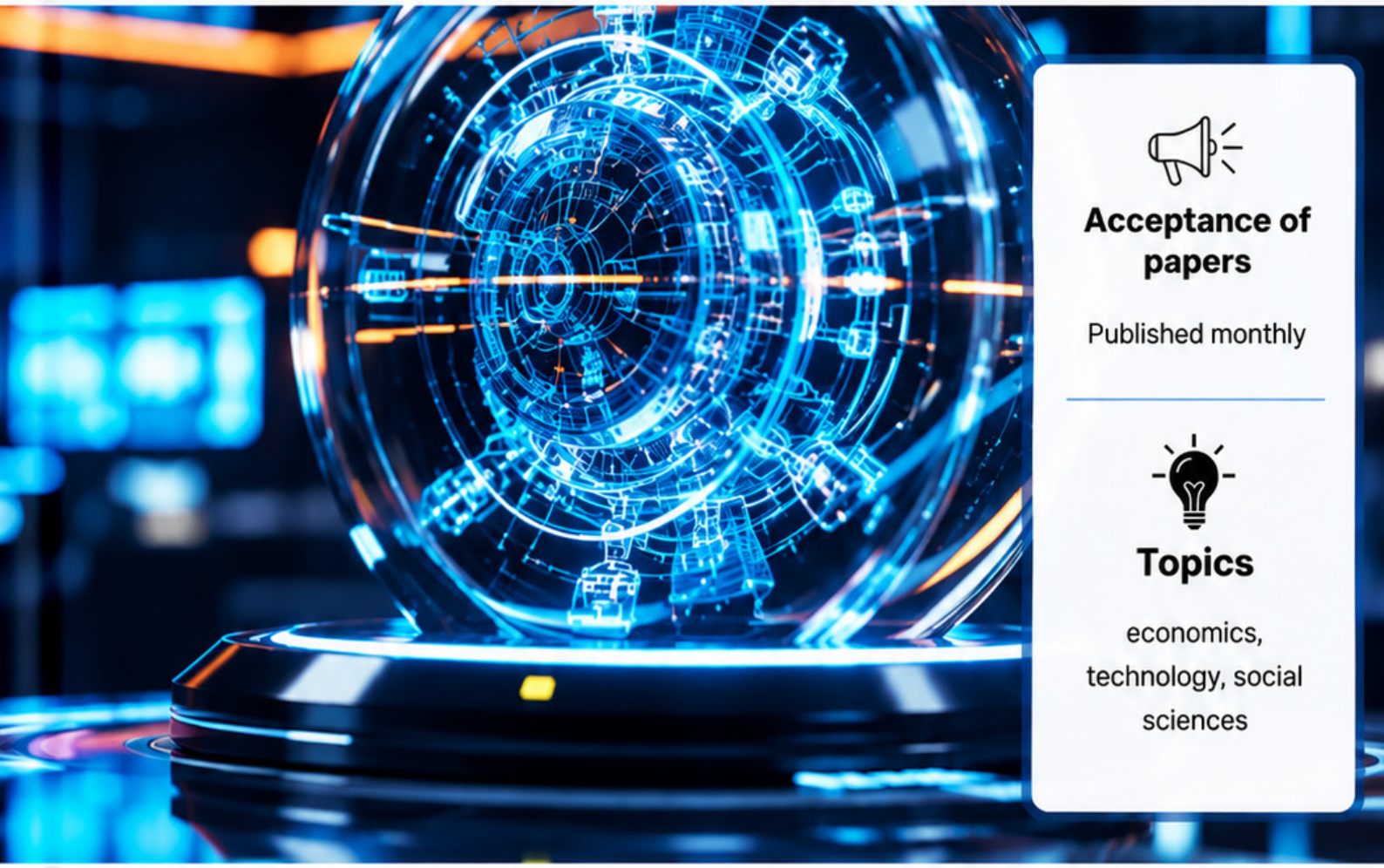
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CONTACTS

Phone: **+998 50 737 87 88**

Website: https://ist-journal.uz

Email: innovationist2025@gmail.com

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Asqaraliyev Odilbek Ulugbek ugli
Tashkent University of Information Technologies named after Muhammad al-Khwarizmi
Associate Professor, Department of Artificial Intelligence, DSc in Technical Sciences
ORCID: 0009-0003-7363-4485
E-mail: oasqaraliyev77@gmail.com

Abdumalikov Akmal Abduxoliq ugli
Jizzakh Branch of the National University of Uzbekistan named after Mirzo Ulugbek
Head of the Department of Research, Innovation and Training of Scientific-Pedagogical Staff, PhD in Technical Sciences, Associate Professor
ORCID: 0000-0001-5432-8632
E-mail: akmalabdumalikov6@gmail.com

Norquziyev Quvonchbek Komiljon ugli
Jizzakh Branch of the National University of Uzbekistan named after Mirzo Ulugbek
First-year doctoral student
ORCID: 0009-0000-3500-5926
E-mail: quvonchbek9535@gmail.com

Abstract: The paper addresses local path planning for autonomous mobile robots that carry loads in a warehouse shared by people and several robots. A planar LiDAR mounted close to the floor observes only the legs of a load-carrying rack, so the costmap marks the space beneath the rack as free and a loaded robot may strike the deck. We propose the RAP method (Rack-Aware, Payload-aware Planning): a two-channel convolutional neural network separates rack legs from people and other robots, the rack pose is recovered from two to four legs by a Procrustes estimator, confirmed with a depth camera, a 3D LiDAR or a monocular camera, and projected into the costmap as a load-carrying volume with a certified safety margin. Depending on the payload height, the robot either passes under the rack or goes around it. The estimator is proved to attain the Cramér–Rao bound, and all theoretical results are verified numerically. In 640 paired episodes RAP achieved 95.0 % success with 1.9 % safety violations, and in Gazebo/ROS 2 experiments the loaded robot never struck a rack deck.

Keywords: warehouse robots, local path planning, load-carrying rack, LiDAR, depth camera, convolutional neural network, ROS 2, Gazebo.

Annotatsiya: Maqolada odamlar va bir nechta robot birga harakatlanadigan omborxona muhitida yuk tashuvchi avtonom mobil robotlar uchun mahalliy yo‘l rejalashtirish masalasi ko‘rib chiqiladi. Polga yaqin o‘rnatilgan 2D LiDAR yuk qo‘yiladigan javonning faqat oyoqlarini ko‘radi, natijada xarajat xaritasida javon osti bo‘sh deb belgilanadi va yuklangan robot javon taxtasiga urilishi mumkin. Muammoni hal qilish uchun RAP (Rack-Aware, Payload-aware Planning) usuli taklif etiladi: ikki kanalli konvolyutsion neyron tarmoq javon oyog‘ini odam va boshqa robotdan ajratadi, javon holati Prokrust masalasi orqali 2–4 ta oyoqdan tiklanadi, chuqurlik kamerasi, 3D LiDAR yoki oddiy kamera ma’lumotlari bilan tasdiqlanadi va kafolatlangan xavfsizlik zaxirasi bilan yuk tashuvchi hajm sifatida xaritaga proyeksiyalanadi. Robot yukining balandligiga qarab javon ostidan o‘tish yoki uni aylanib o‘tish qarori qabul qilinadi. Baholovchining Kramer–Rao chegarasiga erishishi isbotlangan va barcha nazariy natijalar sonli tajribada tasdiqlangan. 640 juftlangan epizodda RAP 95,0 % muvaffaqiyat va 1,9 % xavfsizlik buzilishini ko‘rsatdi, Gazebo/ROS 2 tajribalarida esa yuklangan robot bironta ham javon taxtasiga urilmadi.

Kalit so‘zlar: omborxona robotlari, mahalliy yo‘l rejalashtirish, yuk tashuvchi javon, LiDAR, chuqurlik kamerasi, konvolyutsion neyron tarmoq, ROS 2, Gazebo.

Аннотация: В статье рассматривается задача локального планирования пути автономных мобильных роботов, перевозящих грузы на складе, где одновременно перемещаются люди и несколько роботов. Двумерный лидар, установленный низко над полом, видит только ножки грузового стеллажа, поэтому пространство под стеллажом отмечается на карте стоимости как свободное, и нагруженный робот может удариться о полку. Предложен метод RAP (Rack-Aware, Payload-aware Planning): двухканальная свёрточная нейронная сеть отличает ножку стеллажа от человека и другого робота, положение стеллажа восстанавливается по 2–4 ножкам решением задачи Прокруста, подтверждается данными камеры глубины, трёхмерного лидара или обычной камеры и проецируется на карту как грузонесущий объём с гарантированным запасом безопасности. В зависимости от высоты груза принимается решение проехать под стеллажом или объехать его. Доказано, что оценка достигает границы Крамера–Рао, все теоретические результаты подтверждены численно. В 640 парных эпизодах RAP показал 95,0 % успешных проездов при 1,9 % нарушений безопасности, а в экспериментах Gazebo/ROS 2 нагруженный робот ни разу не ударился о полку стеллажа.

Ключевые слова: складские роботы, локальное планирование пути, грузовой стеллаж, лидар, камера глубины, свёрточная нейронная сеть, ROS 2, Gazebo.

INTRODUCTION

Autonomous mobile robots (AMRs) are widely used to move loads in warehouses and logistics centres [1]. A modern warehouse floor changes constantly: people walk in the aisles, several robots move at the same time, and mobile racks that carry loads are moved during a shift and sometimes left in the middle of an aisle. Most robots perceive this environment with a single 2D LiDAR mounted 0.2–0.3 m above the floor, which is the main source for localisation and obstacle avoidance [2–5].

For load-carrying racks the planar scan is misleading. A rack whose deck holds cartons appears in the scan only as four small returns produced by its legs. A costmap built from these returns marks the legs as obstacles and the area between them as free (Fig. 2). For a 1.6 × 0.8 m rack the 1.42 m gap between the legs is wider than the robot plus its safety margin, so a shortest-path planner sends the robot straight under the rack. Whether this is safe depends on the payload: an empty robot of 0.47 m height fits under a 0.70 m deck, whereas the same robot carrying a 0.45 m tote is 0.75 m tall and strikes the deck. The problem has been observed even in systems that fuse LiDAR and RGB-D data [6], and actively pointing a camera between the legs is too slow for a fast robot [7].

The object of the study is a four-wheel load-carrying AMR in a warehouse shared by people and several robots. The subject of the study is methods for recognising load-carrying racks from sensor data and for payload-aware local path planning. The aim is to develop a local planning algorithm that recognises a rack from its legs, confirms it geometrically, projects it into the map as a load-carrying model and, depending on the robot's payload, decides whether to pass under the rack or go around it. The tasks are: to separate racks, people and robots; to estimate the rack pose and justify its accuracy theoretically; to derive a safety margin and a payload-dependent decision rule; and to test the method in a statistical simulator and in Gazebo/ROS 2.

REVIEW OF LITERATURE ON THE SUBJECT

Occupancy grids [2] remain the main world model in navigation. The ROS navigation stack [3], layered costmaps [4] and Nav2 in ROS 2 [5, 8] provide obstacle, inflation, keepout and voxel layers, and local controllers such as the dynamic window approach [9] and model predictive control [10] rely on this 2D map only. Obstacles above the scan plane are usually handled with 3D sensors: octree maps [11] project point clouds up to the robot height into the map, and Al-Tawil et al. [6] fuse RGB-D virtual scans with LiDAR and report that the empty space between table legs causes collisions.

Recognising racks from their legs has mainly been studied for docking, where the robot drives under the rack and lifts it: shelf models with least-squares fitting [12] or a learned detector [13] are used. Our objective is the opposite — not to enter under a rack if the load does not fit. People have been detected in 2D scans with geometric features [14] and convolutional networks [15], and confusion of table legs with human legs is known [16]. Human-aware navigation [17] and chance-constrained planning [18] require prediction of agent motion, while four-wheel skid-steer platforms are modelled through the instantaneous centre of rotation [19, 20]. None of the reviewed works combines rack recognition from legs, separation of racks from people and robots, confirmation with any available sensor, a certified safety margin and a payload-dependent decision.

RESEARCH METHODOLOGY

Rack and robot model. A rack is described as $T = (\vec{c}, \varphi, \kappa)$, where $\vec{c}$ is the centre, φ the yaw and κ the index of the rack type in a catalogue (length L, width W, deck clearance h, leg side s, corner inset e). The leg centres are

$$\vec{p}_i = \vec{c} + R(\varphi)\,\vec{q}_i, \quad \vec{q}_i \in \{(\pm a, \pm b)\}, \quad a = \frac{L}{2} - e - \frac{s}{2}, \quad b = \frac{W}{2} - e - \frac{s}{2}. \quad (1)$$

The robot (Fig. 3) is a four-wheel skid-steer platform with wheel radius $r = 0.08$ m and track width $B = 0.42$ m. Following the instantaneous-centre-of-rotation model [19, 20],

$$v_x = \frac{r(\omega_R + \omega_L)}{2}, \omega = \frac{r(\omega_R - \omega_L)}{\chi B}, \qquad \dot{x} = v_x \cos\theta, \quad \dot{y} = v_x \sin\theta, \quad \dot{\theta} = \omega, \quad (2)$$

where $\chi \geq 1$ is the slip factor. To prevent an unsecured tote from sliding, the lateral acceleration is limited ($\mu_{min} = 0.1$, safety factor $S = 2$):

$$|v_x\,\omega| \leq a_{max}(m) = \min\left(\frac{\mu_{min} g}{S}, \frac{g\,w_l}{h_l}, \frac{gB}{2h_{cg}}\right) \approx 0.5 \text{ m/s}^2. \quad (3)$$

The robot at pose $\vec{x}$ collides with a rack if its footprint $\mathcal{F}(\vec{x})$ touches a leg, or if it enters the deck footprint $\mathcal{P}(T)$ while its height $h_r(m)$ is not smaller than the clearance:

$$\text{coll}(\vec{x}, T, m) \Leftrightarrow \mathcal{F}(\vec{x}) \cap \bigcup_i \mathcal{L}_i(T) \neq \varnothing \;\vee\; (\mathcal{F}(\vec{x}) \cap \mathcal{P}(T) \neq \varnothing \wedge h_r(m) \geq h). \quad (4)$$

The local planner selects a control sequence whose probability of being collision-free is at least $1 - \alpha$. It is proved that if $2a - s > w_r + 2r_{inf}$ (w_r – robot width, r_{inf} – inflation radius), the free space of a 2D costmap contains poses under the rack deck; for a 1.6 × 0.8 m rack $2a - s = 1.42$ m and $w_r + 2r_{inf} = 1.00$ m.

The RAP algorithm (Fig. 1) performs the following steps every 0.1 s. First, the scan is segmented into clusters, and clusters not wider than 0.18 m are taken as leg candidates. Second, a two-channel convolutional neural network (CNN) assigns each candidate to the class rack leg, human leg or robot part; its input is a $2 \times 32 \times 32$ raster with the current scan in channel 0 and the scan taken 0.5 s earlier in channel 1, so static legs coincide in both channels while moving objects are displaced. Third, the rack pose is computed from the static legs $\{\hat{\vec{p}}_k\}$ by the closed-form solution of the Procrustes problem [21]:

$$\hat{\varphi} = \text{atan2}\left(\sum_k \tilde{\vec{q}}_k \times \tilde{\vec{p}}_k, \sum_k \tilde{\vec{q}}_k \cdot \tilde{\vec{p}}_k\right), \qquad \hat{\vec{c}} = \bar{\vec{p}} - R(\hat{\varphi})\,\bar{\vec{q}}. \quad (5)$$

A hypothesis must lie inside the workspace and pass the negative information test: if all beams in the direction of an expected but unobserved leg reach more than $\mu = 0.15$ m beyond it, the beam has passed where the leg should stand and the hypothesis is rejected. Fourth, racks are tracked with a Kalman filter, and points returned from the deck underside by the depth camera or 3D LiDAR and leg feet in the image are added as confirming evidence:

$$P(\text{rack} \mid Z_{1:t}) = \sigma(\ell_{geo} + \ell_{cue}), \quad (6)$$

where σ is the logistic function, ℓ_{geo} the geometric and ℓ_{cue} the sensor log-odds. The deck clearance $\hat{h}$ is estimated as the lower decile of the heights of elevated points, capped at the catalogue value. Finally, if $h_r(m) + \epsilon < \hat{h}$ ($\epsilon = 0.05$ m) the robot may pass under the rack and only the legs enter the map; otherwise the deck footprint inflated by the margin δ_k is marked as impassable. People and robots are predicted 2 s ahead with Kalman filters, and the planner chooses the cheapest arc that satisfies (3).

Theoretical results. If the leg coordinates have normal noise of variance σ^2, the estimator (5) is unbiased to first order, and its covariance equals the inverse Fisher information, i.e. the Cramér–Rao bound [22]:

$$\text{Var}(\hat{\varphi}) = \frac{\sigma^2}{S_q}, \qquad \text{Cov}(\hat{\vec{c}}) = \frac{\sigma^2}{n} I + \frac{\sigma^2}{S_q} (RJ\bar{\vec{q}})(RJ\bar{\vec{q}})^T, \qquad S_q = \sum_k \| \tilde{\vec{q}}_k \|^2. \quad (7)$$

With the margin $\delta_k = k\left(\sqrt{\text{trCov}(\hat{\vec{c}})} + \rho\sqrt{\text{Var}(\hat{\varphi})}\right)$, $\rho = 1/2\sqrt{L^2 + W^2}$, the probability that the true deck footprint lies inside the inflated estimate is bounded from below:

$$\Pr[\mathcal{P}(T) \subseteq \mathcal{P}(\hat{T}) \oplus \mathcal{B}(\delta_k)] \geq 1 - e^{-k^2/2} - 2(1 - \Phi(k)), \quad (8)$$

and the bound improves to $1 - e^{-k^2} - 2(1 - \Phi(k))$ when four legs are observed. If at least a fraction π_0 of the height samples comes from the deck underside, the decision based on the lower quantile makes a wrong “pass under” decision for the loaded robot with probability at most

$$\Pr[\text{wrong decision}] \leq \exp(-2N(q - p)^2), \qquad q = \pi_0\,\Phi(\epsilon/\sigma_z). \quad (9)$$

Experimental setup. The experiments were carried out in three stages: each theoretical result was checked by Monte Carlo simulation; paired episodes were run in a statistical 2D simulator of a 20.5 × 11.6 m warehouse; and closed-loop tests were run in Gazebo Harmonic 8.10 [23], ROS 2 Jazzy [24] and RViz2 (Figs. 5–6). The warehouse contains 24 mapped racks, up to five unmapped (abandoned) racks, three pedestrians and two other AMRs. Scenarios: S1 – mapped racks only, S2 – additional abandoned racks, S3 – people and robots, S4 – all together; each scenario was run in 20 random worlds with the loaded and the empty robot. Compared methods: A – 2D costmap [4, 5], B – keepout mask [8], F – LiDAR and depth-camera voxel fusion [6, 11], and the proposed RAP. Results were evaluated with Wilson confidence intervals [25] and the paired McNemar test (Figure 1, 2, 3) [26].

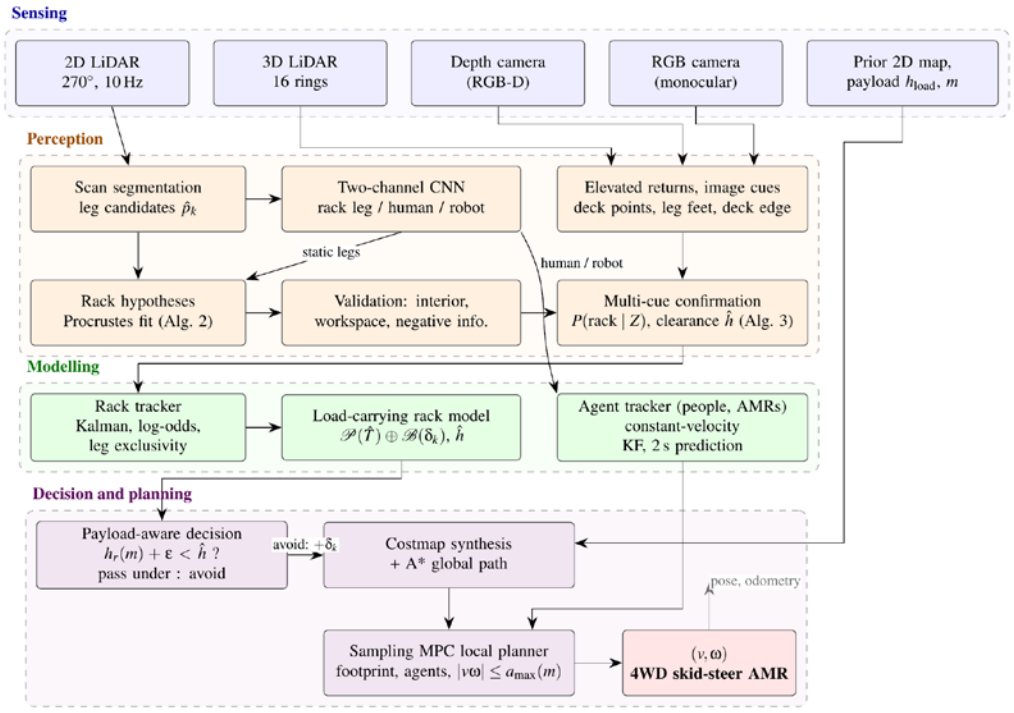


Figure 1. Block diagram of the RAP method[1]

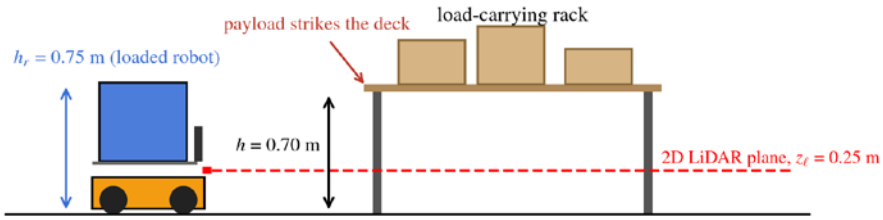
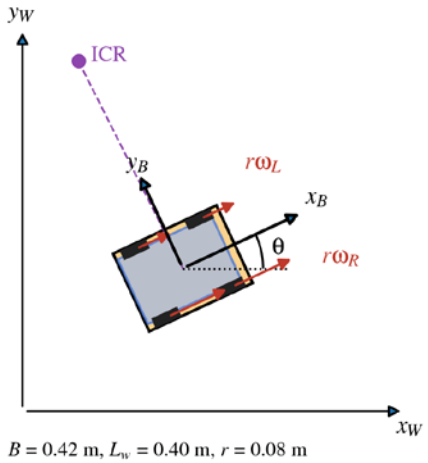


Figure 2. Leg illusion: the 2D LiDAR plane crosses only the rack legs, while the loaded robot is taller than the deck clearance[2]

1 Source: Author's own work.
2 Source: Author's own work.



$$v_x = r(\omega_R + \omega_L)/2$$

$$\omega = r(\omega_R - \omega_L)/(\chi B)$$

$$v_y + x_{\mathrm{ICR}}\,\omega = 0$$

$$\dot{x} = v_x \cos\theta, \quad \dot{y} = v_x \sin\theta, \quad \dot{\theta} = \omega$$

$$|v_x| + \chi B|\omega|/2 \le r\Omega$$

$$|v_x \omega| \le a_{\max}(m) = \min(\mu_{\min} g/S,$$

$$g w_l/h_l,\ gB/(2h_{cg})) \approx 0.5\ \mathrm{m/s^2}$$

Figure 3. Kinematic model of the four-wheel skid-steer AMR and the payload stability condition[3]

ANALYSIS AND RESULTS

Verification of the theory. Table 1 compares Monte Carlo estimates (trials) with the theoretical values. The rack centre and yaw errors agree with the Cramér–Rao bound within 0.8 %; with the inflated estimate contained the true deck in 99.81 % of the trials for three legs and 99.94 % for four legs, with a margin of only 5–6 cm. Under the influence of points returned from the sides of cartons the median estimate was biased by up to 7.3 cm and led to wrong decisions, whereas the lower decile produced no wrong decision (Table 1).

Table 1. Monte Carlo verification of the theoretical results[4]

Quantity	Condition	Monte Carlo	Theory
Centre error, cm	2 / 3 / 4 legs, σ=2 cm	2.099 / 1.683 / 1.419	2.101 / 1.683 / 1.414
Yaw error, °	2 / 3 / 4 legs	1.102 / 0.876 / 0.708	1.102 / 0.869 / 0.709
Containment probability, (8)	3 / 4 legs, k=2	0.9981 / 0.9994	≥ 0.819 / ≥ 0.936
Depth error (monocular), cm	d=2 / 4.5 / 7 m	4.24 / 21.18 / 51.57	4.16 / 21.05 / 50.95
Wrong decision, median	N=20, π_0=0.15	$1.6{\cdot}10^{-3}$	–
Wrong decision, lower decile, (9)	N=20, π_0=0.5	0	≤ $1.8{\cdot}10^{-3}$

Obstacle-type recognition. On 15 607 clusters from 80 unseen warehouse layouts (13 459 rack legs, 1 452 human legs, 696 robot parts) the two-channel CNN reached an accuracy of 0.979 and a macro-F1 of 0.925; only 0.6 % of rack legs were assigned to the moving classes (Table 2).

Table 2. Obstacle-type recognition results (recall per class)[5]

Classifier	Accuracy	Rack leg	Human leg	Robot part	Macro-F1
Two-channel CNN (proposed)	0.979	0.994	0.895	0.864	0.925
One-channel CNN	0.972	0.995	0.841	0.799	0.901
Classical rule (motion + width)	0.816	0.868	0.687	0.089	0.489
Two-channel CNN, Gazebo scans	0.981	0.986	0.920	0.916	–

Navigation in the 2D warehouse. Fig. 4 and Table 3 present the 640 episodes of the main experiment. In scenario S1 all methods reached 100 % success, which shows that the shared planners do not influence the result. Abandoned racks separate the methods sharply: with method A the loaded robot struck a deck in 10 of 20 episodes in S2 and in 14 in S4, with method B in 6 and 7, whereas F and RAP produced no deck strike. Over all scenarios RAP achieved 95.0 % success with 1.9 % safety violations, compared with 76.2/21.2 %,

3 Source: Author's own work.
4 Source: Author's own work.
5 Source: Author's own work.

80.6/12.5 % and 90.0/5.6 % for A, B and F. The McNemar test showed that the superiority of RAP over A and B is statistically significant (), while the difference to F is not significant at this sample size (). With the loaded robot RAP produced no safety violation in 80 episodes. The empty robot in S4 drove on average 1.44 m under racks per episode, so rack awareness did not cost the shorter routes. In additional experiments RAP never struck a deck with any sensor configuration, including the 2D LiDAR alone; when the depth camera failed completely, the success of method F fell from 100 % to 50 %, while RAP kept 83 % (Figure 4; Table 3).

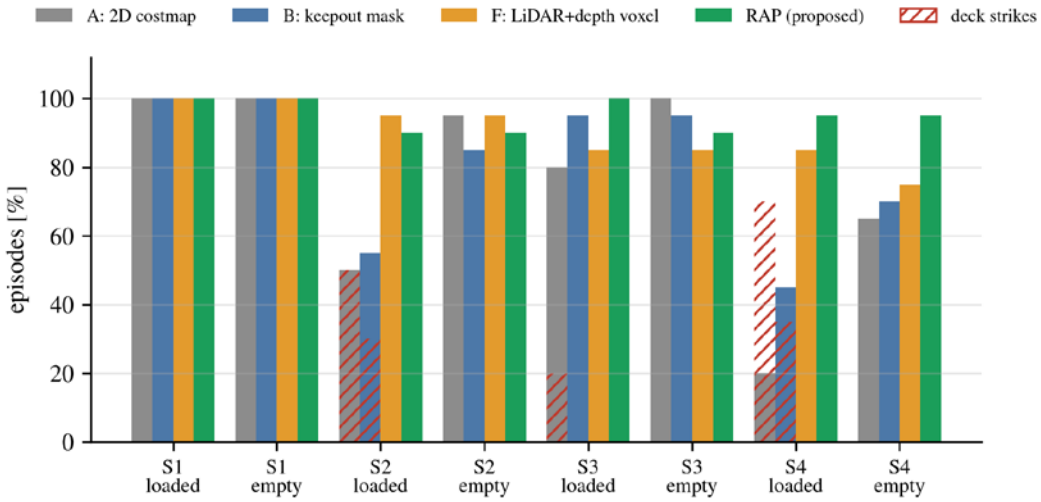


Figure 4. Success rates of the methods in the main experiment (20 paired episodes per bar); hatched part – deck strikes[6]

Table 3. Results of the main experiment: success, % (safety violations / deck strikes)[7]

Scenario	Payload	A: 2D costmap	B: keepout	F: LiDAR+depth	RAP
S1	loaded	100 (0/0)	100 (0/0)	100 (0/0)	100 (0/0)
S2	loaded	50 (10/10)	55 (6/6)	95 (0/0)	90 (0/0)
S2	empty	95 (0/0)	85 (0/0)	95 (0/0)	90 (0/0)
S3	loaded	80 (4/4)	95 (1/0)	85 (2/0)	100 (0/0)
S4	loaded	20 (16/14)	45 (9/7)	85 (2/0)	95 (0/0)
S4	empty	65 (4/0)	70 (3/0)	75 (4/0)	95 (1/0)
S1–S4	all	76.2 (21.2 %)	80.6 (12.5 %)	90.0 (5.6 %)	95.0 (1.9 %)

Closed-loop tests in Gazebo/ROS 2. Eight Gazebo worlds of type S4 were generated from the simulator seeds: 29 racks with cartons, three pedestrians, two AMRs and the URDF model of the robot equipped with a 2D LiDAR, an RGB-D camera and a 3D LiDAR. With method A the loaded robot struck a deck in 6 of 9 tests (Fig. 5, a), whereas with RAP it never entered under a rack in 18 tests of two independent series and reached the goal in 14 (Fig. 5, b). The per-step log confirmed that no rack was ever labelled “passable” for the loaded robot. In RViz2 (Fig. 6) every rack is shown as a load-carrying volume together with its confirmation probability and the decision taken (Table 4; Figure 5, 6).

6 Source: Author’s own work.
7 Source: Author’s own work.

Table 4. Results of the closed-loop tests in Gazebo (number of outcomes)[8]

Method	Payload	Series	Tests	Success	Deck strike	Leg contact	Agent	Stuck
A: 2D costmap	loaded	–	9	2	6	0	1	0
RAP	loaded	I	9	6	0	0	1	2
RAP	loaded	II	9	8	0	0	0	1
RAP	empty	I	6	3	0	1	0	2
RAP	empty	II	6	4	0	0	0	2



Figure 5. Gazebo environment, loaded robot: a) method A – the robot drives between the rack legs and strikes the deck; b) RAP – the racks are avoided[9]

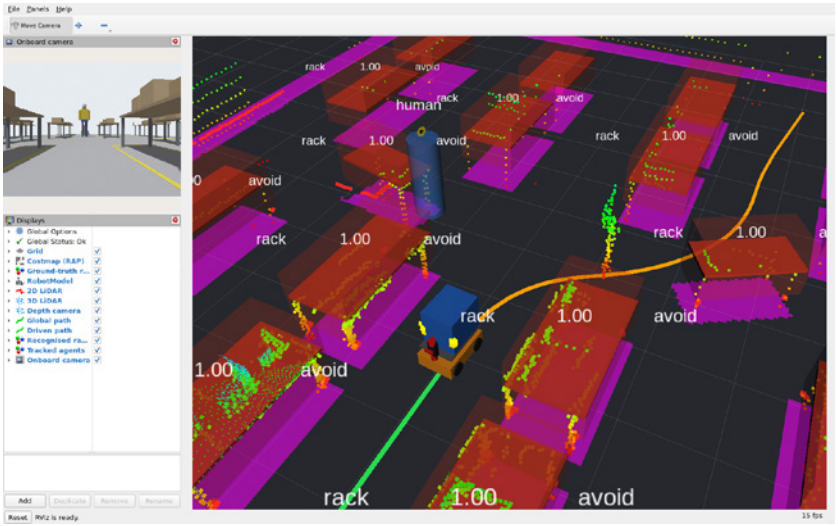


Figure 6. RViz2 view during a RAP run: point clouds, costmap with inflated deck footprints, racks with confirmation probability and decision, tracked person, global (green) and driven (orange) paths[10]

The Gazebo tests also revealed a weakness of the first version of the method: the median of the heights rose to 0.81 m because of the cartons, and two racks were labelled passable for the loaded robot. The median was replaced by the lower decile, bound (9) was proved and all tests were repeated. Limitations of the study: all experiments were carried out in simulation, localisation was assumed to be exact and the catalogue of rack types is known in advance.

8 Source: Author's own work.
9 Source: Author's own work.
10 Source: Author's own work.

CONCLUSIONS AND SUGGESTIONS

A 2D LiDAR mounted close to the floor sees the legs of a load-carrying rack but not its deck, so an ordinary costmap sends a loaded robot under the rack. The proposed RAP method recognises the rack from its legs, separates it from people and other robots with a two-channel CNN, confirms it with any available sensor and projects it into the map as a load-carrying volume with a certified margin; the robot's payload decides whether to pass under or go around the rack and limits the lateral acceleration.

The estimator attains the Cramér–Rao bound, and all theoretical bounds were confirmed numerically. In 640 episodes RAP achieved 95.0 % success with 1.9 % safety violations and no violation with the loaded robot; in Gazebo/ROS 2 tests the ordinary costmap struck a deck in 6 of 9 tests, whereas RAP never drove the loaded robot under a rack in 18 tests. Future work: implementing the method as a Nav2 plugin, adding the robot's localisation uncertainty to the margin, and testing on a physical AMR in a real warehouse.

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