NomadZ Call For Participation 2025

Axel Wagner[1,2], Qingyi (Molly) Sun[1,3], Arka Mitra[1], and Zichong Li[1]

[1] ETH Zurich, Rämistrasse 101, 8092 Zürich, Switzerland
[2] Automatic Control Laboratory, Physikstrasse 3, 8092 Zürich
[3] Computer Vision and Learning Group, Universitätstrasse 6, 8092 Zürich
[4] NCCR Automation, Physikstrasse 3, 8092 Zürich

Abstract. NomadZ is a student team affiliated with ETH Zürich, working on Nao V6 for playing soccer in the Standard Platform League of Robocup. In RC25, we plan to deploy our improved ROS2-based framework, which would represent an important contribution for the whole league due to the virtually unbounded potential and countless opportunities for further pursuit.

1 Team information

We are Team NomadZ [5] from ETH Zürich. The team was founded in 2012 by the Computer Vision Lab (CVL) and the Automatic Control Laboratory (IfA) of the Department of Information Technology and Electrical Engineering. Our team is composed of 10 students and alumni who work together to develop the main football framework, while academic projects run to investigate advanced research questions. The academic projects can last between 280 to 400 hours depending on the amount of credits they provide, and are managed by scientific supervisors: Dr. Raffaele Soloperto from the Automatic Control Lab (IfA) and Yan Wu from the Computer Vision and Learning Group (VLG). Professor John Lygeros (IfA) and Professor Siyu Tang (VLG) officially head the organization, which is supported by NCCR Automation.

Our team currently has 10 NAO V6. However, we are planning to bring only 6 due to poor hardware conditions and warranty issues. The robots are used during competitions as well as for public events. At Robocup 2025, we wish to participate in the soccer tournament, Challenge Shield, due to the limited number of reliable robots.

2 Code Usage

Until 2023 we competed with our legacy codebase, which was based on B-Human's 2013 code release. In the last few years, however, we have been developing a new robot soccer framework based on ROS 2 which was intended to

[5] Website: https://nomadz.ethz.ch/
Teamleaders: Axel Wagner, Qingyi (Molly) Sun
Video Presentation: `https://youtu.be/fslm4bvHorM?si=PDct57J12G-ZQp12`

completely substitute our previous modules. In 2024, we finally rebuilt our codebase from ground-up, integrating it with approaches used by other teams as well as open source robotics packages. This is still an on-going process, which will take few more months to reach its envisioned target state. Our code is publicly available on GitHub [6].

2.1 ROS2

We are rewriting our existing modules on top of a new core framework based on the latest version of ROS 2, which unlike ROS 1 has been designed with real-time performance constraints in mind. We believe that this transition will significantly increase our development speed, as ROS 2 encourages modularity and isolation between components by design, and makes it simpler for newcomers to contribute. It also provides a widely popular collection of open source packages for robot software development actively maintained by a large community. With our codebase, the porting of modules developed by other teams in c++ or python is also possible with limited effort, allowing an easy integration of many functionalities developed by the robotics community, as well as an easier collaboration among the SPL teams and beyond.

2.2 Perception

For perception, we also have a component framework in our pipeline that is designed to simplify and standardize the development of new components while ensuring efficient execution and parameter management. The framework enables modular development, where components can be easily added or replaced without modifying the entire system. The architecture also ensures flexibility in tuning settings and adapting to different scenarios efficiently. The source code for the framework and its implementation are structured in dedicated modules.

Specifically, there are modules for the generation of scan lines, the generation and detection of ball spots, the generation of body contours, the detection of fields, the detection of intersections and the generation and detection of penalty marks, which are derived from the algorithms used by BHuman 2023 but modified so that they can be run with the ROS2 framework. Most detections are based on the patches spawned by the provider from scan lines. For instance, the penalty marks provider module takes input as scan lines and output candidate patches, which will be fed to and filtered by the penalty marks detector module. The modules for robot detection, whistle detection, and visual referee challenges are adapted from our codebase from 2024. The models used for ball, robot, field boundary, whistle and referee action have been retrained and optimized using TensorFlowLite to run on the robots. The different field features are then used to provide an estimation of the robot's location in the field.

Those modules are disentangled and implemented in different files and finally imported into the pipeline class that invokes their interface to process data sequentially.

[6] https://github.com/nomadz-ethz/nomadz-code-release

For a better debugging experience, we adopted Foxglove [7], a multimodal data visualization and management platform to visualize predicted labels either on 2D images or 3D scene.

Our vision-based self localization has been based on the implementation provided by BHuman 2023. By matching detected landmarks, such as field lines, intersections, penalty marks and center circle, to their current best estimates, position updates are computed using an Unscented Kalman Filter (UKF). Multiple UKF proposals are combined in a Particle Filter to increase the robustness of the method.

2.3 Behavior

We developed a completely new behavior module, changing from the previous state machine logic to behavior trees. We believe the hierarchical nature of trees guarantees a more reactive behavior as well as a streamlined flow of decisions from general logic to more task-specific ones.

All of the behavior algorithms are internally developed, following few essential principles: i) optimization processes should be always used over handcrafted logic, ii) the algorithm which runs on all field players (except for the goalkeeper) is the same, iii) simplicity and generalizability are priorities. Our resulting strategy is role-independent, and only differentiated into field players and goalkeepers at the last stage of the ramifications. No hard-coded positions are provided anymore, everything is updated online to adjust to field size and number of players. Robots continuously change the way they play according to their (partial) understanding of the environment, driven by few ground rules and main optimization objectives. The resulting behavior is similar to what a learning-based strategy would perform like, and we look forward to deploy our RL-based multi-agent strategy in the coming years to make some comparisons. We believe this should be the direction globally pursued within the RoboCup Soccer domain.

To implement our algorithms we use BehaviorTree.CPP [8], a self-contained libraries which guarantees efficiency and readability. It also provides a useful graphical interface via Groot2. We would like to thank Auryn Robotics for their support.

2.4 Motion Control

Conceptually, the motion control algorithms were taken from our legacy code base, which was cloned from the BHuman 2013 code base. But we have built a new architecture around the core implementations for smooth integration in the ROS2 framework.

To abstract away some complexity in controlling a humanoid robot, we subdivided the control into separate engines, where each one is responsible for a

[7] https://foxglove.dev/product

[8] https://www.behaviortree.dev

subset of joints or motions. The engines are subdivided into the following categories: *Walk, Kick, Arm, Head, Special Actions*. Note that the special action engine handles special cases such as a predefined "stand-up" motion. The engines are coordinated and activated by a master control node, which implements the corresponding logic. The master control node has a single control loop which runs at a specific rate and collects data, updates the engines outputs and sends the desired joint positions to the robot. We use the nao_lola [9] package to communicate with the NAO's Lola middle-ware. To test our code iteratively we use Cyberbotics' Webots [10] simulator.

3 Own Contributions

The development of a new framework allowed us to integrate some features we have been working on in the past years, result of in depth research projects carried on together with our supervisors and with external laboratories.

- **Gaussian Splatting** | Gaussian Splatting is a powerful view synthesis method, enabling fast rendering. Aiming to develop 3D environments across diverse environments in the RoboCup competition setting, we proposed a framework to achieve realistic 3D reconstruction, using Nao robot with dual-camera setups. To address challenges posed by motion blur and the low quality of onboard camera images, a robust and reproducible data collection pipeline is designed, synchronizing high-resolution and realistic perspective images using ROS. A deblurring pipeline[5] incorporating a flat-field prior is implemented to refine 3D reconstructions and improve accuracy. Furthermore, a transfer model is developed to adapt high-quality Realsense reconstructions to the robot's perspective through extrinsic calibration with optimized training configuration.
  The proposed methods demonstrate significant improvements in reducing artifacts and generating sharp, accurate reconstructions of RoboCup field environments. By addressing the sim-to-real challenges, this work provides a scalable solution for training transferable vision models, ensuring adaptability across varying competition settings and advancing the capabilities of robotic applications.

- **CycleGAN for data generation** | CycleGAN is an approach for converting images in one domain to so similar images in another domain. We used this approach to generate datasets for our ball and intersection detection. The performance of many of the models improve when more channels are provided as input. Although there is a lot of data, most of the data only has one channel. We created a dataset, with three channels and transformed it into one channel. On this dataset, training was done so that the model can learn to generate three channels from only one. After the training, the

[9] https://github.com/ros-sports/nao_lola
[10] https://cyberbotics.com

public datasets with one channels were converted to contain information for three channels. Neural architecture search was performed to find a model architecture that gave similar latency but better performance on the new dataset and those models are deployed on the robots.

– **Distributed Robotic Swarms Coordination** | During RC23 we introduced an optimal positioning planner based on the Feedback Equilibrium Seeking algorithm [2]. By using generalized equations which can model a broad spectrum of useful objectives and accounting for the local information each robot can extract from the environment, our approach can be used for any number of robots without variations. Last year, we improved these results by including additional costs to shape the playing tactics according to the current game scenarios [10]. To integrate the position planner with an action optimizer we leveraged game-theoretic self-organization theory, defining a graph-based algorithm used for high-level decision making in the offensive phase. Our ball holder robot periodically computes the expected scoring probability based on a world model approximated by Gaussian distributions, with a 3-action prediction horizon. The other players keep optimizing their position as before, with our design ensuring that this inherently increases the goal scoring probabilities for the robot in ball possession.

– **Multi-Agent RL** | Besides model-based methods, we have investigated the feasibilty of using model-free reinforcement learning to solve the football multi-agent objective function. RL has been often used to learn decision-making logic for single agents; however, when dealing with systems of multiple robots, some pitfalls arise due to the non-convex nature of the problem. In order to obtain a multi-robot cooperative behavior, we tackle the exploration-exploitation trade-off with innovative viewpoints, so that agents continuously try to learn improved strategies according to an ever-changing scenario. This is achieved by exploiting adversarial training [7], where two teams try to beat each others by learning new skills, and adapting to the one developed by the opponents. Despite many local competing optima exist, this approach guarantees a more dynamic learning which is less likely to stall in suboptimal strategies.

– **MPC Locomotion** | Model Predictive Control (MPC) is a powerful optimization based approach for controlling legged robots [9]. However, its adoption has been a challenge due to the NAO robot's constrained computational resources and inability to accept joint velocity or torque commands. Despite these restrictions, we wanted to develop an MPC framework that could be deployed in the future on a more advanced robot platform. The MPC uses centroidal dynamics [4], efficiently computed with the Pinocchio dynamics library, and CasADi to formulate the optimization problem. The state consists of centroidal momentum and generalized coordinates, and the input consists of joint velocity commands and desired ground reaction forces. To solve the optimization problem we use the constrained nonlinear FATROP solver, which significantly outperforms the standard Ipopt solver. Ideally, a low-level whole-body controller would be used to compute the desired joint torques [9]. Since this is not an option, we are working on integrating the MPC into our framework by testing whether position tracking of the MPC solution is sufficient for hardware deployment.

– **RL Bipedal Walking |** Reinforcement Learning (RL) proved to work more reliably than model-based control for locomotion on challenging terrain [6], able to embed robustness to the controller without the need of a complex mathematical formulation. Since in the past our team struggled in achieving competitive locomotion performances when testing in different venues, we decided to investigate the feasibility of RL walking controllers. Utilizing domain randomization, our training environment encompasses various terrains with differing friction, reaction forces, and inclines. By adding noise to observations, we further ease the sim-to-real transfer, enhancing the policy's adaptability to different hardware variations. Additionally, curriculum learning [3] facilitates the acquisition of complex skills by progressively increasing the difficulty level. The policy learned in such conditions is able to generalize well enough to any NAO V6 robot in any competition settings.

4 Past History and Results

In 2014 we participated at our first events, the German Open in Magdeburg, the Night of Science in Frankfurt and the RoHOW in Hamburg. We continued in 2015 with the Iran and German Open, the drop-in player competition and technical challenges at RoboCup 2015. In 2016 the European Open in Eindhoven and RoboCup 2016 were attended, followed by the German Open in 2017, the RoboCup event and the Phoenix Contact Robotics Cup. In 2018, we participated in the German Open and the RoboCup, reaching the playoffs. In 2019, we joined the German Open, the RoboCup (playoff), the Night of Science in Frankfurt and the Makerfaire in Rome. We successfully applied for RoboCup 2020 in Bordeaux, which wasn't held due to the Covid pandemic. In 2021, due to persistent Covid restrictions, we only participated in the remote RoboCup 2021. We participated in the 1vs1 challenge, ranking as 5^{th} team, and in the Obstacle Avoidance challenge, ending in position 10. In 2022 we joined the RoboCup 22 in Bangkok, also competing in 2 of the 4 technical challenges. Our results in the soccer competition allowed us to pass the seeding round as 8^{th} team overall. We then lost the quarter-finals match against B-Human. For the challenges, we ranked the 3^{rd} team. 2023 saw us take part in GORE, where we ended up in 9^{th} position, and RoboCup 23 as pre-qualified team, where we also joined 2 challenges. We concluded our Champions Cup league journey at the 6^{th} position, while we ranked 4^{th} for the technical challenges. We finally joined RoboCup 24 in Eindhoven as pre-qualified team. This was the first official competition where we used our newly developed framework in ROS2, which however presented more challenges than expected. This lead us to 10^{th} position in Champions Cup.

5 Impact

We consistently contribute to the university's PR activities by telling students about our exciting project and fascinating them with robotics demonstrations. In the past months, we were involved in few nationally relevant events. In Fall 24 we had the pleasure to host one of the projects during the Zukunftstag, an ETH Zürich event aiming to expose children to STEM subjects. For the second year in a row we participated in the Swiss Robotics Day 24, a globally known conference, which allowed us to reach a broad audience and promote RoboCup and SPL. All these events have been made possible by the support from NCCR Automation.

In recent years we successfully built a consistent publication record [8], [1]. More recently, we worked towards the formalization of our multi-robot behavior frameworks, presented at the Workshop on Humanoid Soccer Robots at Humanoids 24 [10], and ICRA 25 [7], which are flagship robotics conferences. As of February, we are planning to submit a contribution related to these topics also to the RoboCup International Symposium 2025.

Team NomadZ provides ETH students who want to get more experience on a physical robotic platform with a great environment to apply the theory learned during classes and to learn a more practical side of robotics. Over the years the student members of our team have worked on several research projects within the scope of RoboCup; these outcomes have been documented and made available on our website. Table 1 shows a list of the most recent ones. We believe that these projects may be able to provide help for the research of other SPL teams.

Table 1. Most recent projects supervised by our group

NomadZ Student Projects

Title	Year
Gaussian splatting for training transferable vision models	2024
Distributed Optimization for Multi-Robot Systems in RoboCup	2023
Learning Humanoid Locomotion on Small Scale Robots	2023
Distributed Coordination for Multi-Robot Systems in RoboCup	2023
Deep Goal Post Detection for RoboCup SPL	2022
Visual Referee Detection on Nao Robots for RoboCup SPL	2022

Furthermore, we have been organizing a number of classes for ETH Bachelor degree students. From 2020 to 2022, we have provided the lab course "Vision and Control in RoboCup". It covers the theoretical fundamentals required to successfully play and provides the students with first hands-on experience using NAO. Since 2023 the class has been renamed "Robocup: Learning and Control", focusing more on the modeling and control areas. From 2021 to 2024 we have also provided the course "Introduction to Program Nao Robots for Robocup Competition", a more practical class where Bachelor students can code and test basic functionalities on NAO V6 robots.

6 Conclusion

In the past, we have had great experiences at the RoboCup tournaments in Hefei, Leipzig, Nagoya, Montreal, Sydney, remotely in 2021, Bangkok, Bordeaux and Eindhoven. We are looking forward to share again with the RoboCup community this exceptional event. Let's continue the journey with the RoboCup 2025 in Salvador!

Thank you for your work and for keeping Robocup the amazing competition it is. We know from our own experiences that Robocup is able to fascinate many (prospective) students to work in robotics by showing how much fun it can be!

References

1. Albanese, G., Mitra, A., Zaech, J.N., Zhao, Y., Chhatkuli, A., Van Gool, L.: Optimizing long-term robot tracking with multi-platform sensor fusion. In: Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision. pp. 6992–7002 (2024)
2. Belgioioso, G., Liao-McPherson, D., de Badyn, M.H., Bolognani, S., Lygeros, J., Dörfler, F.: Sampled-data online feedback equilibrium seeking: Stability and tracking. In: 2021 60th IEEE Conference on Decision and Control (CDC). pp. 2702–2708. IEEE (2021)
3. Bengio, Y., Louradour, J., Collobert, R., Weston, J.: Curriculum learning. In: Proceedings of the 26th annual international conference on machine learning. pp. 41–48 (2009)
4. Dai, H., Valenzuela, A.K., Tedrake, R.: Whole-body motion planning with centroidal dynamics and full kinematics. 2014 IEEE-RAS International Conference on Humanoid Robots
5. Lee, B., Lee, H., Sun, X., Ali, U., Park, E.: Deblurring 3d gaussian splatting (2024), `https://arxiv.org/abs/2401.00834`
6. Lee, J., Hwangbo, J., Wellhausen, L., Koltun, V., Hutter, M.: Learning quadrupedal locomotion over challenging terrain. Science robotics **5**(47), eabc5986 (2020)
7. Li, Z., Bjelonic, F., Klemm, V., Hutter, M.: Marladona-towards cooperative team play using multi-agent reinforcement learning. arXiv preprint arXiv:2409.20326 (2024)
8. Mitra, A., Molnar, L., Zaech, J.N., Wu, Y., Heo, S., Yu, F., Van Gool, L.: Multi-domain referee dataset: Enabling recognition of referee signals on robotic platforms. In: RoboLetics: Workshop on Robot Learning in Athletics@ CoRL 2023 (2023)
9. Sleiman, J.P., Farshidian, F., Minniti, M.V., Hutter, M.: A unified mpc framework for whole-body dynamic locomotion and manipulation. IEEE Robotics and Automation Letters **6**(3), 4688–4695 (2021)
10. Spinelli, F.A., Ospelt, N., He, C., Palma, E., Montorfani, S., Soloperto, R., Lygeros, J.: A sampling-based algorithm for multi-agent coordination in robocup soccer. In: Workshop on Humanoid Soccer Robots 2024 (2024)