 28, 42, 7, 14, 11, 13, 27, 55]. The choices for such platforms are usually informed by several factors such as the configuration space of the problem, the number of agents involved, and the computational sophistication expected from each agent. For instance, small-scale robots, such as the Turtlebot [51], will frequently be limited in their agility of motion and are restricted in their onboard computing capabilities. On the other hand, while larger robots (Jackal [18] or AutoRally [53]) have greater maneuverability and can carry more compute payloads, operating multiple of them in smaller research spaces can be cost- and space- prohibitive. Successfully testing and developing multi-robot solutions requires platforms that strike a fine balance between these objectives.

¹ <https://proroklab.github.io/cambridge-robomaster>



Fig. 1. We show three snapshots of a swarm of five RoboMasters running a passage scenario [14], in which robots have to break and reestablish formation to move through a narrow constriction. On the right, we show a close-up of one RoboMaster equipped with an NVidia Jetson Orin NX and a forward-facing camera.

In this article, we present an agile and affordable system and platform, shown in Fig. 1 as a multi-robot team setup. Our system, an omnidirectional indoor ground robot based on the DJI Robomaster S1, is *affordable* (starting at USD 689 in the base configuration to USD 1633 with all sensors and an Jetson Orin NX), *agile* (we demonstrate indoor trajectory tracking capabilities of up to 4.45 m/s and accelerations of up to 5 m/s², *versatile* (we show experiments in classical control to zero-shot deployment of MARL policies trained in our simulator VMAS [10]), and is easily *replicable* (our entire stack is open-sourced, requiring minimal construction time). These have been made possible due to our retrofitting of the onboard compute module and careful reverse engineering of the main communication interface. We present two further contributions in this work. Second, through an expansive review of related systems and literature, we contrast our solution against others’ and position our system at the frontier of low-cost agile research platforms. Third, we describe enhancements to our prior work (VMAS [10]) that enable rapid deployment of control policies learnt in simulation onto this platform. We present evaluations and case studies that corroborate the claims presented above, and showcase the wide range of research avenues that this system makes accessible.

2 Related Work

In the last decade, a wide range of (multi-) robot platforms have been introduced to the research community. Here we present an in-depth literature review of commercial as well as research platforms. Our classification scheme will differentiate between them based on their dynamics (Ackermann, differential, and omnidirectional drive, as well as airborne/multirotor platforms), and also based on their specific use-cases in single- or multi-agent research. Since we are primarily interested in multi-robot research, we investigate the tradeoff between cost and speed of these platforms, as agility is an attribute we require in the team (note that we use ‘speed’ and ‘agility’ interchangeably – this is a justified simplification for indoor robots operating in confined spaces), and cost limits the size of the team.

Fig. 2 visualises our survey in a 2D plot, and Tab. 1 provides detailed statistics specifically for omnidirectional drive robots. We find that the majority

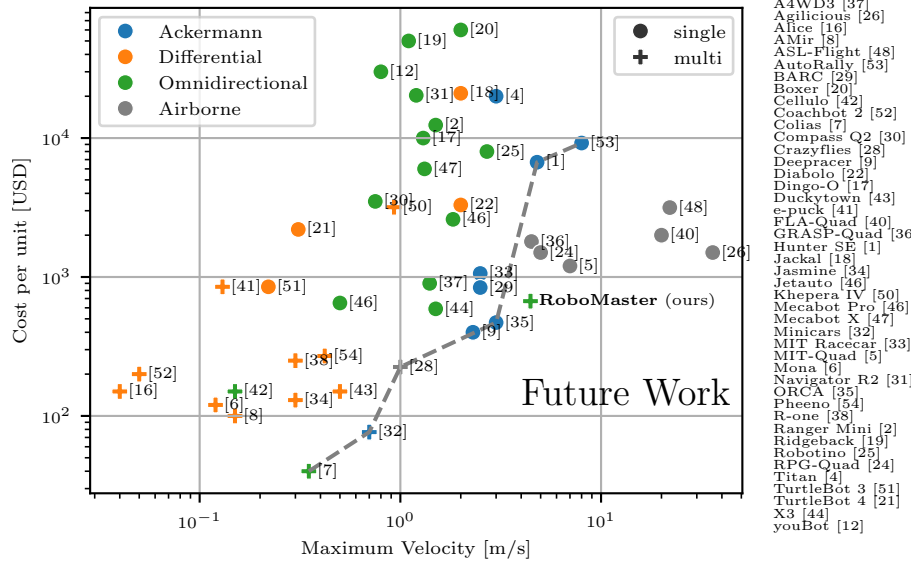


Fig. 2. We compare a variety of different research and commercial robotic platforms concerning their tradeoff between cost per unit and maximum velocity. We differentiate between Ackermann, Differential, Airborne and Omnidirectional platforms as well as between platforms specifically targetting multi-agent research. A clear correlation can be seen between speed and cost, as well as a trend for multi-agent platforms to be low-cost, but as a consequence slow. We draw the pareto front as a dashed line, with our proposed platform pushing the limits on the cost and speed tradeoff.

of multi-agent research platforms utilize differential drive [41, 34, 6, 43, 54, 38, 50, 8, 16], thus positioning them in the bottom left corner of Fig. 2. The reason is that such platforms tend to be designed to minimize cost, with 10s of such agents in mind. The slowest of these platforms is Alice [16] at 4 cm/s, and the fastest is the Khepera IV [50] with 0.93 m/s. Three ground-based platforms are specifically geared towards multi-agent research but use dynamics other than differential drive, specifically the Minicar [32], Cellulo[42], and Colias [7]. More recently, slightly faster commercial differential drive robots have become popular [18, 21, 51, 22], ranging from 0.22 m/s for the Turtlebot 3 [51] to 2 m/s for the Diabolo [22].

From the bottom left, we can see two clusters emerging towards the top and the right. The omnidirectional drive robots [17, 19, 25, 12, 31, 47, 30, 46, 46, 42, 7, 44, 20, 37, 3, 2] tend to move faster than differential drive, ranging from 0.15 m/s (Cellulo [42]) to 3 m/s [37], but are also significantly more expensive, with a mean cost of USD 14k.

Aerial platforms (such as multirotors) on the other hand are moderately priced at a mean of USD 1600, and can move at much higher speeds of up to 36 m/s (Agilicious [26]), but come with other disadvantages compared to ground robots, such as operational overheads like short runtime (minutes as opposed to

Table 1. We list critical specifications for omnidirectional robots from related work. ‘Multi-Agent’ indicates whether the platform is introduced as a multi-agent platform, and ‘Commercial’ indicates whether the platform can be obtained commercially.

Brand/Uni	Product	Vel [m/s]	Cost [USD]	Mass [kg]	L x B x H [mm]	Multi Agent	Commercial
EPFL	Cellulo [42]	0.15	150	0.18	73 × 80 × 80	✓	
Lincoln Uni	Colias [7]	0.35	40	0.01	40 × 40 × 40	✓	
Hiwonder	Jetauto [46]	0.50	650	4.00	324 × 659 × 260		✓
Hangfa	Compass Q2 [30]	0.75	3,500	16.00	430 × 330 × 115		✓
KUKA	youBot [12]	0.80	30,000	20.00	580 × 380 × 140		✓
Clearpath	Ridgeback [19]	1.10	50,000	135.00	790 × 960 × 310		✓
Hangfa	Navigator R2 [31]	1.20	20,300	35.00	520 × 480 × 240		✓
Clearpath	Dingo-O [17]	1.30	10,000	13.00	680 × 510 × 111		✓
RoboWorks	Mecabot X [47]	1.32	6,000	20.50	630 × 581 × 203		✓
Lynxmotion	A4WD3 [37]	1.40	900	5.55	372 × 374 × 152		✓
RDK	X3 [44]	1.50	590	1.93	181 × 236 × 185		✓
Agilex	Ranger Mini [2]	1.50	12,400	64.50	500 × 738 × 338		✓
RoboWorks	Mecabot Pro [46]	1.83	2,600	10.80	541 × 581 × 225		✓
Clearpath	Boxer [20]	2.00	60,000	127.00	550 × 750 × 340		✓
Festo	Robotino [25]	2.70	8,000	22.80	450 × 450 × 325		✓
Cambridge	RoboMaster	4.45	670	3.00	240 × 320 × 200	✓	✓

hours) or more challenging infrastructure needs (recovery and safety mechanisms and the availability of accurate indoor tracking). These issues become particularly noticeable and more pronounced when developing multi-agent systems – the feasibility of an experiment depends on all robots concurrently operating without faults and risks. In a multi-robot system, individual robots requiring additional operator attention and overhead can thus pose a significant barrier to rapid deployment and testing.

To the right of the plot, we observe a cluster of Ackermann drive robots [4, 33, 29, 35, 32, 9, 53, 1]. These platforms move from top speeds ranging from 0.7 m/s for the Minicar [32] (USD 76.5) to 8 m/s for the AutoRally [53] (ca. USD 10k), with an average of USD 4850. While some of these platforms are agile, they tend to be expensive and not suitable for constrained indoor spaces.

Our solution sits at a frontier beyond which agility (speed) is attained only by aerial platforms, and a lower cost is only attained by sacrificing agility. Furthermore, as we will describe in later sections, our software stack supports a wide range of relevant research problems, and has a proven track-record throughout six previous publications over the last three years [14, 11, 13, 27, 55, 15].

3 Technical Details

This section details the background and design decisions made when developing our robot platform. We also cover all the supporting network, control and simulation infrastructure that complement it, and thus enable rapid experimentation.

3.1 Platform

We selected the DJI RoboMaster S1 as our platform’s base, leveraging its design inspired by the RoboMaster competition—a DJI initiative to foster technological

exchange and innovation among regional universities [45]. The S1, an educational robot, integrates a tank-like structure with a spring-dampened beam axle front suspension and a four-wheel omnidirectional drive system, and is designed for indoor use. It features a gimbal-mounted blaster toy gun and an onboard computer. DJI specifies the base platform’s maximum speeds as 3.5 m/s forward, 2.5 m/s backward, 2.8 m/s laterally, and 600 deg/s rotationally, with a weight of 3.3 kg (note that as part of our contribution, we side-step these manufacturer-imposed restrictions). Each wheel has a diameter of 100 mm, is powered by a brushless motor with integrated gears and a driver and supports closed-loop speed control up to 1000 RPM and a maximum torque of 0.25 Nm. This gives the platform a theoretical maximum speed of $(\pi \cdot 0.1 \text{ m} \cdot 1000 \text{ RPM}) / (60 \text{ s/M}) = 5.23 \text{ m/s}$. The system is powered by a 25.91 Wh smart battery, offering 2.4 Ah capacity. [23].

The onboard computer interfaces with a sub-controller, managing all sensors and wheels. We replaced the onboard computer, gimbal, and blaster gun with a custom computing solution. We laser-cut components from acrylic to mount our custom expansion in place of the turret. All our design files are also part of our open-source release.²

3.2 Compute

The stock onboard compute module on the RoboMasters is impractical for running custom algorithms or implementing additional interfaces to cameras, sensors, networks, etc. We therefore upgraded the onboard computer to a more powerful and versatile single board computer (SBC), focusing on the NVidia Jetson Orin family for its recency and lifecycle availability until January 2030³. While the Jetson Orin NX 16GB was selected for its robust processing capabilities and suitability for our research, our design easily admits other cost-effective single-board-computers such as the Raspberry Pi. The Jetson Orin series necessitates a carrier board. Our choice, the AverMedia D131 carrier board, was influenced by the availability of a CAN interface – essential for communicating with the RoboMaster subcontroller – and an optimal balance of interface availability and cost. It accommodates two PCIe M.2 slots, where we installed a 256 GB SSD and an Intel 9260 WiFi module. In an alternative Raspberry Pi setup, on the other hand, we used the built-in ports and interfaces and added an additional CAN shield for communication with the RoboMaster base.

3.3 CAN Communication

DJI offers an API for the RoboMaster EP, the educational counterpart to the RoboMaster S1, which enables control via a secondary computer (e.g., a Raspberry Pi) through USB. However, this platform is not listed for sale on the DJI store, is unavailable in many parts of the world (including the UK), and at around USD 1500, is significantly costlier than the S1 model. The API, which DJI

² <https://github.com/proroklab/cambridge-robomaster>

³ <https://developer.nvidia.com/embedded/lifecycle>, accessed 24/02/22

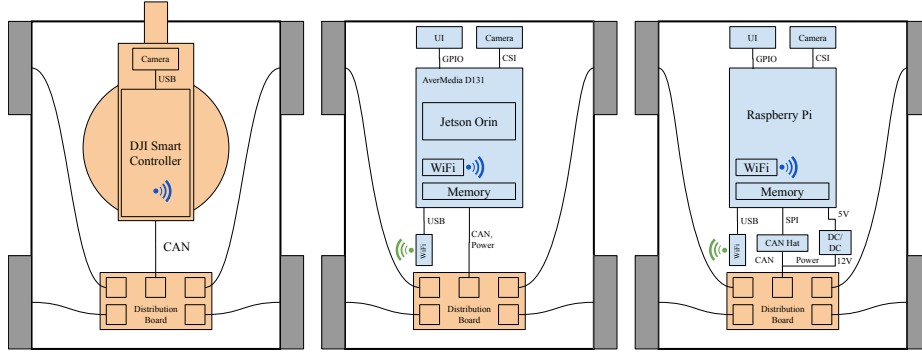


Fig. 3. We modify the RoboMaster S1 Platform by removing the USB Camera, Smart Controller, Blaster and Turret and by replacing them with either a Jetson Orin on an AverMedia D131 carrier board or a Raspberry Pi. The platform is equipped with two WiFi modules, one for infrastructure communication (dark blue) and one specifically chosen for ad-hoc peer-to-peer communication (green).

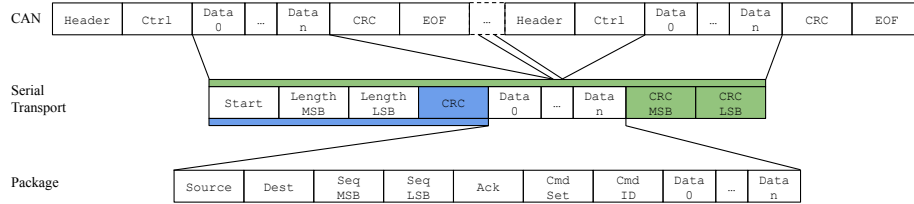


Fig. 4. The CAN-based protocol used in the RoboMasters. DJI uses CAN as transport layer to allow multiple connected devices on the bus to broadcast information. Due to the limited length of CAN frames, a serial transport protocol is built on top, with a higher-level package definition permitting publisher/subscriber-type communication architectures.

has made open-source⁴, served as the foundation for our reverse engineering of the communication protocol between the main computer and the sub-controller. DJI employs Controller Area Network (CAN) for hardware layer transport but overlays it with a simplified serial package-based protocol. This design likely addresses the limitations of CAN’s 8-byte data size per packet while facilitating multi-node network connectivity, leveraging CAN’s collision and arbitration management capabilities. We outline the protocol’s structure in Fig. 4, noting its use of a higher-level transport layer to specify node source and destination IDs, sequence counters for package tracking, various command sets and IDs, and acknowledgments, enabling subscription to specific package IDs for continuous data stream over the network. We release our C++ implementation of the messaging protocol as stand-alone repository.⁵

⁴ <https://github.com/dji-sdk/RoboMaster-SDK>, accessed 03/19/24

⁵ https://github.com/proroklab/robomaster_sdk_can

Table 2. We provide a cost breakdown for six different compute and sensing configurations for our platform at the time of paper writing. Optional equipment, such as sensors, are put in parenthesis. All costs are stated in USD.

Item	Raspberry Pi	Orin Nano	Orin NX
Robot Base: RoboMaster S1	549	549	549
Compute	55	255	670
Carrier: AverMedia D131		185	185
WiFi: Intel 9260		15	15
Mem: Micron MTFDKBA256TFK		65	65
Mem: SD Card 256 GB	30		
Infrastructure: DC/DC Converter	20		
Infrastructure: Waveshare CAN Hat	15		
Infrastructure: Acrylics	10	10	10
Infrastructure: Mounting	10	10	10
Infrastructure: OLED Display	(10)	(10)	(10)
WiFi: Netgear A6210	(50)	(50)	(50)
Sensing: Pi HQ Camera	(50)	(50)	(50)
Sensing: Fisheye Lens	(20)	(20)	(20)
Total Base	689	1089	1504
Total Optional	(819)	(1219)	(1633)

3.4 Infrastructure

Here we describe components of our supporting infrastructure, each of which is a product of over 4 years of refining and development. The high reliability of these subsystems has been vital to our work in deploying multi-agent research. We provide a high-level overview of the infrastructure in Fig. 5

Wireless Communication. Our system employs dual network interfaces to facilitate distinct communication channels: a backbone *infrastructure* network for all participating systems, and, an *ad-hoc* network exclusively for inter-robot communication. For infrastructure-related communication, we utilize an Intel 9260 PCIe module for the Jetson and the integrated WiFi module for the Raspberry Pi that connects to a central WiFi router (described below). This setup integrates with broader infrastructure components, such as desktop systems operating the Multi-Robot Manager UI, a motion capture system, and essential hardware like an emergency-stop button. This network also allows for SSH access into the robots, file sharing, and centralized ROS messaging. In scenarios requiring only centralized control, a desktop machine executes our entire control stack (*Freyja*, described later) for each robot, and transmits low-level wheel commands to each robot via ROS2.

Conversely, for direct robot-to-robot communication, we use Netgear A6210 USB3.0 modules to establish an adhoc multicast network. This configuration does not rely on external infrastructure, enabling seamless peer-to-peer network interactions.

Network. The deployment of an enterprise-grade router proved crucial for centralized robot operation. We opted for a Mikrotik Router, selected for its superior configurability and flexible antenna setup. We employ a structured IP assignment strategy within the 10.x.y.z address range across all devices, and bridge

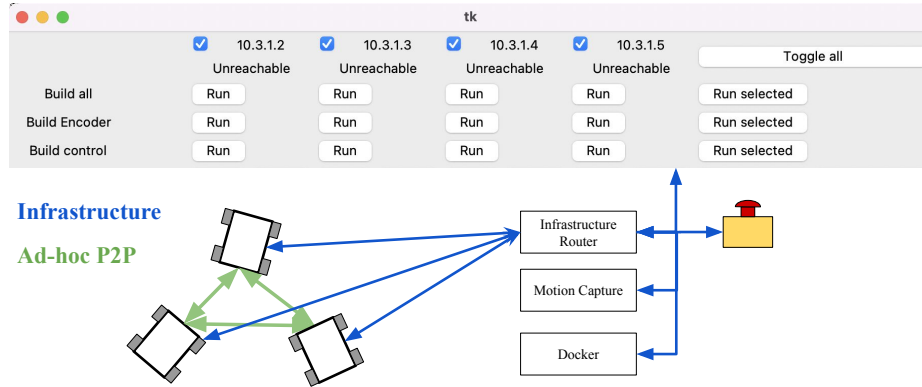


Fig. 5. We utilize two wireless networks, one for infrastructure (blue) and one for ad-hoc peer-to-peer communication between agents. The infrastructure network is used to communicate with fixed infrastructure. The multi-agent user interface to control multiple agents efficiently is displayed in the top. The ad-hoc network is used for experiments requiring decentralized communication.

appropriate subnetworks that contain different categories of devices (robots, computers, guest-devices, etc).

Our router and ad-hoc setups typically operate at a broadcast channel capacity of 26 Mb/s, and we typically observe around 1 Mb/s network load when operating 5 robots concurrently in a centralized mode (transmitting wheel velocity commands to each robot at 50 Hz).

Emergency Stop. Crash prevention is a priority in high-velocity multi-robot experiments, and can be particularly complex to implement in a fully decentralized framework. Inevitable system latencies in re-establishing SSH sessions and the finite interval between terminating a control process and robot immobilization necessitates a more reliable stop mechanism. Consequently, we integrate an emergency stop service into our RoboMaster ROS driver, accessible via the infrastructure network, that immediately halts velocity commands at the lowest level. Additionally, we developed a stand-alone physical emergency stop button, powered by a Raspberry Pi Zero. This button connects to the infrastructure network and features color LEDs to display the connectivity and status of the robots.

On-Robot User Interface. Incorporating on-robot displays has proven advantageous, especially for operations outside the conventional laboratory setting where an infrastructure network may be absent. These displays, compact and economical at 128×64 pixels, present vital statistics including CPU and memory usage, CPU temperature, network details (such as IP addresses and interface connectivity), battery status, and the robot’s hostname. An integrated button allows users to navigate through different information pages and, crucially, activates the emergency stop service if the robot is in motion. This feature is

particularly useful in field deployments, offering a direct control and monitoring mechanism when network access is unavailable.

ROS2 Drivers We implemented a custom ROS2 Driver that accepts both high-level velocity commands in the robot’s body frame as well as low-level wheel speed commands. We use `systemd` to start these drivers automatically during the system boot to make the experimental setup seamless.

Decentralized Deployment For deploying code across multiple robots, we utilize the infrastructure network, employing `rsync` over SSH to synchronize updates from a central workstation to each robot. We extensively leverage Docker containers to remove experimental cross-interference among different users and setups. This approach is particularly beneficial on the NVidia Jetson platform, for which an extensive library of pre-configured containers is available. These containers include environments for ROS, ROS2, PyTorch, and various other learning frameworks, either standalone or in combination⁶. Docker is also configured to manage local image repositories within the infrastructure network, facilitating efficient image sharing among robots.

Multi-Robot User Interface We developed a configurable Python-based User Interface (UI) operated from a workstation linked to the infrastructure network. This UI facilitates connections to multiple nodes through SSH and supports scripting through a configuration file. It is designed to automate the parallel execution of repetitive commands that normally need to be executed in different terminals on different devices, thus significantly reducing the manual overhead associated with logging into individual robots, sourcing workspaces, and running launch files, especially when identical commands are required on multiple robots. A snapshot of the UI is shown in Fig. 5.

3.5 Sensors

Our platform is equipped with an array of exteroceptive and proprioceptive sensors, supported by ROS2 drivers for seamless integration.

Proprioceptive The DJI RoboMaster features an onboard suite of sensors including a 3D attitude sensor, wheel encoders, body velocity sensors, and battery level sensors, all accessible through the CAN interface.

Exteroceptive The D131 carrier board accommodates two camera CSI inputs. We utilize this capability by attaching a Raspberry Pi HQ camera, equipped with a fisheye lens, delivering a rectified image with a 120° field of view (FOV) using OpenCV. Additionally, the RoboMaster is outfitted with physical bumper sensors for enhanced interaction with its environment.

3.6 Control: Freyja

A necessary step in successful multi-robot deployments is the dependability of individuals to track their target trajectories accurately. Towards this end, our on-board control stack, *Freyja* [49], comprises of an optimal feedback controller and

⁶ <https://github.com/dusty-nv/jetson-containers>, accessed on 20/03/2024.

a library of state filters developed entirely in C++ over the ROS2 middleware. The model-based controller is a linear quadratic regulator (LQR) that regulates the position and velocity of the robot along a trajectory by commanding wheel speeds for the low-level driver. Denoting $\mathbf{x} \equiv [\vec{p}, \vec{v}]^\top$ as the state variable (with $\vec{p}$ and $\vec{v}$ as the world-frame position and velocity vectors), we can write a dynamic model for the system as $\dot{\mathbf{x}} = A\mathbf{x} + B\mathbf{u}$, where A and B are system matrices, and $\mathbf{u}$ is the applied control input. Then, for some reference state $\mathbf{x}_{\text{ref}}$, it is possible to design a matrix K for the control law, $\mathbf{u} = -K(\mathbf{x} - \mathbf{x}_{\text{ref}})$ that stabilizes the system to that (possibly time-varying) reference state.

3.7 Simulation: VMAS

Simulation is essential in multi-robot research as it enables safety and efficiency in data collection for machine learning pipelines. State-of-the-art simulators employ GPU vectorization to massively parallelize this process [39], leveraging the Single Instruction Multiple Data paradigm. Towards this end, we provide a model for the RoboMaster platform in the Vectorized Multi-Agent Simulator (VMAS) [10]. VMAS is a simulator consisting of a PyTorch differentiable physics engine and a set of challenging multi-robot tasks. Thanks to this, it is possible to rapidly train and deploy multi-robot policies from the simulator to the real world in a zero-shot manner, as demonstrated in previous work [11] (video here).

To enable this deployment pipeline, we integrated several new features into the simulator. Firstly, to generate the $\vec{v}_{\text{ref}}$ input required by Freyja, we implement a PID controller layer that regulates the input forces required by VMAS based on these reference velocities. This layer allows us to train neural network policies that output desired velocities $\vec{v}_{\text{ref}}$ and directly use them on our physical platform, without any change. Secondly, a key to the real-world deployment was an iterative fine-tuning process for some of the physics parameters in VMAS. These are parameters that depend on the robot platform and its interaction with the environment, such as: friction coefficients, drag, control ranges, state boundaries, and robot geometry. This tuning process can be done once for each robot-environment pair and can be then utilized for any subsequent deployments.

A model for the RoboMaster platform in VMAS enables applications beyond prototyping in simulation and deploying in the real world. For instance, thanks to the accelerated compute available on our platform, policies trained in VMAS on approximated representations of the environment can be fine-tuned on the robot using data collected in the real world.

4 Evaluations

We now demonstrate the characteristics of our platform and the supporting suite of software framework through a wide range of experiments. These explore the versatile and diverse nature of studies that this platform enables, such as,

- running classical model-based control (Freyja) for agile trajectory tracking,
- zero-shot sim-to-real transfer of multi-agent navigation tasks learnt in VMAS,

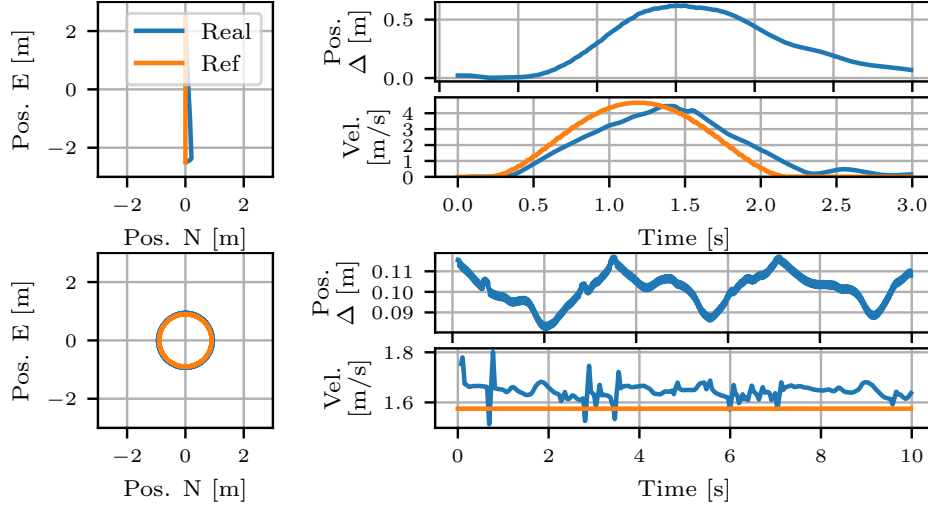


Fig. 6. We demonstrate the efficiency of our platform combined with the Freyja controller suite in two single-agent trajectory tracking experiments, in a straight line trajectory (top) and a circular trajectory (bottom). We report the reference position and velocity (orange) and measured position and velocity (blue) as well as the tracking error dp over time.

- running distributed visual SLAM onboard to track relative position and thus avoid collisions, and,
- utilizing large neural networks based on the DinoV2-s architecture to estimate relative poses and then track trajectories.

Finally, we summarize prior work from our research group that utilizes this platform for real-world deployments of multi-robot systems research.

Classical Trajectory Tracking. We first demonstrate the agility of our platform in a single-robot experiment in which we benchmark the tracking performance of Freyja as well as the velocity of our robot platform at high speeds. We demonstrate this on a straight line trajectory and a circle trajectory in Fig. 6. The straight line trajectory has a length of ca. 5 m, and the circle trajectory a diameter of 1.5 m. We show that the robot reaches a top velocity of 4.45 m/s, thus exceeding the maximum rated speed of the DJI RoboMaster platform by 1.15 m/s, and accelerations of up to 5 m/s^2 in the straight line trajectory with a maximum error of 0.5 m, and maintains a velocity of 1.7 m/s on the circle trajectory with an average error of 0.1 m. In the line trajectory, we are constrained by the size of the laboratory, which prohibits the robots from going faster.

Sim-to-real Multi-Agent Navigation. We now demonstrate zero-shot deployment of MARL policies for a multi-robot navigation task trained in VMAS [10] following the pipeline described in Sec. 3.7. Agents are rewarded for navigating

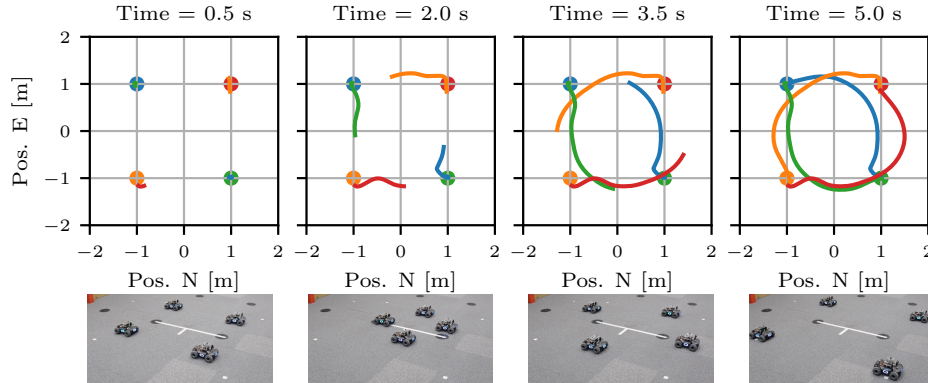


Fig. 7. We showcase our sim-to-real capabilities on a MARL position swapping policy trained entirely in VMAS [10]. Four agents (color-coded) start at the corners of a $1\text{ m} \times 1\text{ m}$ square and attempt to swap positions with the diagonally opposite agent, which leads to a necessary conflict at the origin. The lines indicate their trajectories up to a particular time point, and circles indicate their corresponding goals. Agents are able to seamlessly execute the learned policy in the previously unseen real-world environment. We show snapshots from the real-world setup in the bottom.

to their goal while avoiding collisions with each other, to do so they use the GPPO model ([11]), which leverages a Graph Neural Network (GNN) in the policy for inter-agent communication. The GNN utilizes a 5-layer MLP with a total of 2300 trainable parameters, which can be evaluated on the Jetson Orin NX in 0.5 ms. The results, reported in Fig. 7, show that the agents are able to seamlessly execute the learned policy in the previously unseen real-world environment.

Distributed Visual SLAM. In this demonstration, we showcase the system’s ability to run a decentralized visual SLAM system locally onboard using the optionally attached Raspberry Pi HQ cameras. Our collaborative SLAM system enables the agents to share a *unified* map of the world, thus facilitating relative positioning even when their views do not overlap, and even when the other agent is not explicitly detected in view. To validate the quality of this shared map, we use a nonlinear model predictive controller avoid collisions with both peers and static obstacles. Fig. 8 tests a collision avoidance scenario at an intersection, where two robots (traveling along the horizontal and vertical axes) would nominally collide at the intersection. However, they are able to localize each other close to the origin when common features are available in the environment, and the robot traveling along the vertical axis is able to slow down to avoid colliding.

Multi-robot control using CoViS-Net Foundation Model. In this experiment, we deploy our CoViS-Net foundation model [15], a pre-trained Neural Network to estimate relative poses between two camera frames, on two different

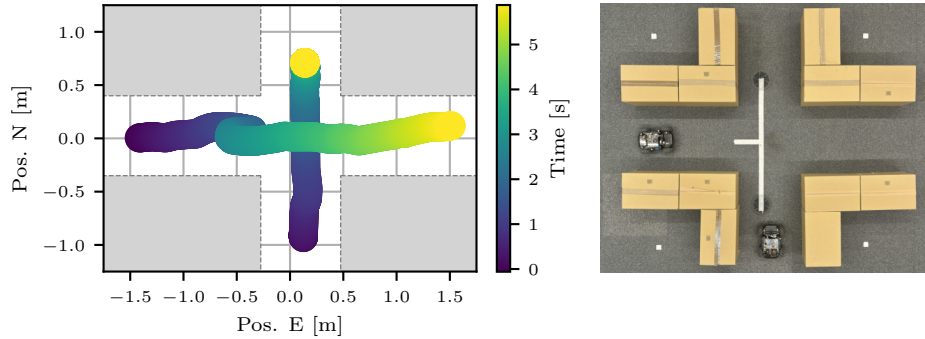


Fig. 8. We demonstrate multi-agent collision avoidance, facilitated by a distributed visual SLAM system running locally on the robots. Two robots are set 90° to each other in an intersection environment (right). The agent travelling along the E axis is given a goal pose on the other side of the intersection, and successfully avoids a collision when the agent travelling along the N axis is pushed through the intersection. The trajectories generated by the SLAM system are presented on the left chart.

robots. The camera images of two robots are encoded, and the features are broadcasted over the ad-hoc network to other robots within communication range. A second model then compares the features in the image to predict the relative pose, which is then used to track a trajectory using Freyja. In this setup, we use two robots, one that serves as origin for the reference coordinate frame of the other robot, which is commanded to move along a shifted circle trajectory. The result, visualized in Fig. 9, shows that we are able to move with a velocity of about 1 m/s on the circle, with an average estimated error of 0.25 m. Our model uses the DinoV2-s base neural network with 21M parameters, which we are able to run in 20 ms on the Jetson Orin NX after optimising with NVidia TensorRT.

Case Studies. Our system has reached this level of maturity over the course of several iterations of research and development in the last four years. Apart from the capabilities demonstrated above, this framework has featured as a primary research platforms in several prior multi-agent work from our group:

- *Multi-agent passage scenario*, where five RoboMasters navigate through a narrow passage, coordinated by onboard decentralized homogeneous GNN [14];
- *Real-world HetGPPO*, where heterogeneous GNNs trained in VMAS deployed on RoboMasters demonstrate superior resilience to real-world noise [11];
- *Visual Navigation*, where a RoboMaster navigates an environment guided entirely using visual sensors and a policy trained in simulations [13];
- *CBFs for multi-agent control*, where four RoboMasters use a control barrier function based GNN strategy to navigate [27]; and,
- *Single-agent search & navigation*, where LQR, CBF and RRT* are combined for safe and optimal single-robot motion planning [55].

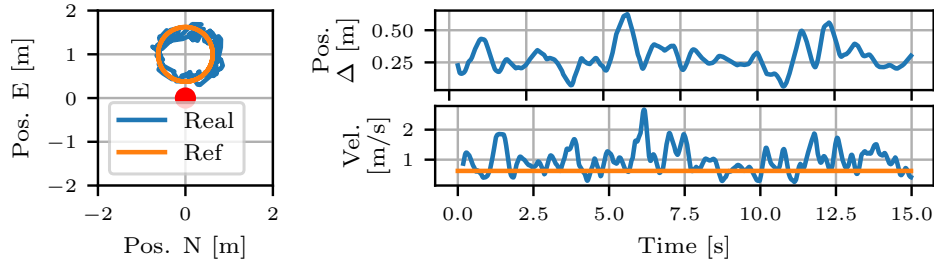


Fig. 9. The decentralized trajectory tracking tracks a reference trajectory relative to a stationary robot (red dot), based on the relative poses estimated by a pre-trained neural network that only utilizes features of the environment itself. We run this Neural Network on-board, in real-time. The position error and velocity is estimated from the predicted poses.

- *Deployment of multi-agent foundation models*, where up to four RoboMaster estimate the relative pose to perform decentralized formation control in real-world scenarios [15].

5 Conclusion

This article introduces a versatile omni-directional ground robot system that is based on extensive modification and enhancement of the original DJI RoboMaster S1 platform. We significantly extend the capabilities of the base platform by providing multiple options for more flexible and powerful compute solutions, on-board sensors, model-based control, and sim-to-real capabilities for distributed RL policies. After an intensive research and development pipeline over four years, our full platform (hardware and software) now serves as a highly reliable testbed well-suited for a wide range of experiments. We showcase its capabilities through four new evaluations, and refer to five case studies from prior work that point to its proven track record.

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