AutonOhm@Work
Team Description Paper 2024

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Abstract. This paper presents the team AutonOhm and their solutions to the challenges of the RoboCup@Work league. The hardware section covers the robot setup of Ωmnibot - V4 (Ωmeg4), which was developed using knowledge from previous robots used by the team. Custom solution approaches for the @Work navigation, perception, and manipulation tasks are discussed in the software section, as well as a control architecture for the autonomous task completion.

1 AutonOhm@Work

History The AutonOhm@Work team at the Nuremberg Institute of Technology was founded in September 2014 and has since participated in various tournaments and was able to win 3 local and 4 global events* (see tab. 1). It consists of a mix of bachelor, master and phd students with various fields of research (see tab. 2).

Robot Since the primarily used robot model, the KUKA Youbot, was discontinued and the only available youbot broke down at the World Cup in 2018, the team started developing a custom robotic platform called Ωnibot, which has been continously improved and reworked since 2019.

Contributions to the League We've started to bundle our knowledge in a repository [22], where many aspects of our solution will be publicly available. With this repository, we want to share our knowledge to provide other researchers with a basic foundation for autonomous robots and task completion.

Fig. 1: Team AutonOhm 2024 with Ωmeg4 (RC Eindhoven)

Table 1: History of AutonOHM@Work

Year	Location	Event	Result	Robot
2015	Magdeburg (Germany)	RC German Open	5th	Youbot V1.2
2016	Leipzig (Germany)	RC World Cup	5th	Youbot V1.3
2017	Magdeburg (Germany)	RC German Open	1st*	Youbot V1.4
2017	Nagoya (Japan)	RC World Cup	1st*	Youbot V1.5
2018	Magdeburg (Germany)	RC German Open	1st*	Youbot V1.6
2018	Montreal (Canada)	RC World Cup	1st*	Youbot V1.6
2019	Magdeburg (Germany)	RC German Open	6th	Ωmnibot V1
2019	Sydney (Australia)	RC World Cup	5th	Ωmnibot V1.2
2020	Virtual Online	RC Asia Pacific	3rd	Ωmnibot V2
2021	Virtual Online	RC World Cup	1st*	Ωmnibot V2.1
2021	Bologna (Italy)	SciRoc Ep5	1st*	Ωmnibot V2.2
2022	Bangkok (Thailand)	RC World Cup	1st*	Ωmn3
2023	Bordeaux (France)	RC World Cup	4th	Ωmeg4

Table 2: Team AutonOHM@Work 2024

Member	Field of Study	Tasks
Marco Masannek	Cognitive Robotics (Phd)	Project Lead Mentor Tech Lead
Sina Steinmüller	Media Engineering (B-Eng)	Team Lead Marketing Software
Hannes Haag	Mechatronic Systems (M-Sy)	Hardware Lead
Usukh-Erdene Batbold	Mechatronics (B-Eng)	Hardware Dev
Ingrid Nodem Labou	Mechatronics (B-Eng)	Tech Support
Rolf Schmidt	Perception Sensors (Phd)	Tech Support
Dong Wang	Perception Sensors (Phd)	Software Management Localization Obstacle Detection
Tim Lachmann	Media Engineering (B-Eng)	Arm Controller
Lukas Fuchs	Mechatronics (B-Eng)	Gripper
Hannes Duske	Mechatronic Systems (M-Sy)	Robotic Manipulation
Dennis Trescher	Applied Research (M-Sc)	Object Perception

2 League Description

The RoboCup@Work league, established in 2012, focuses on the use of mobile manipulators and their integration with automation equipment for performing industrial-relevant tasks [1]. Participating robots must be able to navigate in a previously known arena, reach different service areas and perform manipulation tasks. Therefore, each robot must be able to correctly identify a requested object on various background surfaces and pick and place the objects that vary in shape, appearance and weight. With low participation numbers of teams after the COVID-19 pandemic in the first on-site robocup at the world cup 2023 in Bangkok, Thailand, major changes to the structure of the competition have been made with the intention to ensure the future of the league. The main idea is to make setting foot in the league more easy for newer teams, while still keeping the ambition to target scientific problems in robotics in the more advanced stages of the competition. Therefore, the competition has been split into two main sections, the beginner and the advanced section. The Beginner Section isolates or simplifies some of the requirements for the robots so teams without much experience can successfully participate without having a competitive setup in relation to the more advanced teams. The Advanced Section introduces a new (more difficult) set of objects, aswell as incorporating Precise Placement and Rotating Table tasks into the newly introduced Advanced Transportation Tests. The standalone Tests have therefore been removed from the competition schedule. As these changes increase the upper treshold of skill required to do all tasks without making mistakes, the option to replace the real objects with april-tagged cubes has been introduced to relax the problem of object detection and manipulation.

3 Hardware Description

Version 4 of our Ωnibot, Ωmeg4, is built on a customized Evocortex[3] R&D platform. The platform is equipped with an omnidirectional mecanum drive, an aluminum chassis capable of carrying loads up to 100 kg and a Li-Ion Battery with a nominal voltage of 48V. In our configuration, the platform does not include any sensors, power management or computation units, which means it only serves as our base. Every further component needed was mounted in or on the chassis.

3.1 Sensors

Lidars Mapping, navigation and the detection of physical obstacles is dependent on sensory detection of the environment. Three 2D LiDAR sensors from Sick were used in the previous version of the robot platform (Ωmn3). The optimized version uses the Rplidar S2E from Slamtec, a 360°2D LiDAR sensor, which is mounted centric below the robot. The positioning of the Mecanum wheels results in areas that cannot be detected by the laser scanner (blind spots). For this purpose, two infrared sensors provided by Evocortex are attached to each corner of the robot platform to fill the sensing gap (see fig. 4).

Fig. 2: Image of our Ωmeg4

Fig. 3: Robot bottom

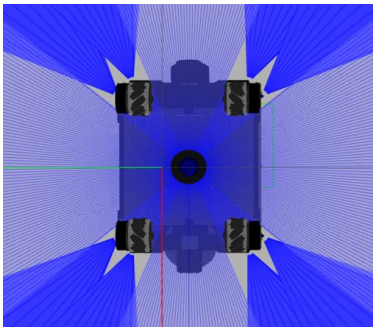


Fig. 4: Laser scan area

Cameras We use an Intel RealSense D435 3D-camera for the object perception. It is attached to the sensorhead so that it can be positioned above the workstations to detect the surface and the position of the objects.
For barriertape detection, multiple ELP USB fisheye cameras can be mounted around the robot, which enables a 360° view. During the competition, we usually rely on a single fisheye camera mounted on the sensorhead because we have observed that all the barriertape is still detected.

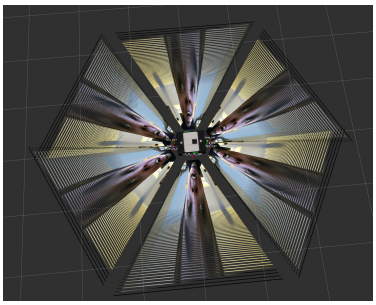


Fig. 5: 360°fisheye camera setup

3.2 PC

The newly introduced neural networks require a GPU for computation onboard of the robot. As embedded GPU chips such as the Nvidia Jetson TX2 do not provide enough processing power for the task optimization and navigation algorithms, we designed a custom PC solution consisting of an AMD Ryzen 7 5700X processor, a mini-ATX mainboard and a low power Nvidia A2000 graphics card,

which is connected to the mainboard with a riser cable. This enabled us to build a flat case with both the mainboard and the graphics card safely mounted inside. The form factor of the case makes it possible to slide it into the robot's back, similar to a server rack.

3.3 PSU

We developed a custom PSU circuit board containing emergency switches for the actuators, a main power switch and voltage controllers for 5V, 12V and 24V. It is equipped with a custom designed plug system with selectable voltage, so every peripheral device can be connected using the same plug type. In addition to that, we use an extra DC-DC controller for the power supply of the manipulator, as its power consumption exceeds the limits of the onboard controllers. For the custom PC system, we use a standard 250W automotive ATX power supply.

3.4 Manipulator

Arm We use the 6 DOF Cobot ReBeL from igus as the arm (see fig. 2). We decided on this arm because it could be realized within the budget and integration into the system was possible without an external control box for the arm. This saves space on the platform itself and reduces the weight of the platform compared to other options.

Sensorhead Our sensorhead concept realizes a plug-in solution for a variety of robotic arms. Our all-in-one design includes a customized parallel gripper with tilting fingers, a 3D camera for object detection, a fisheye camera for barriertape detection, a status led ringlight and customized electronics, which allows us to connect the sensorhead to any robot using a USB and power connection.

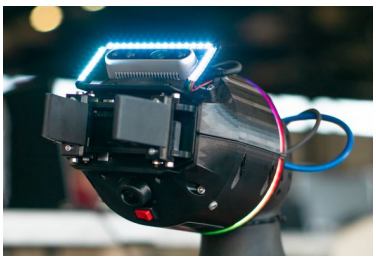


Fig. 6: Sensorhead

Gripper Our customized parallel gripper is equipped with a guide rail for the fingers which allows for a circular tilting motion towards the maximum open angle, as well as a specially developed linear gear drive that converts the circular motion of a Dynamixel MX28 motor to a linear motion of the finger sleds.

We use customized fin-ray fingers printed with TPU and foam rubber to allow for firm and object enclosing grasping motions. The force feedback from the fingers is transferred to the motor via the linear gears and can be used for grip detection or to calculate the grasping force.

4 Software Description

We use Linux Ubuntu 20.04 and ROS Noetic [4] as our operating systems. A custom software architecture was created to simplify the overall structure and to regain system flexibility. Our new design is displayed in fig. 7.

The idea derives from the Model-View-Controller software design pattern, which is adjusted to the usage of the ROS framework. Regarding the frequent use of hardware, an additional driver layer is added below the model layer. Models that need data from hardware, e.g. sensor data, can get them from the individual driver programs. The view layer is realized with each program using interfaces to RVIZ or simple console logging, which makes custom implementations obsolete. Components that require additional control features, such as the robot arm, have dedicated controllers providing simple interfaces for the brain layer, which is responsible for the actual task interpretation and execution. The individual layer components will be explained in the following sections.

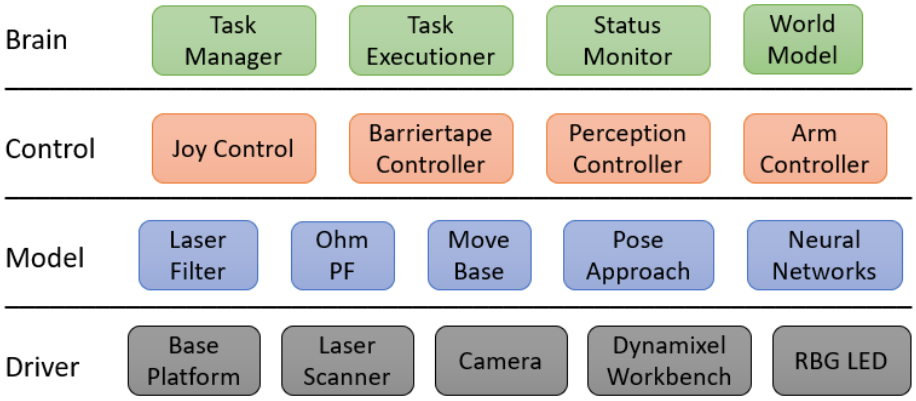


Fig. 7: Software Architecture - BCMD

4.1 Driver

The driver layer only contains actual hardware control programs, such as the sensor interfaces. The idea here is that the whole layer can be replaced with simulation tools such as Gazebo.

Base Platform The base platform driver converts incoming cmd_vel messages into wheel rpm and calculates the odometry from obtained rpm. It stops the robot automatically if the incoming commands time out to prevent uncontrolled movements. An additional twist_mux node throttles incoming commands from the joy_controller, move_base and the pose_approach.

Laser Scanner The rplidar node provides the interface to the scanner with given IP address and scan area configuration. However, as the Lidar is prone to measurement errors such as shadows or reflections, custom laser filters are applied to the raw data for later computation.

Infradar The Infradar driver from our sponsor Evocortex enables real time data-reading from 8 infradar sensors via CAN-BUS and publish Infradar data as 3d point clouds.

Camera We use the Intel Realsense SDK with the provided ROS wrapper. The fisheye cameras are accessed via the ROS usb_cam package[20].

Dynamixel Workbench The parallel gripper is controlled with a controller instance of the dynamixel_workbench package. It provides access to motor variables (e.g. position, torque, ..) which are used for precise grip controls.

Igus Rebel We use the igus rebel [25] 6-DoF driver to control the robot arm. The driver follows a given trajectory and provides feedback about its position, velocity and accelerations during the trajectory execution.

4.2 Model

Our models contain all algorithms used to challenge the problems of the tasks in the @Work league. This includes localization, navigation and perception. The task planner is not included as a model but in the brain layer because it is more convenient to attach it directly to the task manager, as discussed in section 4.4.

Laser Filter As mentioned in section 4.1, we filter the raw laser data before computing. The first filters are simple area filters to delete the robot's wheels from the scan. The second filter is a custom jumping point filter implementation. We faced problems with reflections of the alu profile rails used for the walls of the arena, which caused the robot to mark free space as occupied. The filter calculates the x- and y-position for each scan point and checks if there are enough neighbors in close range to mark a point as valid. All points with less than n neighbors in the given range will be handled as measurement errors and therefore deleted.

Ohm PF For localization in the arena, we use our own particle filter algorithm. Its functionality is close to amcl localization, as described in [5] and [13]. The algorithm is capable of using multiple laser scanners and an omnidirectional movement model. Due to the Monte Carlo filtering approach, the localization is robust and accurate enough to provide useful positioning data to the navigation system. Positioning error with the particle filter is about 6 cm, depending on the complexity and speed of the actual movement.

Move Base We use the ROS navigation stack [10] for global path planning and the local path control loops. Path cost calculations are performed by using the costmap 2D plugins. The base layer is a 2D laser map created with gmapping [11,12]. On top of that, we use a barriertape map layer which contains all detected barriertape points. For local obstacle avoidance, we added an obstacle layer which includes laser data from laser scanner and and our own developed 3D infradar layer for infradar sensors. All layers are combined in the final inflation layer. Global path planning is computed with the mcr_global_planner [17] while the path is executed using the TEB local planner [6,7,8,9]. As the local planner is not able to precisely navigate to a given goal pose, we set the goal tolerance relatively high. Once we reached our goal with move_base, we continue exact positioning with our custom controller, the pose_approach.

MoveIt We use the MoveIt [26] motion planning library to calculate inverse kinematics and trajectories for the robot arm and connect it to the igus driver.

Pose Approach The pose_approach package utilizes a simple PID controller to move the robot to a given pose. It utilizes the robot's localization pose as input and the target pose as reference. As the controller does not consider costmap obstacles, the maximum distance to the target is 20 cm to prevent collisions. A laser monitor algorithm checks for obstacles in the current scan and stops the robot if necessary.

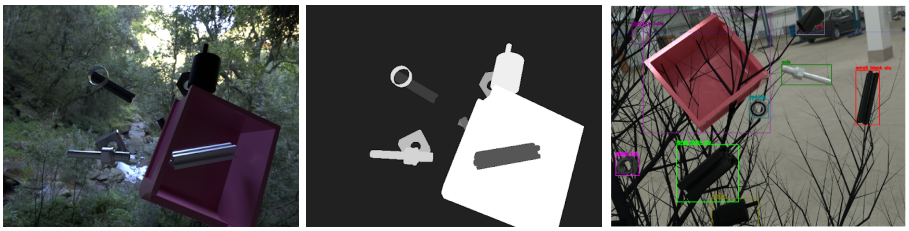
Fisheye rectification The raw fisheye images need to be rectified to be used as input for the detection network. A specific image_pipeline fork [21] is used, which contains this functionality.

NN - Barriertape For the barriertape detection, we use a U-Net with manually labelled datasets. The ROS node receives raw input images and returns a masked binary image. We have ported the network node from Python to C++ to increase the detection rate from around 5Hz up to 20Hz.

NN - Objects The detection and classification of objects is done with a fine-tuned yolo-v7 network [23]. The node receives a raw input image and returns a vector with the ID, bounding box and confidence of all objects that were found. As the generation of a dataset specially for the contest would require more than 10,000 labelled images, which would require a high amount of time to create, we have implemented an automated dataset creation method using Blender and Python. It basically changes environments, illumination, camera and object pose as well as object appearance in pre-defined bounds. The script creates rendered images as well as bounding box, segmentation and 6DoF labels. With this data generation method, data which is quite similar to the original scene can be created, as well as rather abstract data (Figure 8). We are currently

also working on data generation for deformable objects, such as the objects used in the SciRoc Challenge 2021 - Episode 5: Shopping Pick & Pack [19].

Using an original to artificial image ratio of 1:10, we achieved a detection reliability of over 90% for most scenes. Our data generation scripts are public and free to use [15]. The trained network is converted to TRT-Engine using code from the TRT-YOLO-App from the Deepstream Reference Apps [16]. This increases performance as the CUDA cores will be used more efficient, and makes a detection rate of up to 60Hz possible. In the future, other network types such as segmentation networks and 6DoF networks will be explored.



(a) (b) (c)

Fig. 8: abstract image (a) corresponding mask label (b) abstract image with bounding box label (c)

As an alternative detection there is also an AprilTag detection which implements a ROS wrapper of the AprilTag 3 visual fiducial detection algorithm [24]. It provides full access to the core AprilTag 3 algorithm's customisations and makes the tag detection image and the detected tags' poses available via ROS topics to detect objects via apriltags.

4.3 Controller

Model nodes that require additional control features are connected to control nodes, which then provide interfaces for the brain layer. They use our robot_custom_msgs interfaces to share information about the subtask, workstation, or objects. Nodes may have specific subtask types implemented into their behaviour to react optimized.

Joy Control We use a PS5 joystick to move our robot manually (e.g. for mapping). For this, we have implemented a custom teleop_joy_node with similar functionality. We also plan to implement the usage of the PS5 feedback functions such as rumble.

Barriertape Control The barriertape controller is a custom mapping implementation for visual obstacles. It throttles the input images to the barriertape

network and computes the masked images. Looping through multiple cameras enables us to perform 360°barriertape detection.

Received masked images are converted into a point cloud with a predefined density. This pointcloud is then transformed from the individual camera frame into the global map frame. Afterwards, all new points are compared to the existing map points. New barriertape points that are already occupied are ignored to save computation. As we faced problems with image blur and therefore resulting non-precise barriertape detection, we also compute pixels that mark free space (no barriertape detected). They are compared to existing points, which get deleted if they overlap.

The whole map is converted into an occupancy grid and then published periodically, so it can be included in the costmap of the move_base node. The node is controlled via service calls, which enable or disable the detection loop. The map is always published once the node finishes the init process.

Arm Control The arm is controlled via ROS services or a development GUI for debugging. For the solution of the inverse kinematics we use MoveIt, which works together with a custom arm controller. When using the services the arm controller receives the target position and checks whether the arm should move to a trajectory via defined safety positions. MoveIt then controls the arm and performs the calculations. The arm executes a full task using the given information, which means, in case of a pick task, it moves the TCP to the object position, closes the gripper, and stores the object. After the subtask finishes, feedback of the exit status is returned to the caller.

Perception Control The perception control node is responsible for the workstation analysis and object detection from a given scene (3D Pointcloud and RGB image). First, the surface equation of the workstation is calculated using the RANSAC [14] algorithm. If a valid result is obtained, raw images are sent to the object perception network (4.2). All found objects are then localized using the pinhole camera model, the workstation plane and the bounding box pixels. Finally, the position is transformed into the workstation frame and saved. For moving objects, multiple positions are recorded and then used to calculate the movement equation with RANSAC.

4.4 Brain

The brain layer provides nodes which contain the intelligence of the robot, which means the tracking of itself, its environment and the received tasks.

Worldmodel All data obtained about the robot's environment is stored in the worldmodel database. This includes the map, all workstation positions and all detected objects on the workstations. The data can be accessed using service calls.

Status Monitor The status monitor keeps track of the robot itself. It saves the current pose, inventory and state. The associated color code is sent to the RGB LED driver node.

Task Manager The robot can receive tasks from multiple sources, such as the RefBox or voice commands. In order to process different input formats, different parsers are used to standardize the input for the task manager.

When the robot receives a new transportation task, it is analysed and planned before the execution. All extracted subtasks are managed by the task_manager node, which replans the order of all subtasks. With the increasing numbers of transportation tasks in the competition, high efficiency is crucial to achieve perfect runs. The score of a single subtask is calculated considering expected duration, points, and the risk of failure. These factors may change if certain conditions are met, for example, the navigation time is set to zero if the robot already is at the given position.

Before even starting the planning of subtasks, the received task is analysed for impossible tasks. This would be the case if the target workstation is unknown or unreachable, or an object is lost. All subtasks that cannot be executed are moved to a deletion vector.

A self developed planning algorithm then calculates the raw score of the remaining subtask vector, followed by a simple nearest neighbour search (NN). This result is then fed to a recursive tree calculation method, which searches for the optimal solution. A branch is only fully calculated if the score sum does not exceed the best solution found with the NN. This way, we have achieved an overall planning time for the BTT3 challenge (14 subtasks) of around 10s. For subtask numbers below 12 the planning only takes 2s. If the task load exceeds 14 tasks, we skip the recursive strategy, as planning time grows exponentially and therefore cannot produce results in the given time frame of a run.

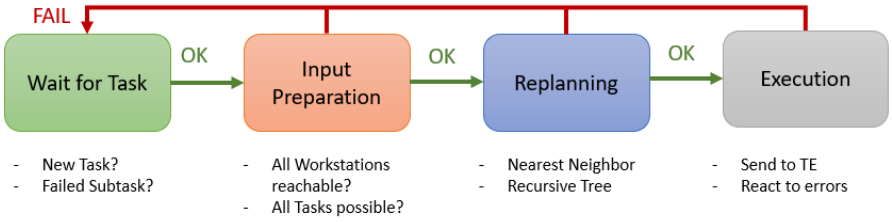


Fig. 9: Task Manager States

After planning, every subtask is sent to the task executioner (section 4.4). If the execution was not successful, the task is moved to a failed subtask vector and deleted from the current working STV. The short planning times enable us to replan every time a subtask fails, or new data is available. This is necessary because even simple changes can cause serious errors in the intentional plan. If certain paths are blocked, the navigation time for transportation tasks can increase dramatically, causing a huge loss of efficiency. A final garbage collection

checks all deleted and failed subtasks for plausibility again and adds retries for possible subtasks.

Task Executioner Subtasks that are sent to the Task Executioner get run through an interpreter to extract the actions that are necessary for the task execution. All actions are performed in custom states, which can be adjusted via parameters at creation. The interpreter uses information from the status monitor, the worldmodel and the given subtask to create substates accordingly. The resulting state vector is iterated until finished or failed. While executing, the node reads and modifies the data in the status monitor and worldmodel package. This way, every change is immediately available for all other nodes too.

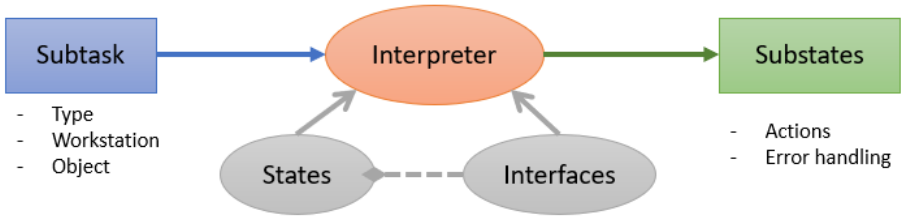


Fig. 10: Task Executioner - Subtask Interpretation

5 Conclusion and Future Work

During the last season, we optimized our robot concept and built a completely new robot (Ωmeg4). The robot arm concept has been reworked and improved, a new operation interface and sensor concept has been implemented, as well as the step up at to 48V base voltage.

In the coming season we plan on improving our object detection by using other network architectures such as segmentation, 6DoF and grasp detection networks. We are also reworking our gripper concept to enable the use of force feedback, which may benefit our task management system. We also want to introduce performance monitoring, allowing us to identify bottlenecks and plan future improvements. Finally, we plan to extend the above-mentioned repository by adding more documentation as well as some theses from our students.

We are very much looking forward to the upcoming season, where we aim to benchmark our systems performance at the RoboCup 2024 in Eindhoven.

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