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Dynamical Problems in Mechanical Systems
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DYNAMICAL PROBLEMS IN MECHATRONIC SOLUTIONS APPLIED TO SURVEILLANCE OF MECHANICAL SYSTEMS

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FACULTY OF MECHANICAL ENGINEERING

Gdańsk / Danzig

Gdansk University of Technology

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FACULTY OF MECHANICAL ENGINEERING

- about 25000 students
- 9 faculties
- 7 kinds of doctorate courses
- 29 fields of study
- 40 postgraduate courses
- 1200 academic teachers

GDAŃSK UNIVERSITY OF TECHNOLOGY | 111 YEARS

Faculty of Mechanical Engineering

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- 250 graduates annually
- 6 fields of study
- 3 postgraduate courses
- doctorate course
- 123 academic teachers

Main topics

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- Vibration surveillance during machining
- Control of 2-wheeled mobile platforms / mobile robots
- Systems' surveillance by the optimal control at energy performance index
- Modal parameters' identification

Dynamic systems surveillance

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Dynamic systems surveillance - a set of intentional activities, aimed at securing the desired performance of a dynamic process.

The **systems surveillance** depends upon:

- **monitoring** of physical quantities, which affect the process quality (e.g. vibration level, amplitude of displacements)

- **generation** of instantaneous values of control command, in accordance with a proper rule being applied.

Publications

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1. **Chodnicki M., Kaliński K. J., Galewski M.**: *Vibration surveillance during milling of flexible details with a use of the active optimal control*. Journal of Low Frequency Noise, Vibration and Active Control, Vol. 32, No. 1&2 2013.
2. **Kaliński K. J., Mazur M., Galewski M.:** *The optimal spindle speed map for reduction of chatter vibration during milling of bow thruster blade*. Solid State Phenomena 2013, Vol. 198, s.686-691.
3. **Chodnicki M., Panasiuk-Chodnicka A.A., Ławreszuk D., Kulwicki Ł., Jażdżewski M.**: *Innovative Autonomous Underwater Vehicle (AUV) for research of state of environment in hard condition*. XXXIII SCAR Biennial Meetings 2014 Open Science Conference, Auckland.
4. **Kaliński K. J., Galewski M. A.**: *Vibration Surveillance Supported by Hardware-In-the-Loop Simulation in Milling of Flexible Workpieces*. Mechatronics 2014, 24, 8,1071–1082.
5. **Kaliński K. J., Galewski M., Mazur M., Chodnicki M.**: *Vibration surveillance for efficient milling of flexible details fixed in adjustable stiffness holder*. JVE International Ltd. Vibroengineering Procedia.Vol. 3, 2014.
6. **Kaliński K. J., Galewski M. A.**: *A modified method of vibration surveillance by using the optimal control at energy performance index*. Mechanical Systems and Signal Processing 2015, 58-59, 41-42.
7. **Kaliński K. J., Buchholz C.**: *Mechatronic Design of Strongly Nonlinear Systems on a Basis of Three Wheeled Mobile Platform*. Mechanical Systems and Signal Processing 2015, 52-53, 700-721.
8. **Kaliński K. J., Galewski M. A.**: *Optimal spindle speed determination for vibration reduction during ball-end milling of flexible details*. International Journal of Machine Tools and Manufacture 2015, 92, 19-30.
9. **Kaliński K. J., Chodnicki M., Kowalska B., Kmita P.**: *Analysis of crash computation on a basis of principle of linear momentum and kinetic energy*. In: Mechatronics: Ideas, challenges, solutions and applications. Editors: Awrejcewicz J., Kaliński K. J., Kaliczyńska M., Szewczyk R. Springer, 2015 (in publishing).
10. **Kaliński K. J., Galewski M., Mazur M., Chodnicki M.**: *Modelling and simulation of a new variable stiffness holder for vibration surveillance system*. Acta mechanica et automatica, 2015 (in publishing).
11. **Kaliński K. J., Mazur M.**: *Optimal Control at Energy Performance Index of the Mobile Robots Following Dynamically Created Trajectories*. Mechatronics 2015 (in publishing).
12. **Galewski M. A.**: *Spectrum-based Modal Parameters Identification with Particle Swarm Optimisation*. Mechatronics 2015 (in publishing).

ICM Conference

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International Conference
MECHATRONICS
Ideas for Industrial Applications

MAY 11-13, 2015 – GDAŃSK, POLAND

Organising committee

ICM Conference

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Project TANGO1/266350/NCBR/2015

Zastosowanie wybranych rozwiązań mechatronicznych do nadzorowania procesu skrawania przedmiotów wielkogabarytowych na wieloosiowych centrach obróbkowych.

Application of chosen mechatronic solutions to surveillance of the cutting process of large size objects on multi-axes machining centres.

* Carousel lathe machine FKD 80/60 Feichter. Energomontaż-Północ Gdynia

MODELLING AND SIMULATION OF A NEW VARIABLE STIFFNESS HOLDER FOR VIBRATION SURVEILLANCE SYSTEM

Vibration reduction in milling

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We know many different methods for reduction and surveillance of the chatter vibration, i.e.:

- Using the cutting edge chamfers
- Using mechanical dampers
- Using smart materials
- Robust optimal control
- Active structural control
- Active holder
- Active damping
- Cutting with variable spindle speed
- Matching the spindle speed to the optimal phase shift between subsequent passes of the tool cutting edges
- Variable spindle speed
- Raising spindle speed
- Matching the spindle speed to natural frequency of vibrating system

Optimal spindle speed

Optimal spindle speed

- The speed, at which chatter vibration amplitude approaches minimum

Generalised Liao-Young condition

In case, when only one dominant resonance is observed in the workpiece vibration spectrum

$$\frac{zn_\alpha}{60} = \frac{f_\alpha}{0{,}25 + k}, \quad k = 0,1,2,\ldots$$

$f\alpha$ – determined natural frequency of the workpiece [Hz],
$n\alpha$ – sought optimal spindle speed [rev/min],
z – number of mill edges

New variable stiffness holder

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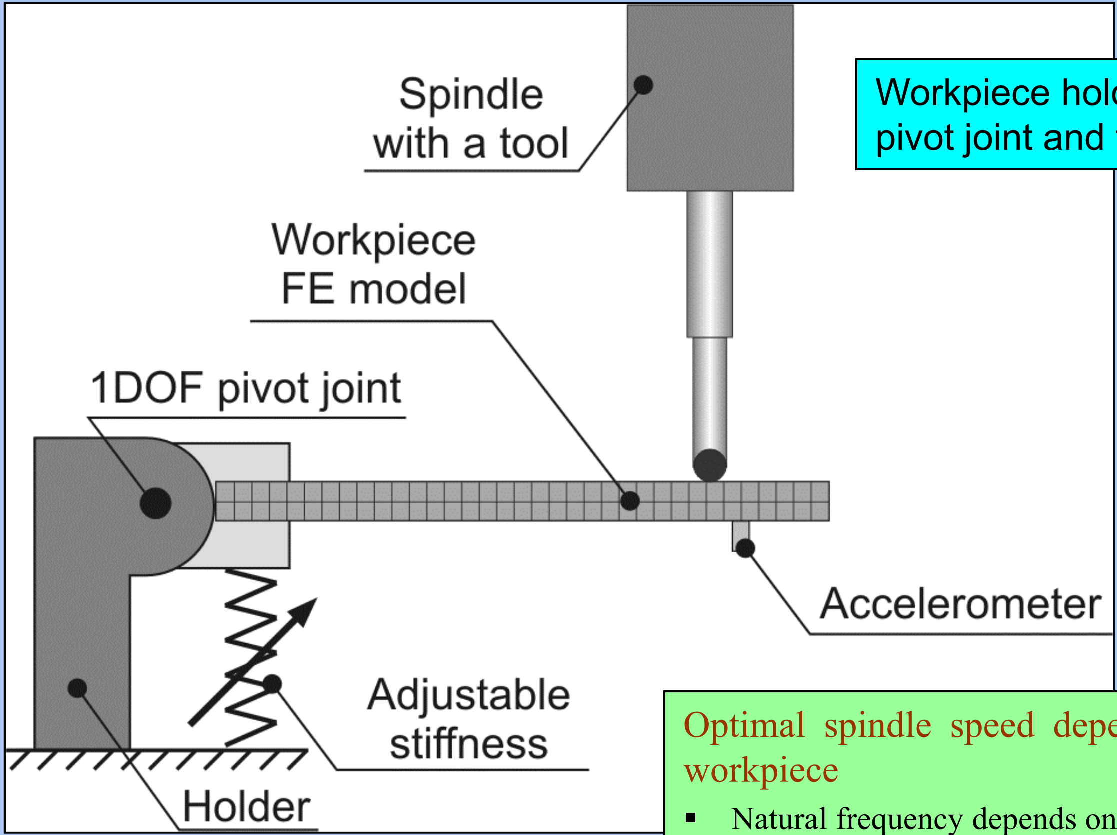

Workpiece holder with adjustable stiffness and 1 DOF pivot joint and the FEM model of the workpiece

Optimal spindle speed depends on dominant natural frequency of the workpiece

- Natural frequency depends on workpiece dynamic properties.
- The workpiece is mounted in a holder with adjustable stiffness and whose behaviour is based on 1 DOF pivot joint.
- Thanks to the adjustable stiffness, it is possible to modify dynamic properties of the whole system (consisting of the holder and the workpiece) and to modify its natural frequency.

Cutting process model

Proportional model

Cutting force components depend proportionally on cutting layer thickness, and on variable in time depth of cutting

$$F_{yl1}(t) = \begin{cases} \mu_l k_{dl} a_l(t) h_l(t), & a_l(t) > 0 \ \wedge \ h_l(t) > 0, \\ 0 \quad , & a_l(t) \leq 0 \ \vee \ h_l(t) \leq 0, \end{cases}$$

$$F_{yl2}(t) = \begin{cases} k_{dl} a_l(t) h_l(t), & a_l(t) > 0 \ \wedge \ h_l(t) > 0, \\ 0 \quad , & a_l(t) \leq 0 \ \vee \ h_l(t) \leq 0, \end{cases}$$

$$F_{yl3}(t) = 0$$

where:

$$a_l(t) = a_{pl}(t) - \Delta a_{pl}(t)$$

$$h_l(t) = h_{Dl}(t) - \Delta h_l(t) + h_l(t - \tau_l)$$

Holder, workpiece and tool system model

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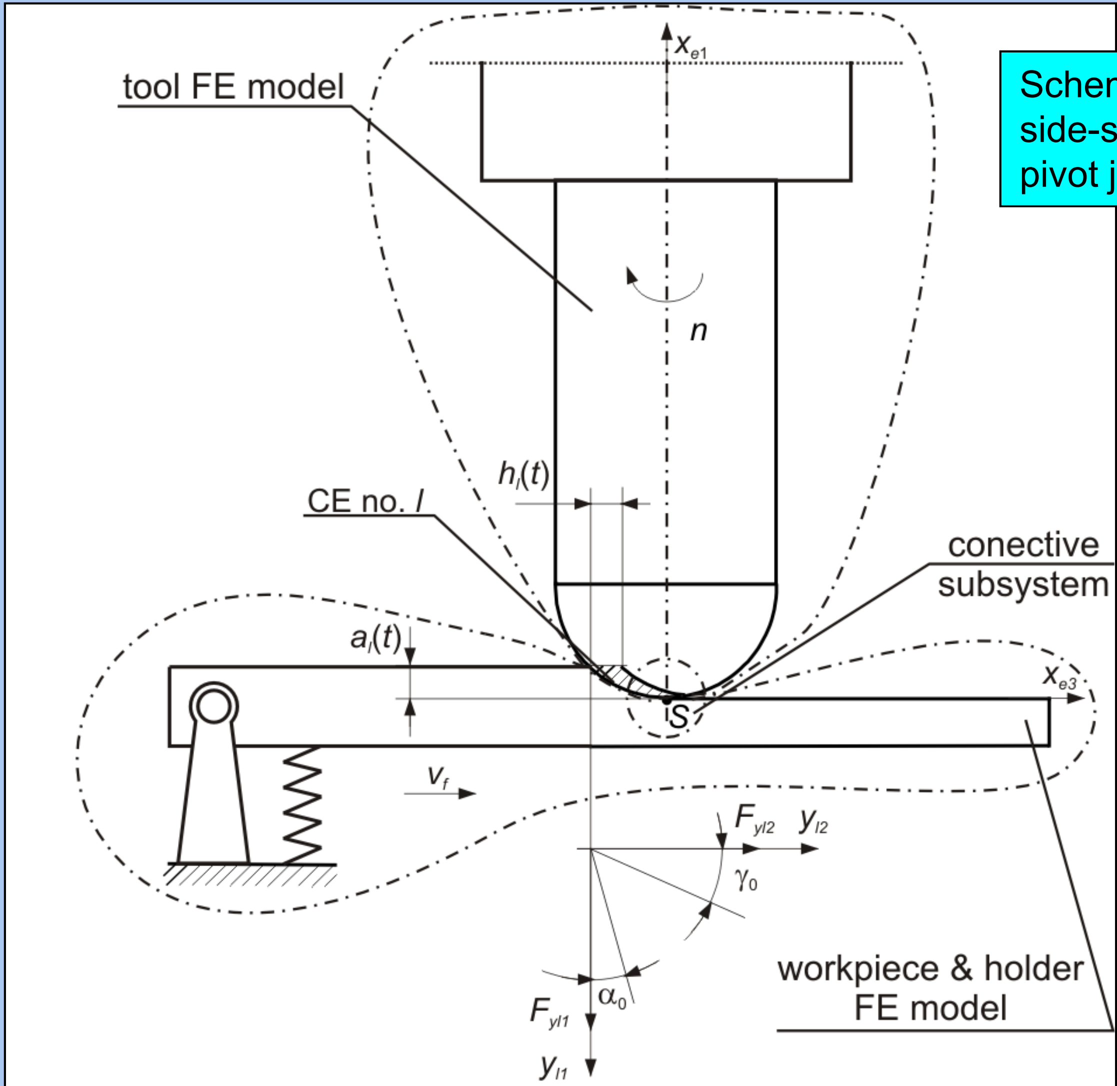

Scheme of a slender ball-end milling of one-side-supported flexible workpiece in a 1 DOF pivot joint.

Hybrid approach

- **modal subsystem:**
  stationary model of one-side-supported flexible plate, which displaces itself with feed speed *vf*.
- **structural subsystem**
  non-stationary discrete model of ball-end mill and cutting process.
- **connective subsystem**
  conventional contact point S between the tool and the workpiece.

Simulations

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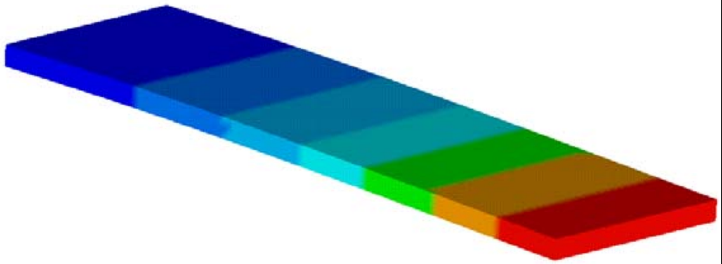
Natural frequencies of two first modes of variable stiffness holder with workpiece

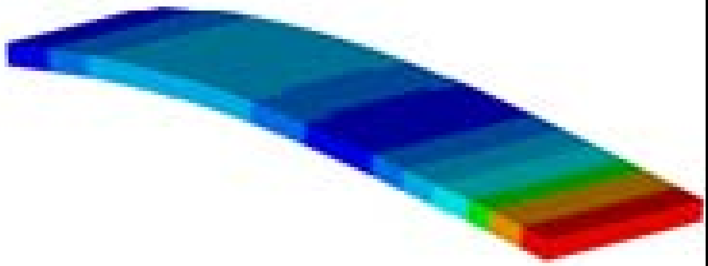
Spring stiffness [N/mm]	1st natural frequency [Hz]	2nd natural frequency [Hz]
14800	138.62	468.67
11000	131.36	427.48
8500	124.08	398.47
6800	117.16	377.87
5600	110.78	362.93
4700	104.83	351.54
4000	99.27	342.60
3470	94.36	335.80
3050	89.94	330.39
2670	85.43	325.50

Both natural frequencies change due to adjustment of the spring stiffness. It was also noticed that both normal modes of the holder with the workpiece are well coupled with the workpiece

First normal mode (110.78 Hz) of the stiffness holder with the workpiece at spring stiffness 5600 N/mm



Second normal mode (362.93 Hz) of the stiffness holder with the workpiece at spring stiffness 5600 N/mm



Simulations

Standard deviation of displacements [mm]. Expected optimal pairs marked with gray background.

Spindle speed [rev/min]	Holder spring stiffness [N/mm]						
	14800	11000	8500	6800	5600	4700	4000
17651	0.002366						
16745		0.007657					
16651	**0.002539**	0.005380					
15869			0.002711				
15745	0.003676	**0.002613**	0.002671	0.002523	0.002193		
15651	0.003866						
15284					0.002547		
15047				0.002860			
14869		0.004322	**0.002926**	0.002787	0.002927		
14745		0.004957					
14581						0.002810	
14284					0.003170		
14047			0.006864	**0.003431**	0.003163		
13869			0.008736				
13784					0.003831		
13581						**0.003441**	
13284				0.008378	**0.004034**	0.004537	**0.003627**
13047				0.010622			
12581					0.015531	**0.020466**	0.031396
12284					0.024176		
11932						0.059660	**0.059596**
11581						0.078220	

Simulations

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Amplitude of the 1st natural frequency [mm]. Expected optimal pairs marked with gray background. Obtained optimal pairs in bold.

Spindle speed [rev/min]	Holder spring stiffness [N/mm]						
	14800	11000	8500	6800	5600	4700	4000
17651	0.001584						
16745		0.007286					
16651	**0.000310**	0.004502					
15869			0.001615				
15745	0.001045	**0.000317**	0.001557	0.001632	0.000666		
15651	0.001282						
15284					0.000942		
15047				0.001510			
14869		0.002834	**0.000472**	0.000848	0.001501		
14745		0.003316					
14581						0.001212	
14284					0.001103		
14047			0.004760	**0.000747**	0.005021		
13869			0.006904				
13784					0.001447		
13581						**0.000357**	
13284				0.006728	**0.000521**	0.002755	**0.002057**
13047				0.008114			
12581					0.005560	**0.021472**	0.033184
12284					0.029790		
11932						0.074891	**0.073382**
11581						0.082545	

Simulations

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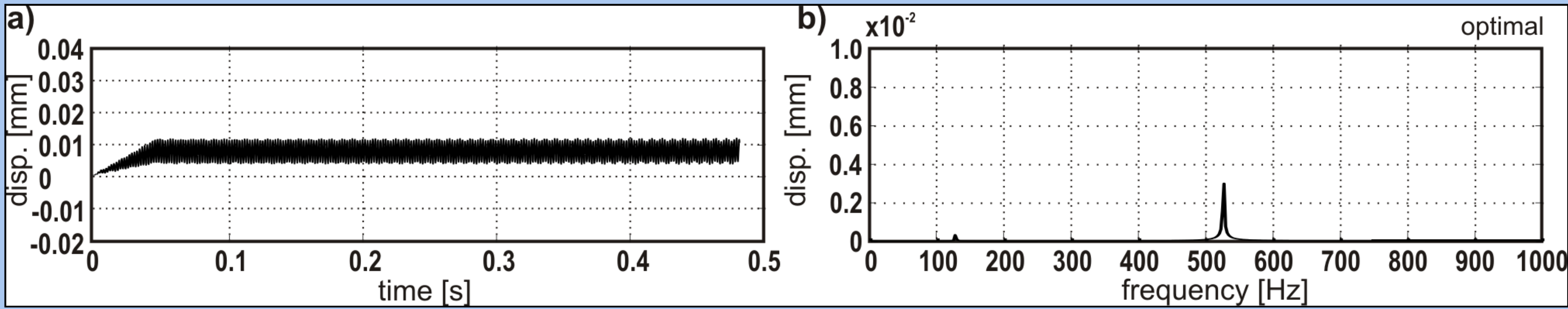
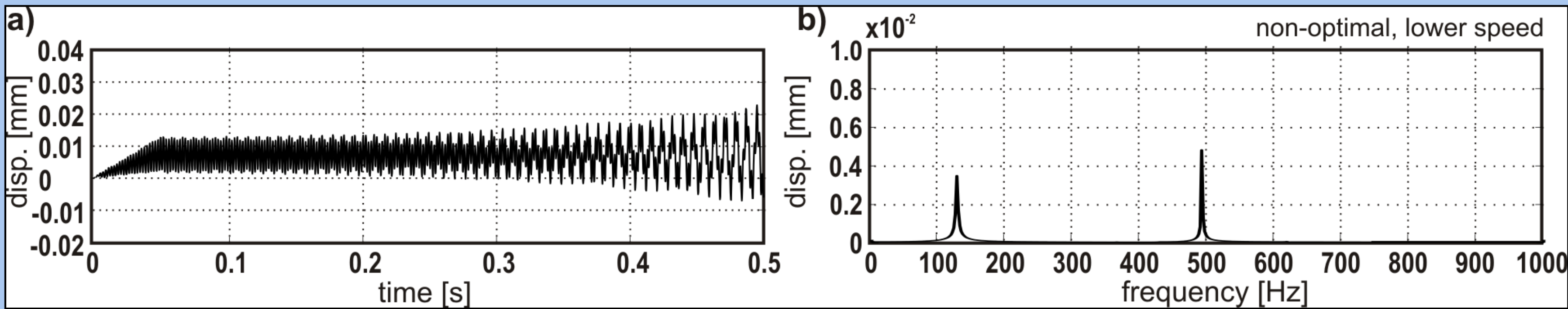


Displacement (a) and its spectrum (b) for optimal pair of spindle speed **n=15745 rev/min** and holder stiffness **11000 N/mm**.



Displacement (a) and its spectrum (b) for non-optimal pair of spindle speed **n=14745 rev/min** and holder stiffness **11000 N/mm**

Simulations

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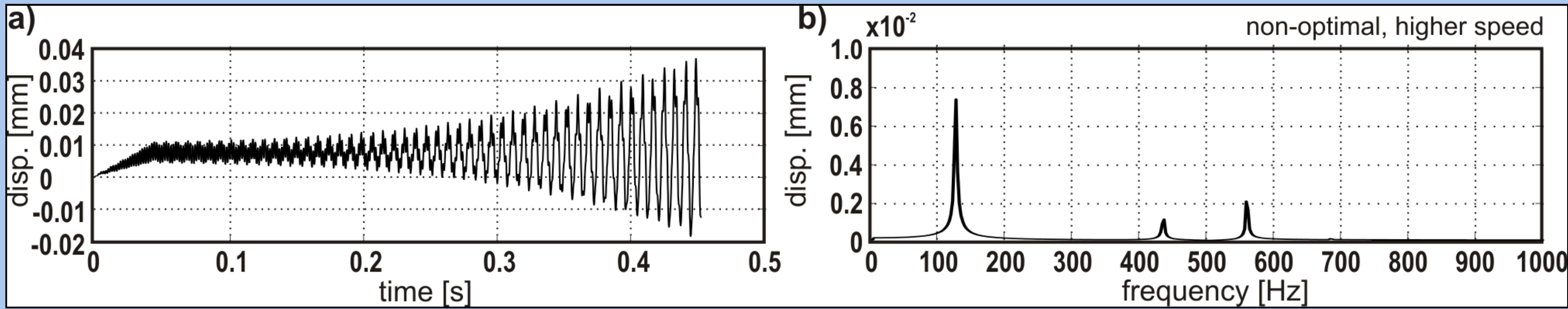
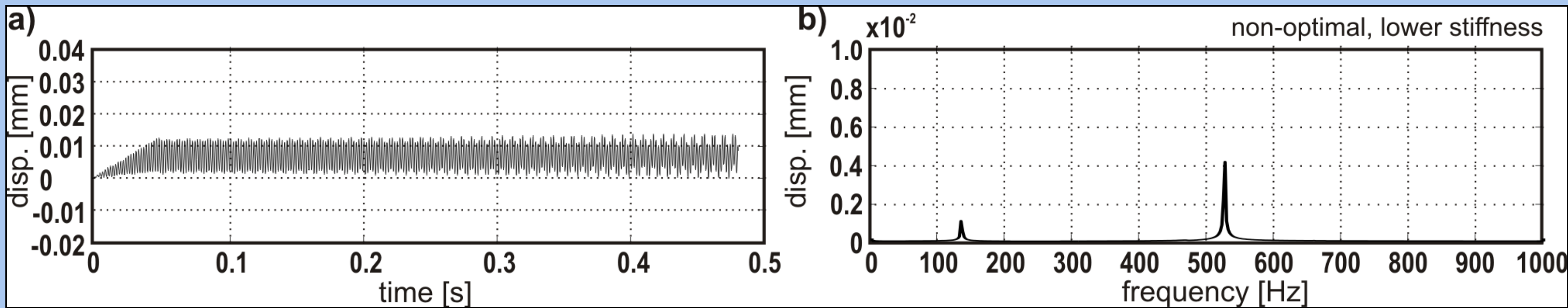


Displacement (a) and its spectrum (b) for non-optimal pair of spindle speed **n=16745 rev/min** and holder stiffness **11000 N/mm**



Displacement (a) and its spectrum (b) for non-optimal pair of spindle speed **n=15745 rev/min** and holder stiffness **8500 N/mm**.

Simulations

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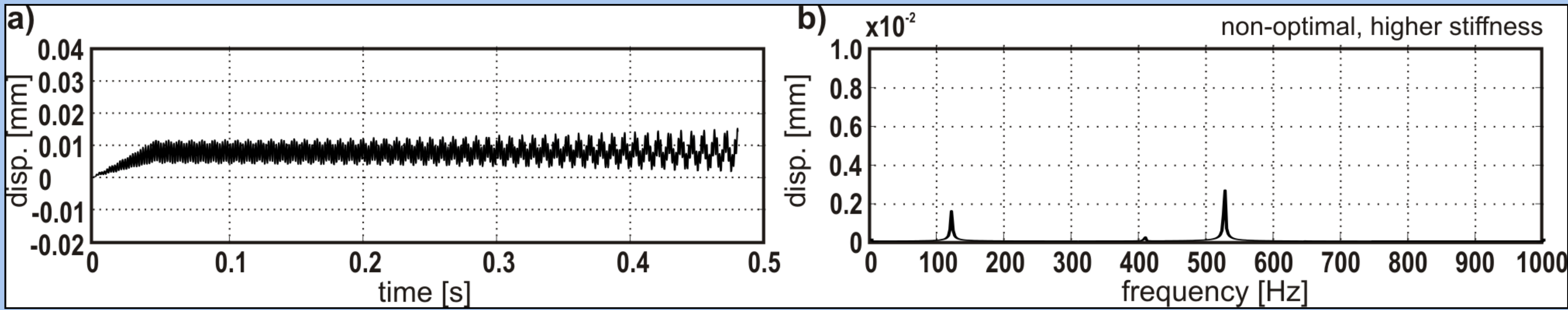

Displacement (a) and its spectrum (b) for non-optimal pair of spindle speed **n=15745 rev/min** and holder stiffness **14800 N/mm**

Conclusion

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Modifying the holder-workpiece system dynamic properties is possible with the use of he proposed new workpiece holder

- However – the range of modification is limited
- Confirmed by preliminary modal experiments on holder prototype

Simulations for different pairs of holder stiffness and spindle speed show that only in ase of a proper, optimal combination of these two parameters, vibrations are the owest

Proposed variable stiffness holder has a potential to overcome the problem of limited et of optimal spindle speeds calculated from Liao-Young condition

- Arbitrary given spindle speed may be optimal after holder stiffness adjustment

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TIMAL CONTROL AT ENERGY PERFORMANCE DEX OF THE MOBILE ROBOTS FOLLOWING DYNAMICALLY CREATED TRAJECTORIES

Introduction

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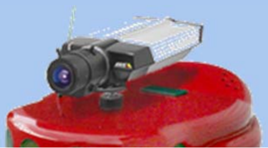
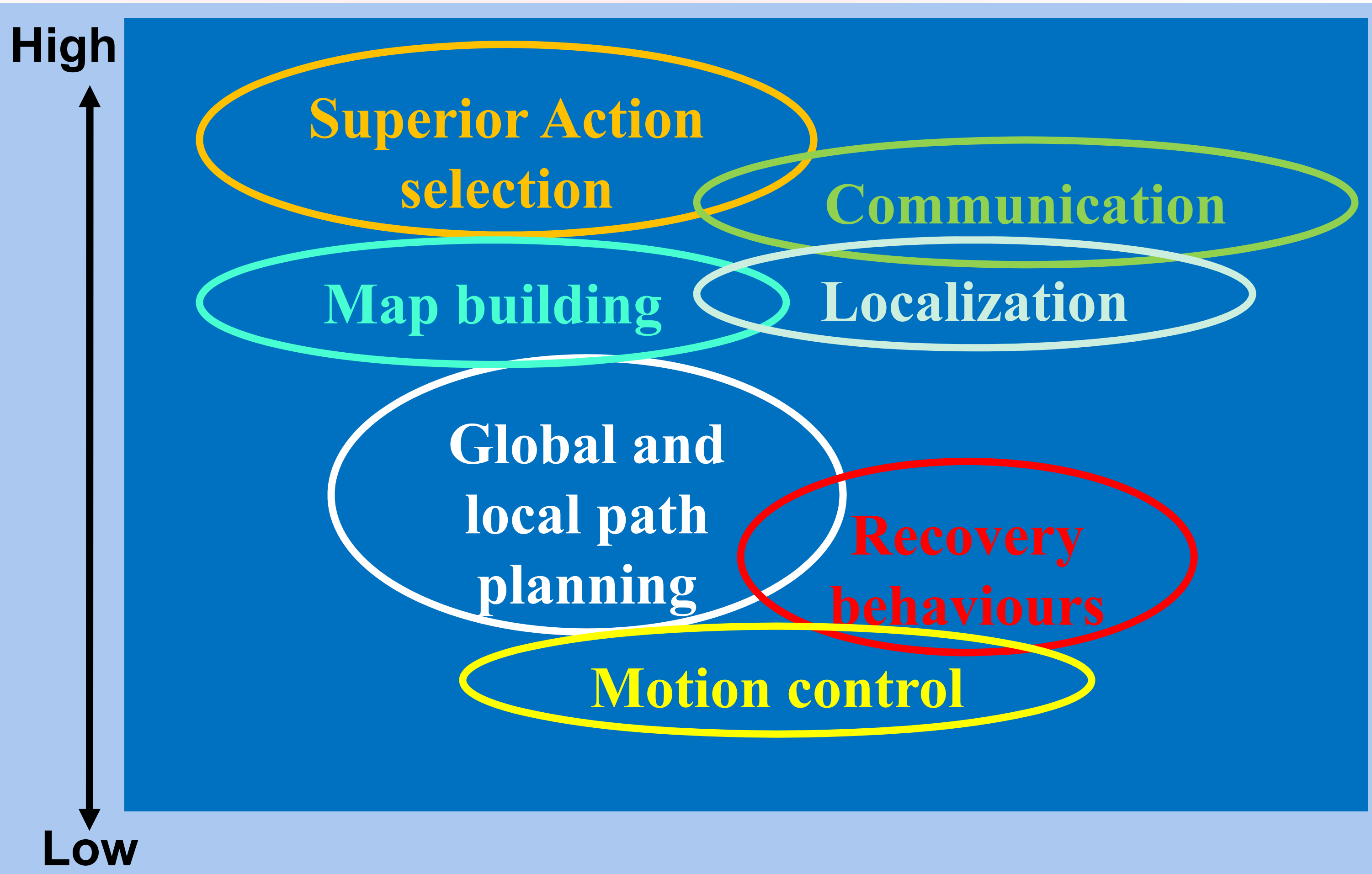
Examples of application:



Introduction



obot’s motion control is also called as low level control and is

Introduction

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ple methods of movement control:

egulators – limited accuracy and efficiency

cial neural networks – ability of loosing stability
– accuracy depends on the teaching process

logic – based on the uncertain calculation model

tic algorithms – time consuming and uncertain model

st control – too high torques leading to slippages

tive control – system should be appropriately excited what could limit accuracy

Deterministic model

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presented control method is based on the deterministic model ng following features:

ameters of the calculation model are known

figuration of the calculation model is known as well

trolled system is bounded by non-holonomic constraints

ion trajectory is known

2-wheeled mobile robot

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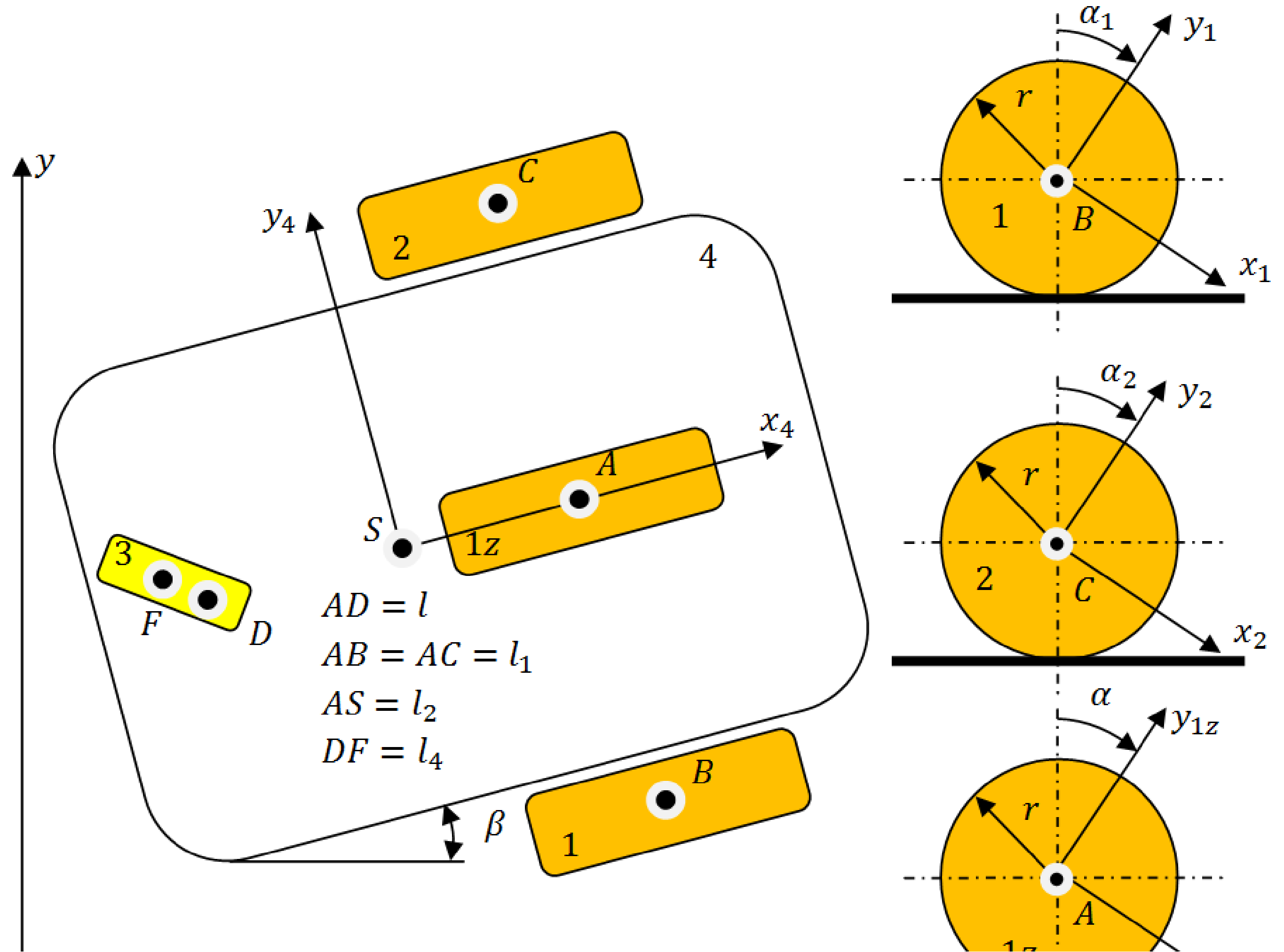

Kinematics

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umptions:

obot moves over flat horizontal surface
otion without slippages
heels and other robot's parts are perfectly rigid
wo independent velocities are known

uations of forward kinematics:

$$v_A = \frac{(\dot{\alpha}_1 + \dot{\alpha}_2) r}{2},$$

$$\dot{\beta} = \frac{(\dot{\alpha}_1 - \dot{\alpha}_2) r}{2 l_1},$$

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pell-Gibbs equations:

$$\frac{\partial S}{\partial \dot{\mathbf{w}}} = \mathbf{f}(t,\dot{\mathbf{q}},\mathbf{q}) + \mathbf{B}_u(t,\dot{\mathbf{q}},\mathbf{q})\mathbf{u}$$

$$\dot{\mathbf{q}} = \mathbf{C}_0^T(\mathbf{q})\mathbf{w} + \mathbf{G}_0(\mathbf{q})$$

$(\mathbf{q},\mathbf{w},\dot{\mathbf{w}})$ the Appell's function, computed similarly as kinetic energy, but instead of generalised velocities the generalised accelerations are considered

$[\quad]^T$

nergy Performance Index

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$$J(t)=\frac{1}{2}(\dot{\mathbf{q}}-\dot{\bar{\mathbf{q}}})^T\mathbf{Q}\,\mathbf{M}\,(\dot{\mathbf{q}}-\dot{\bar{\mathbf{q}}})+\frac{1}{2}\mathbf{u}^T\mathbf{R}\mathbf{u}$$

ptimal control signal – time-instant values are computed *on-line* :

$$\mathbf{u}=-(\mathbf{R}+\mathbf{R}^T)^{-1}\int_t^{t+\Delta t}\mathbf{B}^T(\tau)\mathbf{\Phi}^T(t,\tau)d\tau\cdot\mathbf{T}^T(\mathbf{M}^T\mathbf{Q}^T+\mathbf{Q}\mathbf{M})(\dot{\mathbf{q}}-\dot{\bar{\mathbf{q}}})$$

$\mathbf{R}$ - matrix of control command effect

$\mathbf{Q}$ - matrix of dimensionless weighing coefficients

2-wheeled mobile robot

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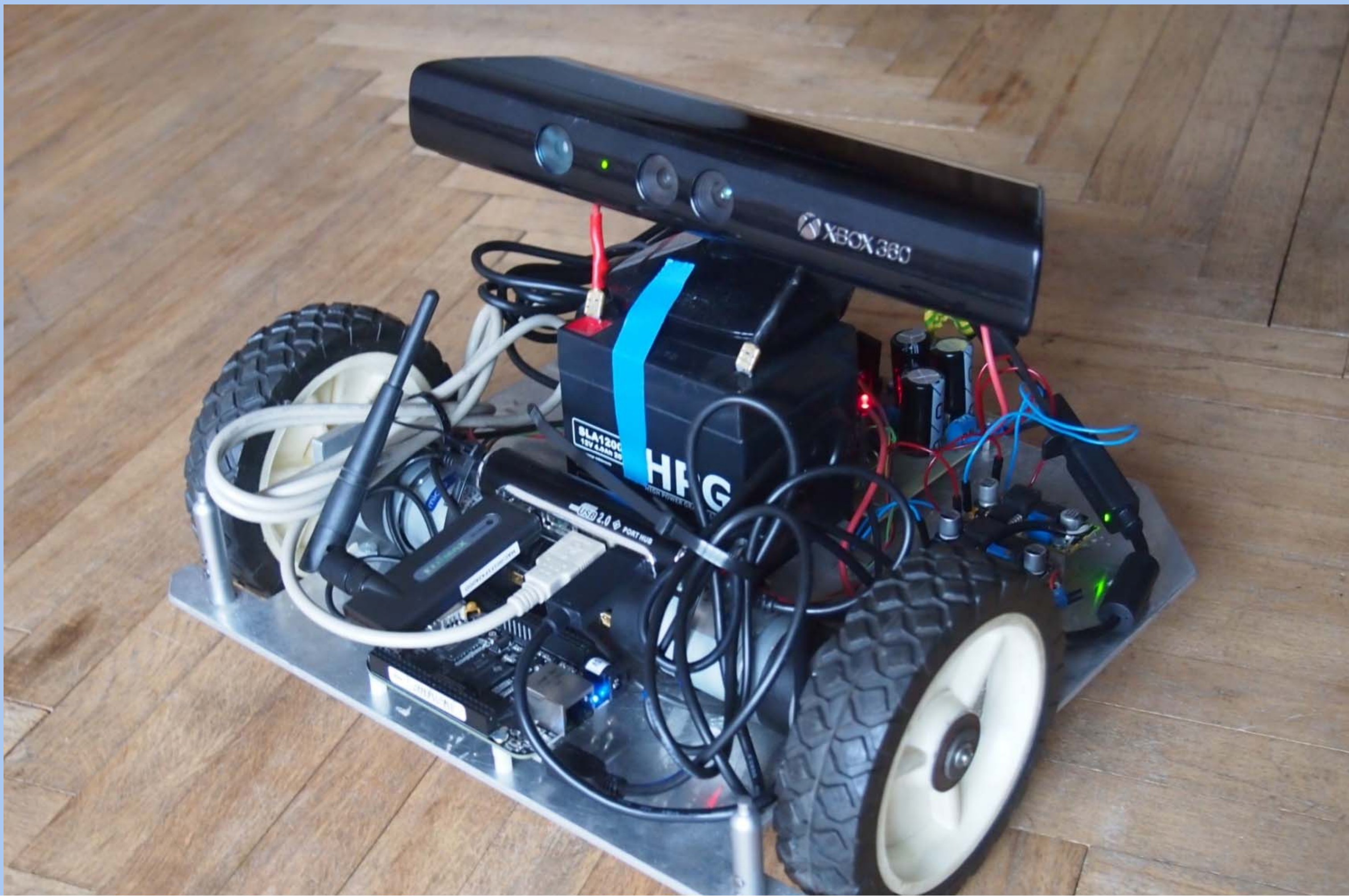

mulation – static trajectory

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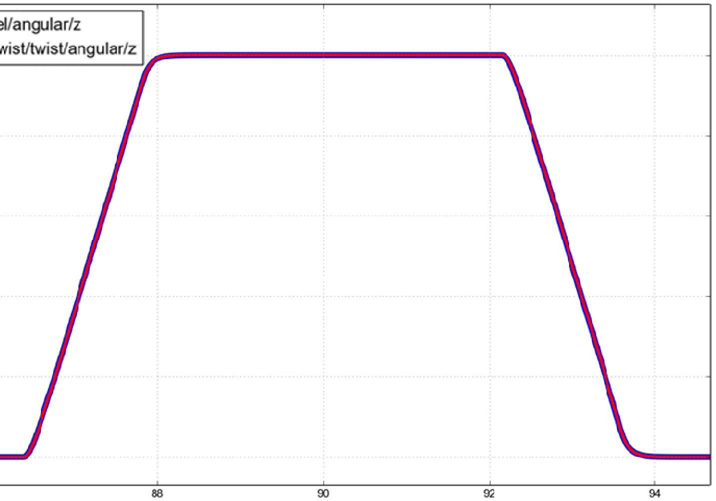

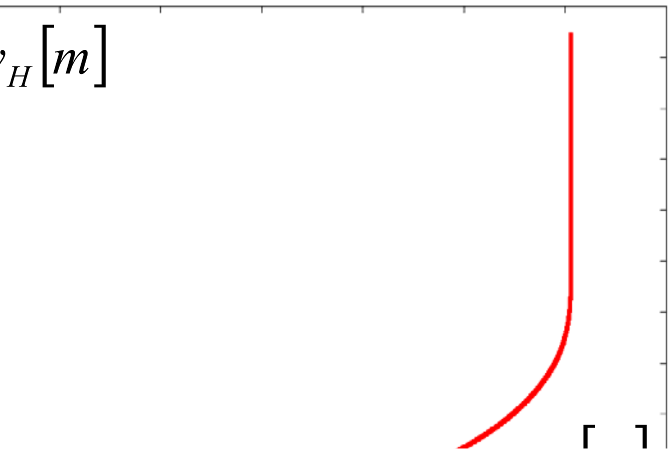

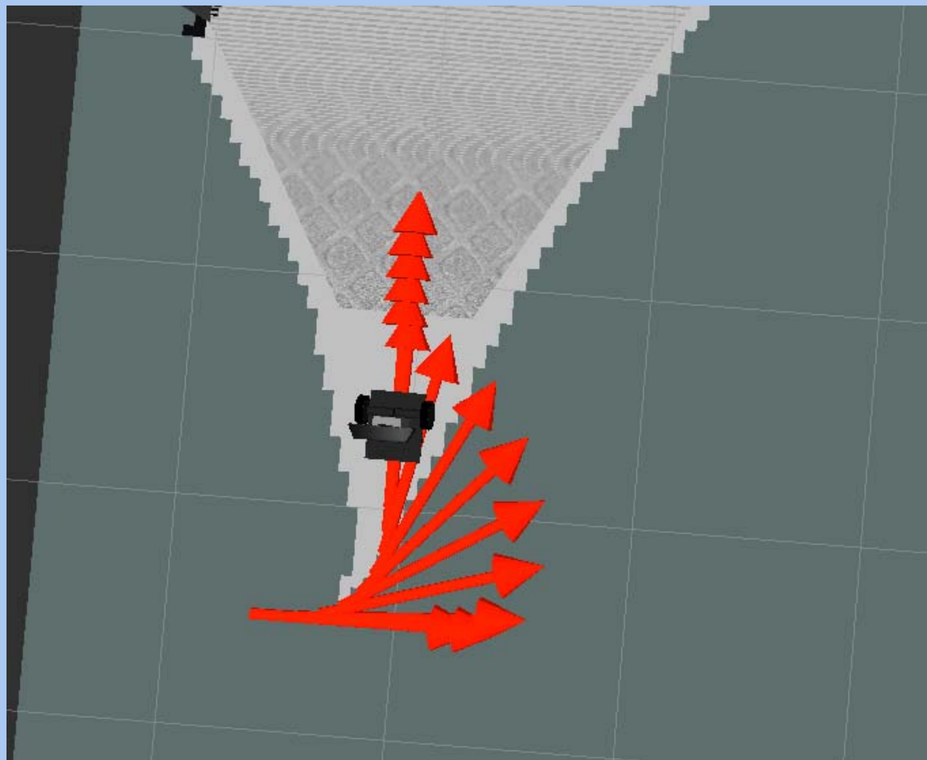

imulation – map building

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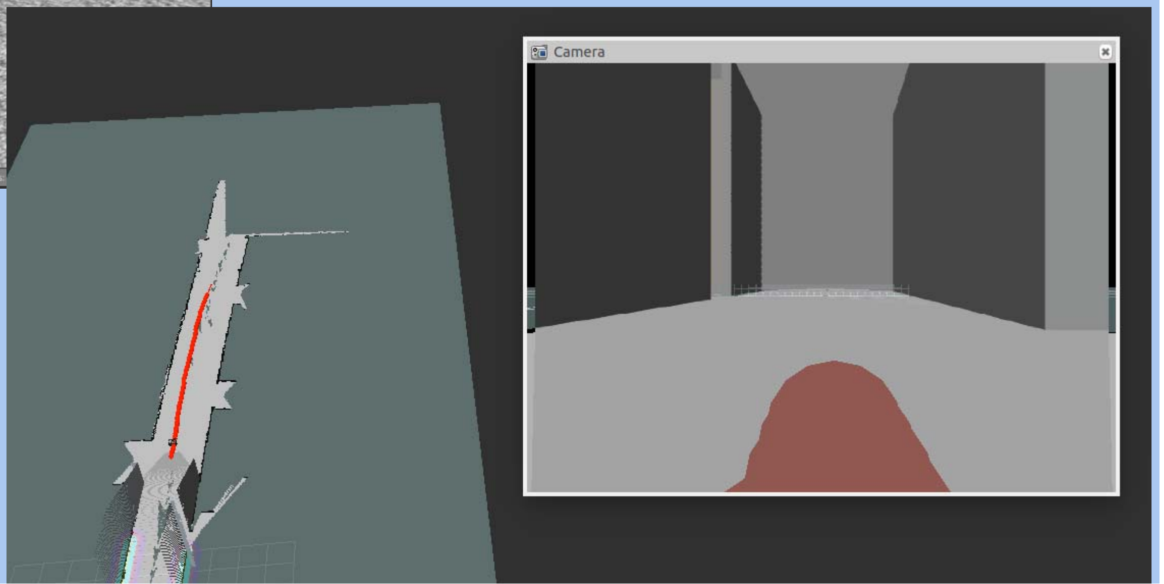
RGB-D vision system simulated in Gazebo



ation with ROS 2D
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ng with SLAM
em solving tool –
pping

Simulation

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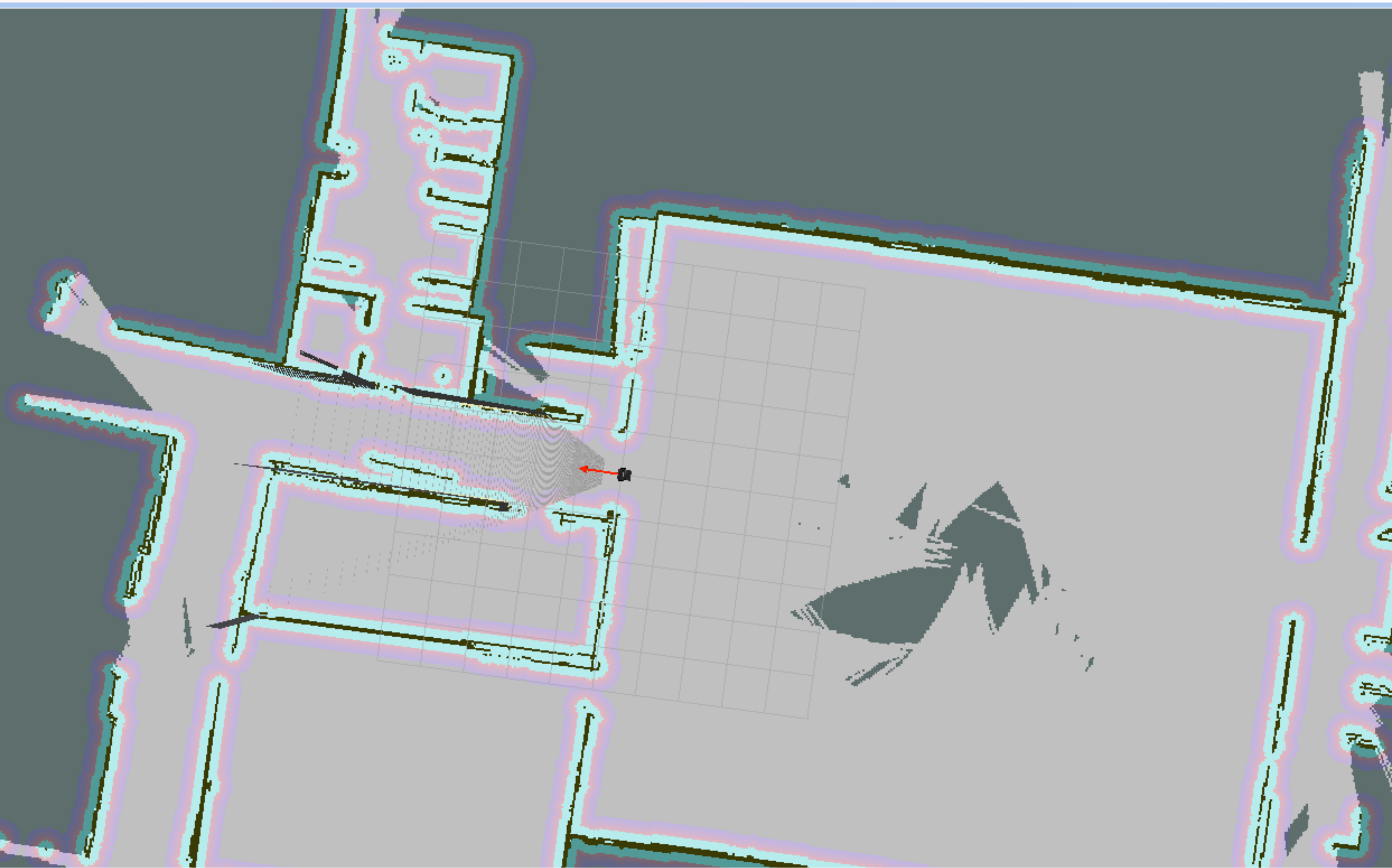

Simulation

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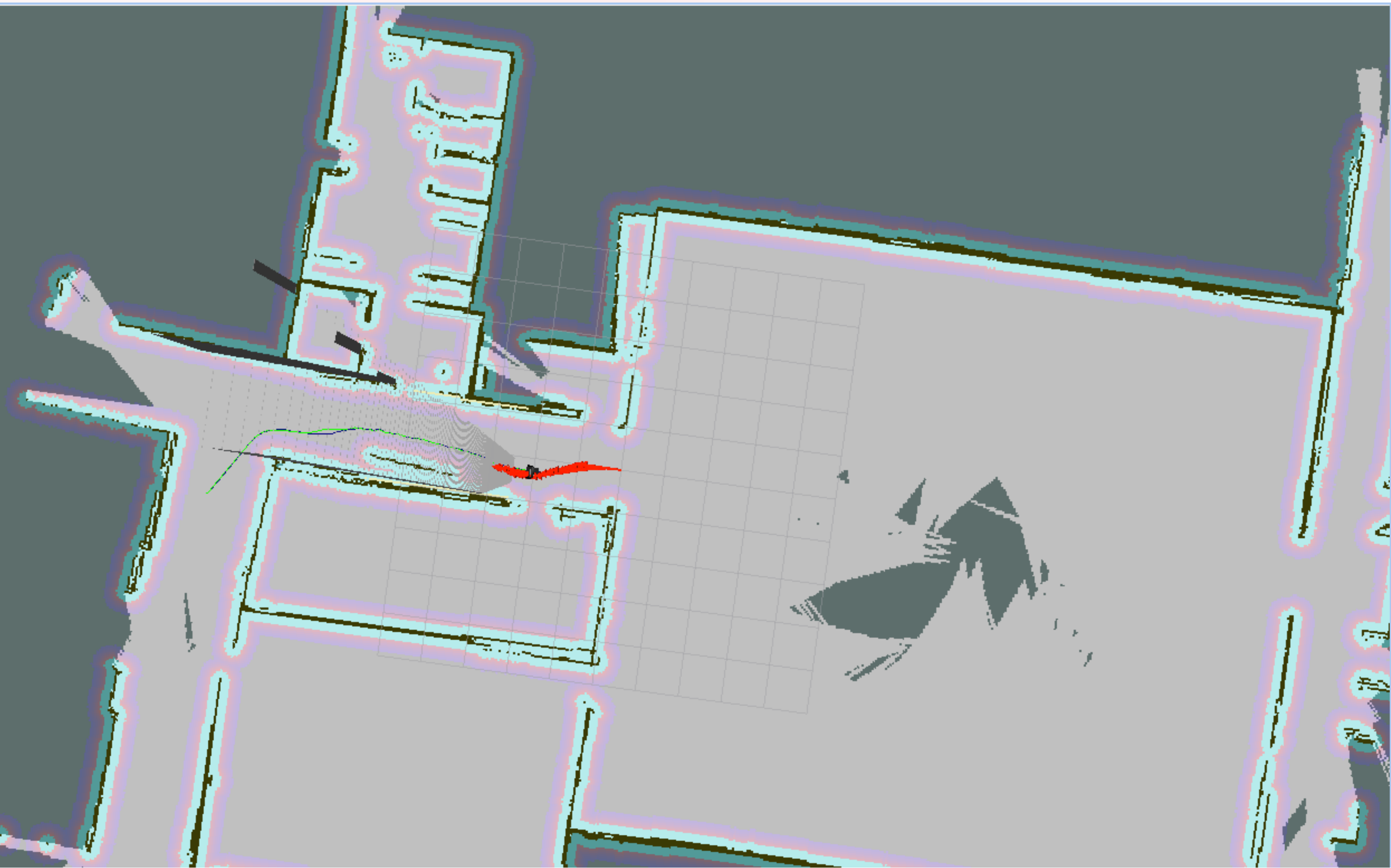

Simulation

Simulation

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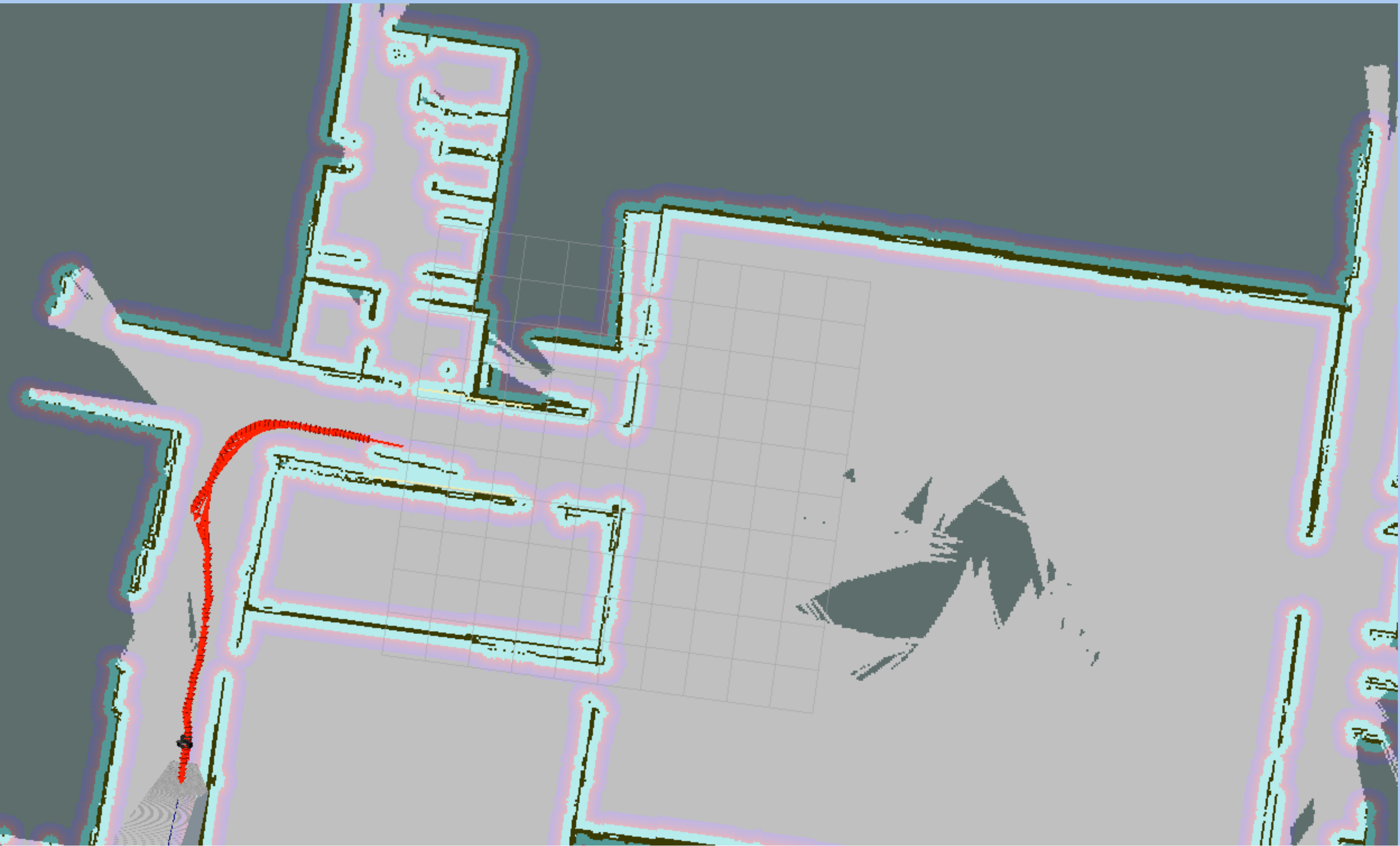

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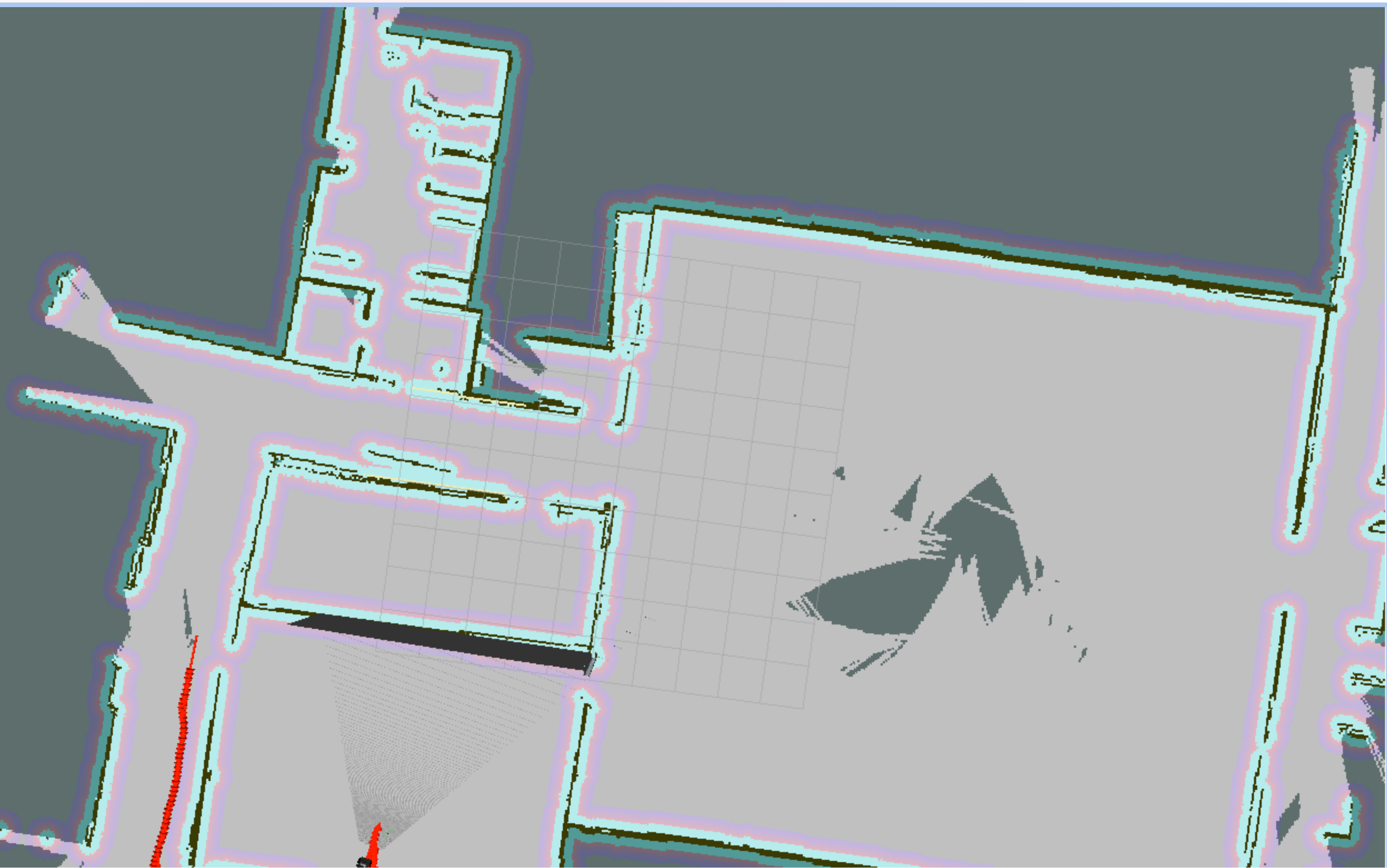

Simulation

Simulation

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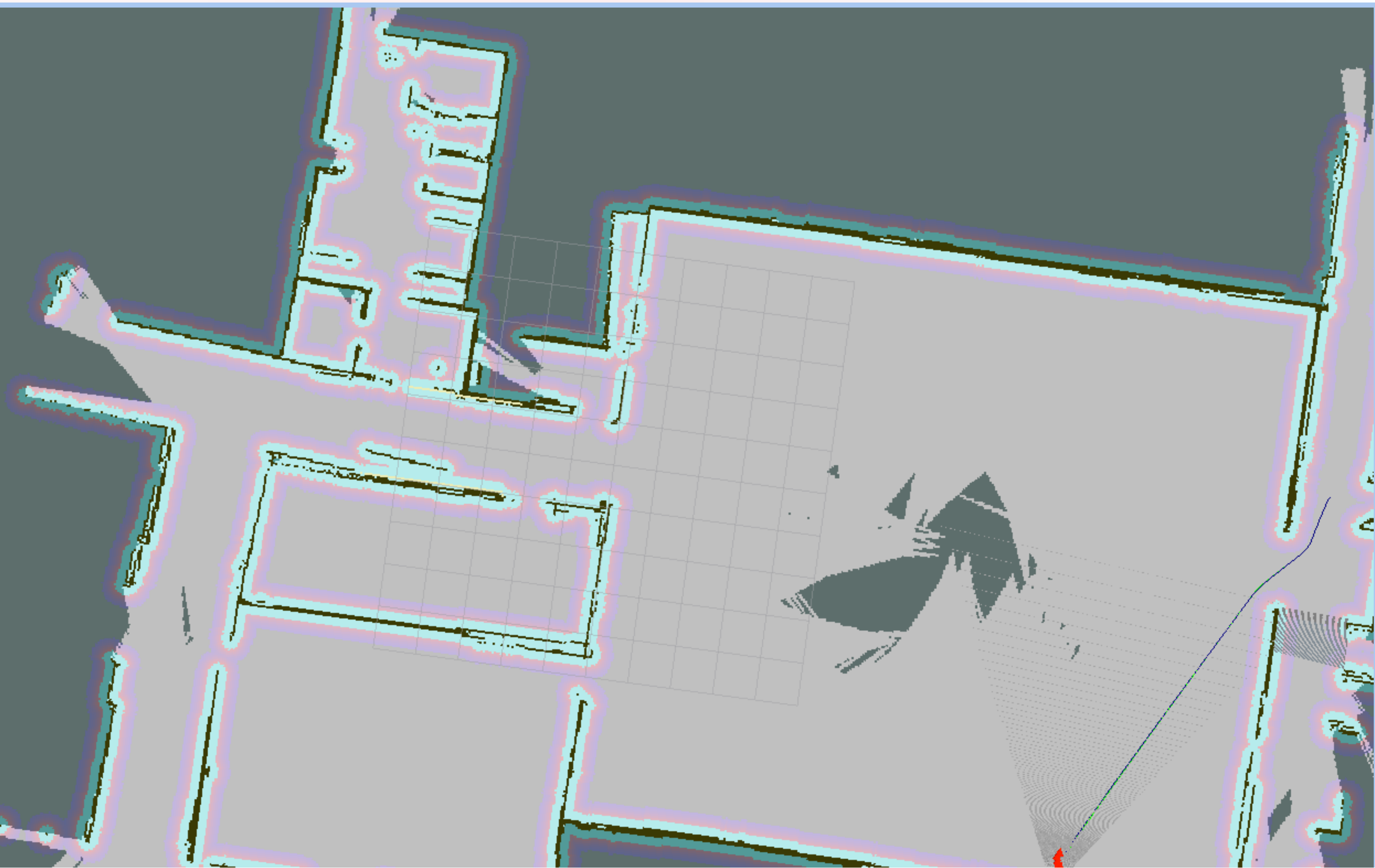

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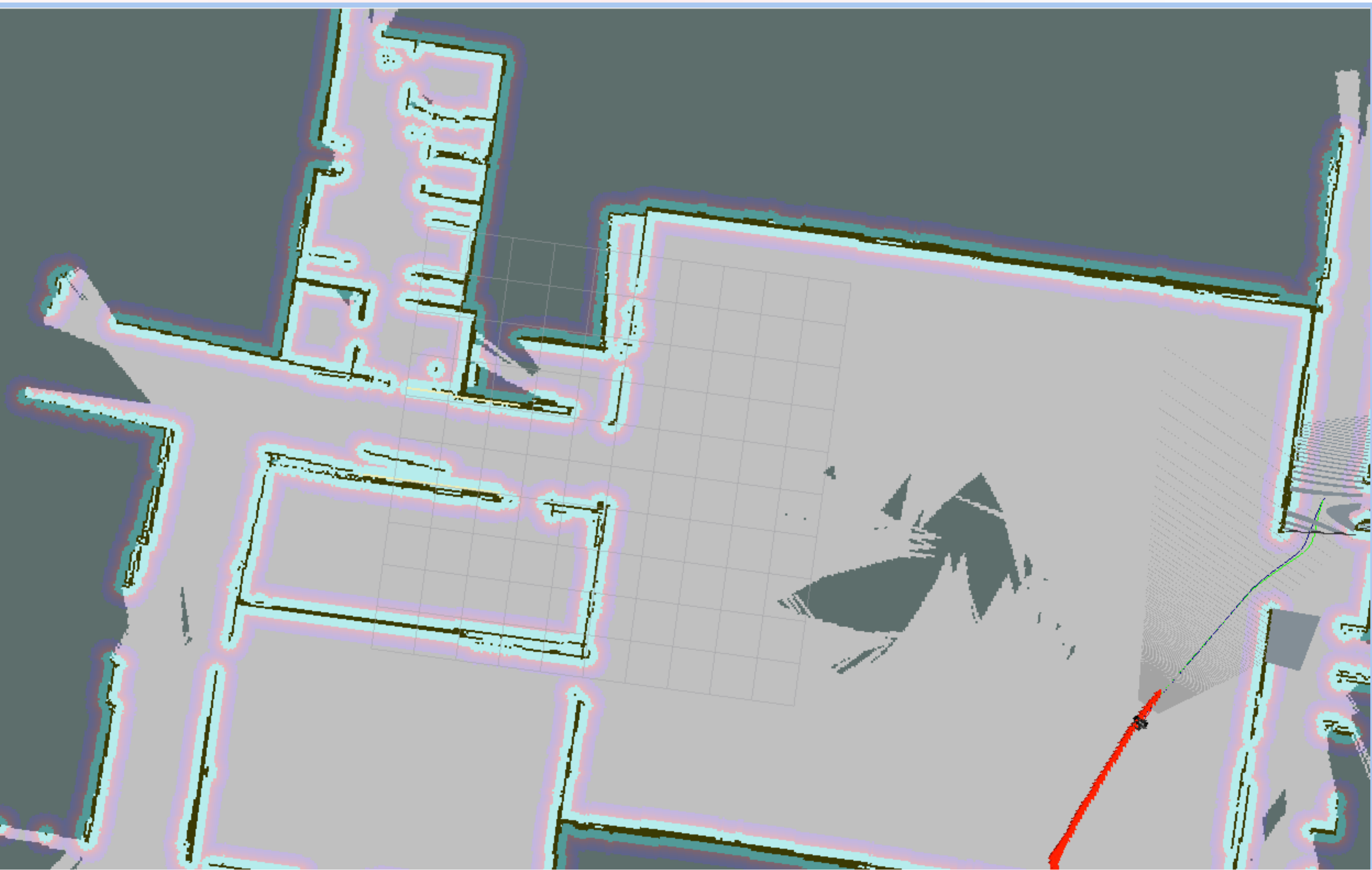

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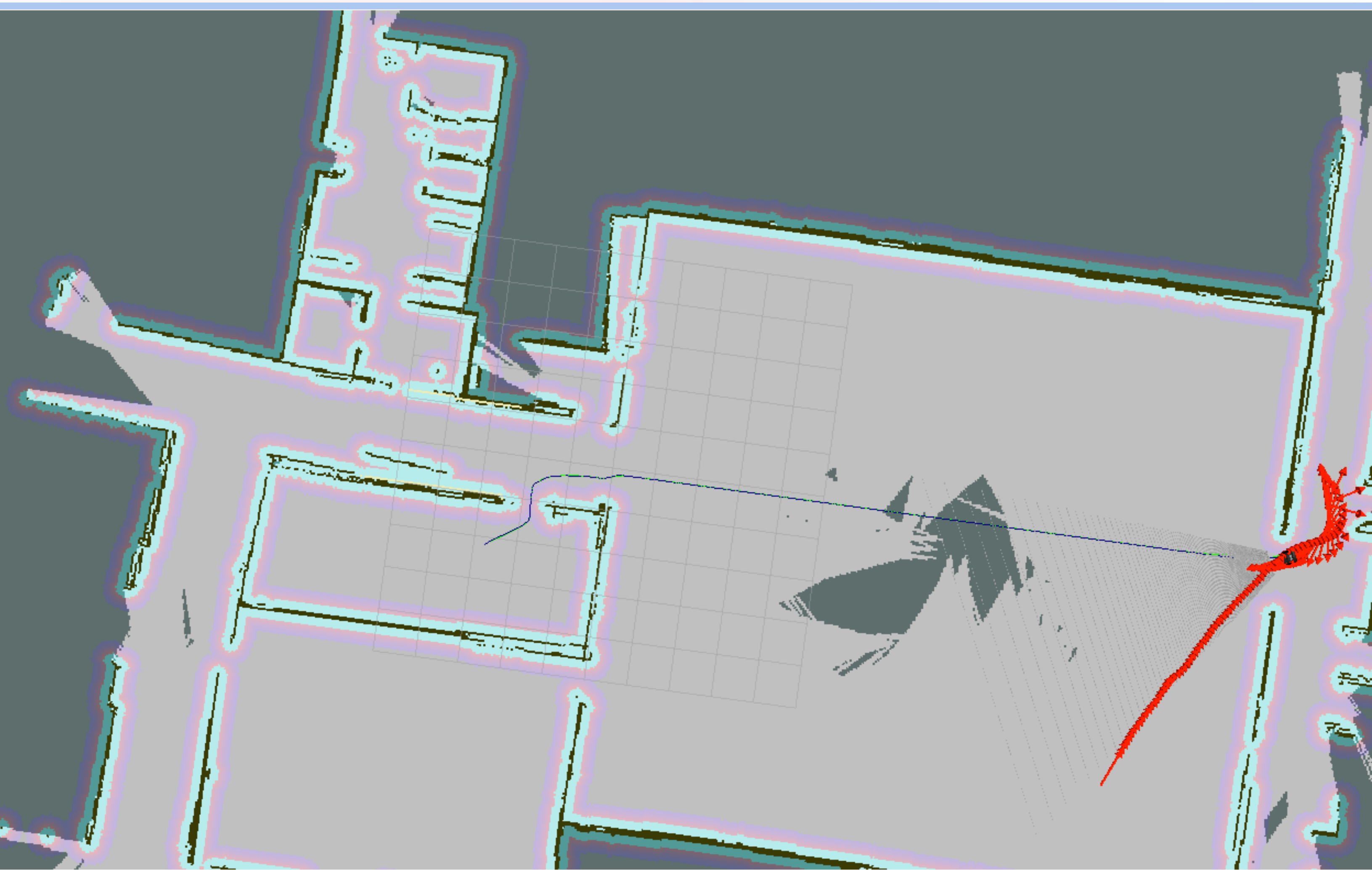

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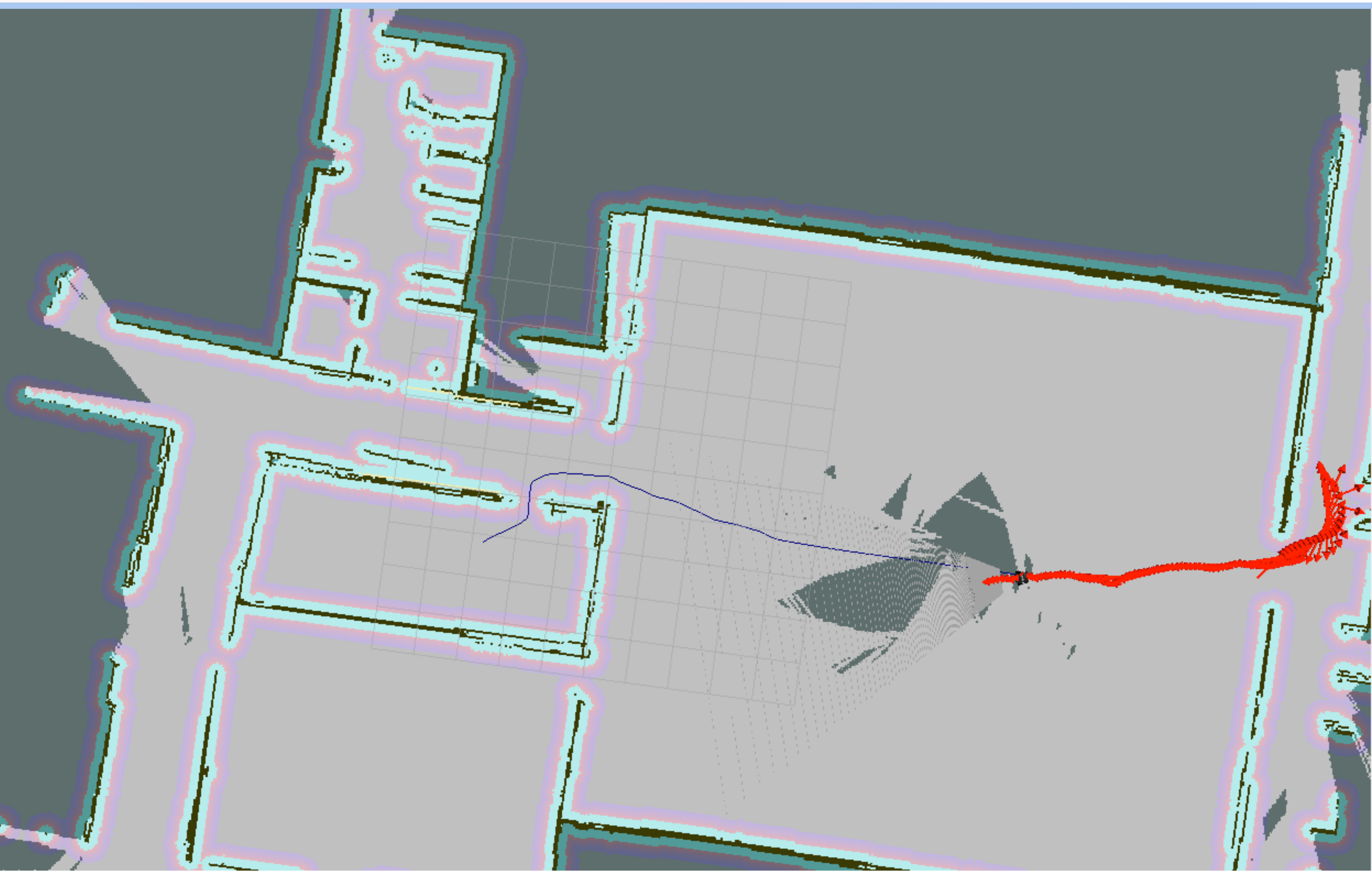
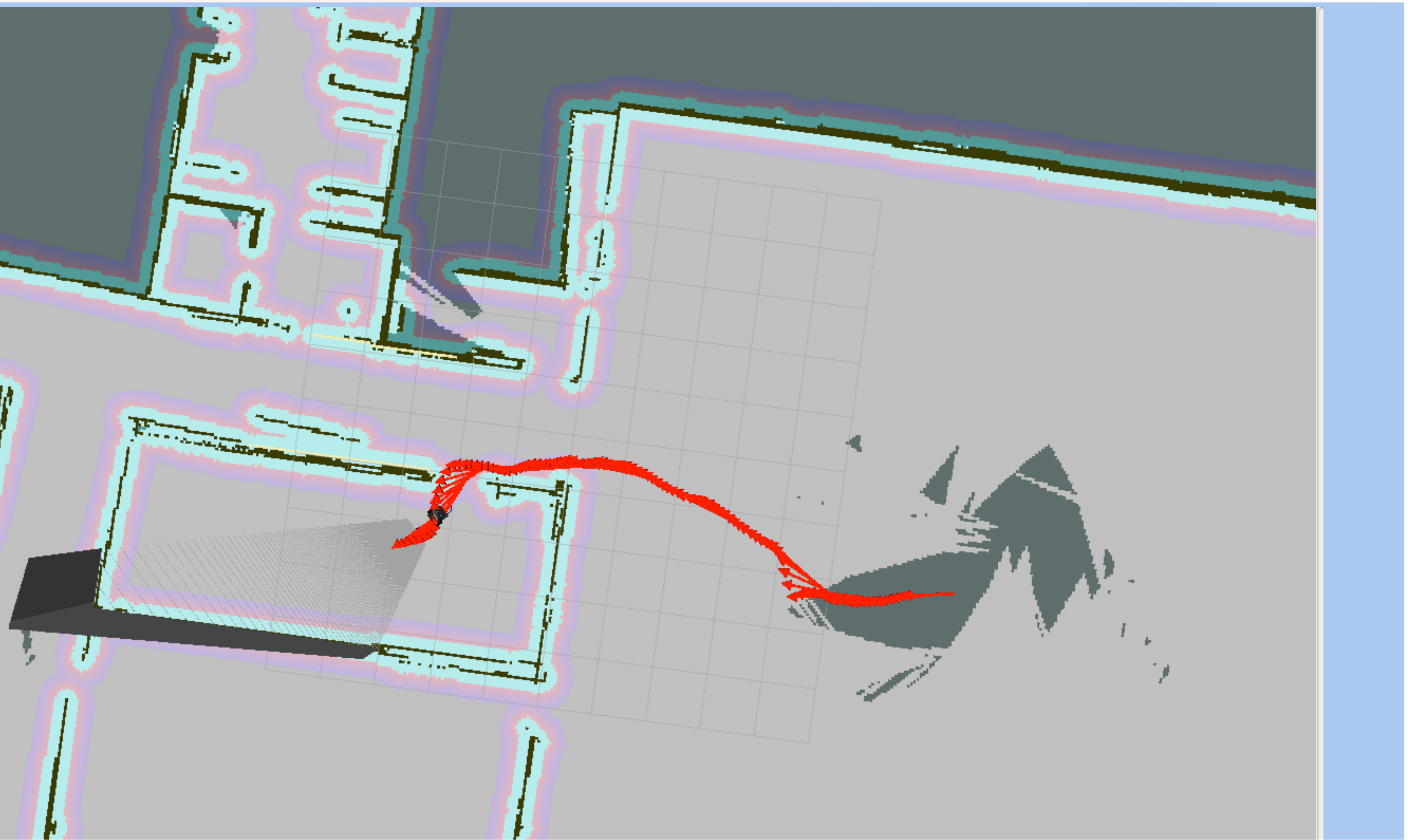


Simulation



Experiments

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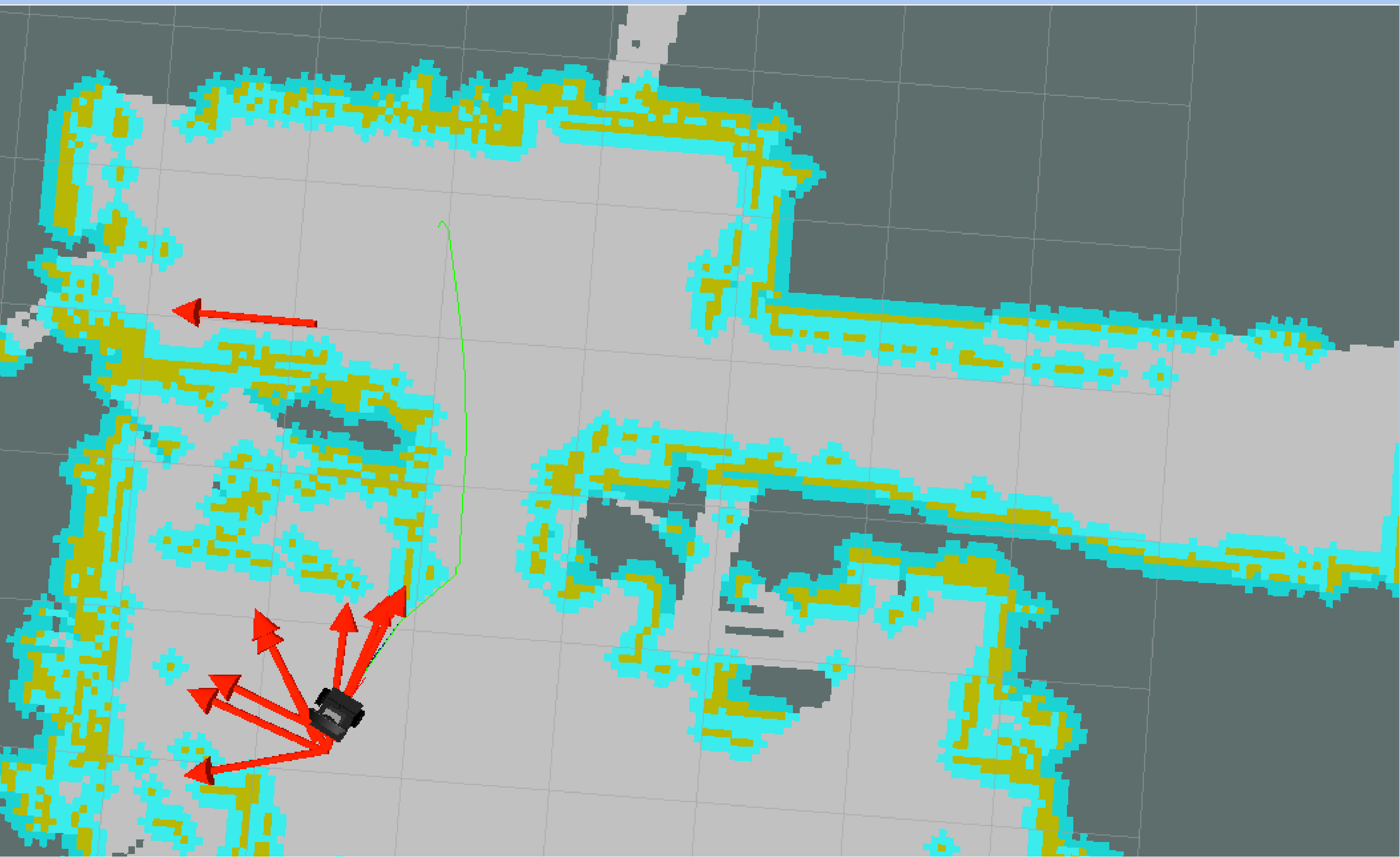

Experiments

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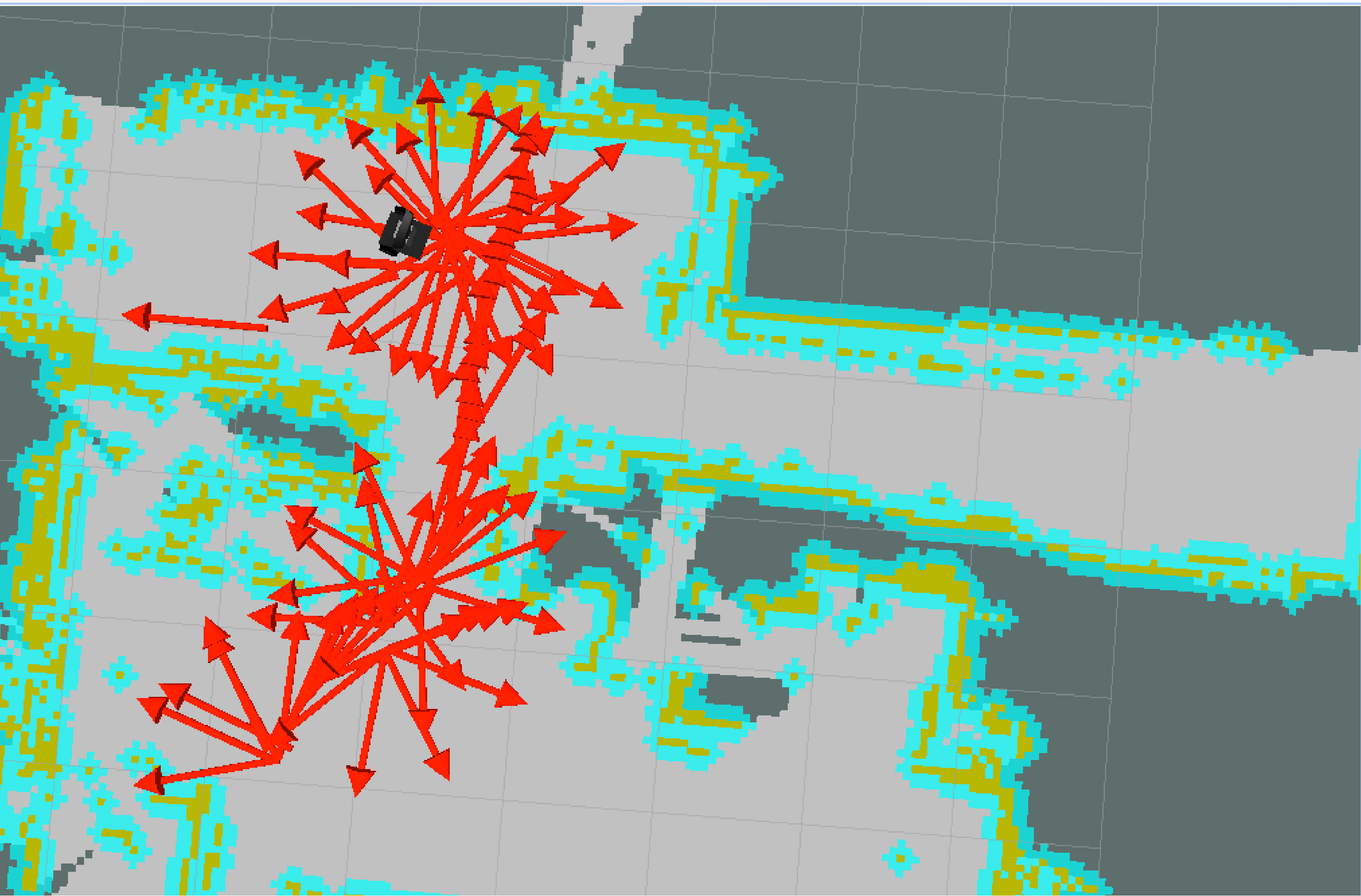

Experiments

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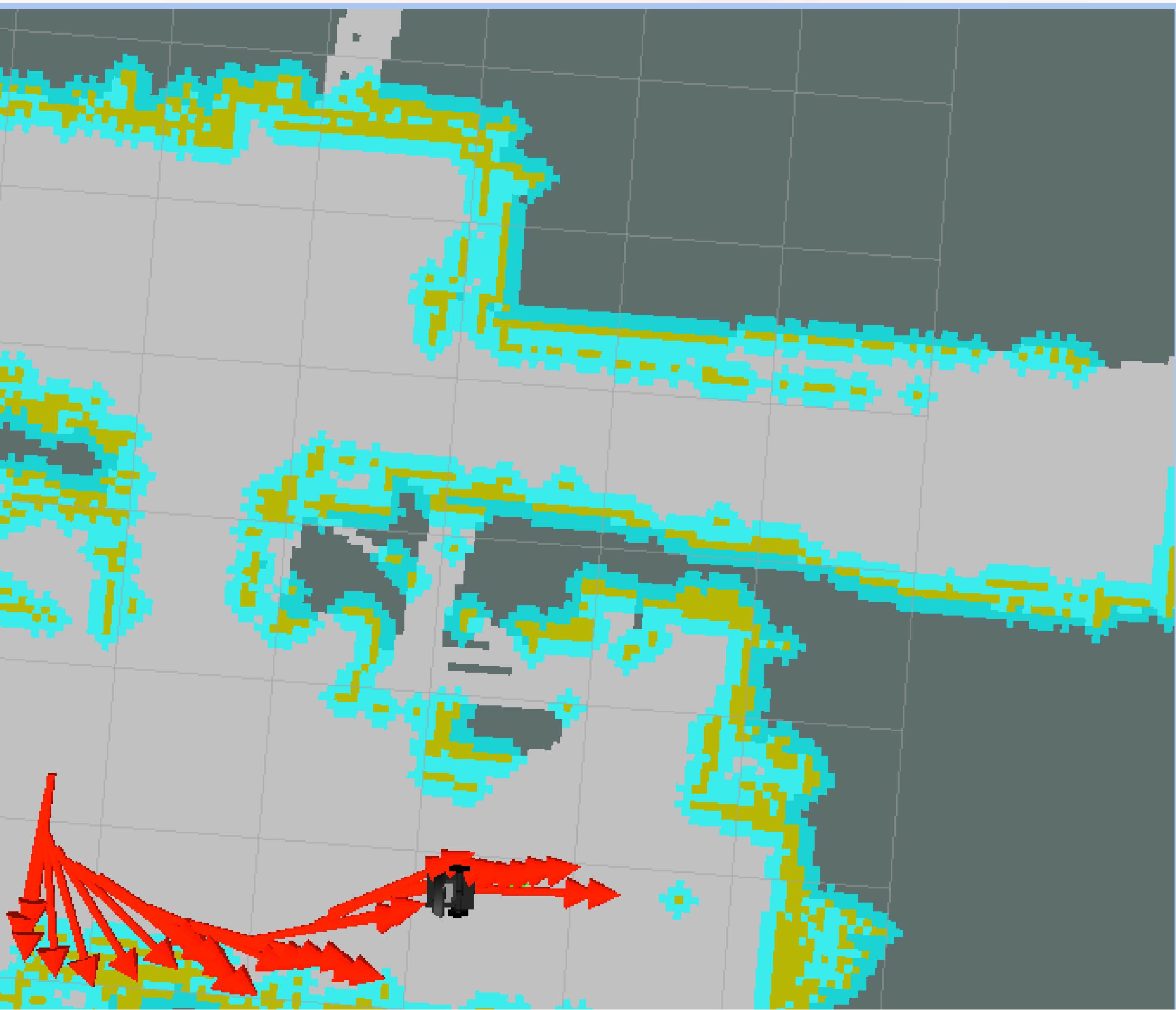

Summary

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vo-wheeled mobile robot is an example of strongly nonlinear system, nich is restricted by non-holonomic constraints.

avigation and motion control of such systems is not trivial and can lead great requirements that in practice are not always meet. Thus motion ntrol method must be reliable and stable, even if the controlled system under both external and internal disturbance.

e proposed method was effective solution to the problem of motion ntrol during all performed simulations and experiments. With the use the proposed method the overall reliability of an autonomous or semi-tonomous mobile robot system can be improved in significance.

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Spectrum-based modal parameters identification with Particle Swarm Optimisation

Modal parameters

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Modal test → impact test → free vibration

Free vibrations consist of many, exponentialy damped sine waves

$$y(t)=\sum_{m=1}^{nm} Y_{0m} e^{-2\pi f_m \xi_m t} \sin\left(2\pi f_m \sqrt{1-\xi_m^2}\, t\right)=\sum_{m=1}^{nm} Y_{0m} e^{-\beta_m t} \sin\left(\omega_m \sqrt{1-\left(\frac{\beta_m}{\omega_m}\right)^2}\, t\right)$$

where:

Y_{0m} – initial amplitude of vibration mode *m*,
ξ_m – dimensionless damping coefficient of mode *m*,
f_m – natural frequency of mode *m*,
t – time,
nm – number of modes.

entification - optimisation

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entification

- Search for unknown parameters: f_m , ξ_m
  and additionally: Y_{0m} - dependent on initial conditions

ay be treated as optimization problem

- Find f_m, ξ_m, Y_{0m} that minimizes some fitnes function

rticle Swarm Optimisation – PSO

- Artificial Intelligence evolutionary computational technique (R. C. Kennedy and J. Eberhart in 1995)
- Solves a problem by moving a number of possible solutions (”particles”) over the search space
  - Each particle has:
    - its own “memory” of the current and best solutions found so far

rticle Swarm Optimisation

Standard algorithm

Arbitrary select ω, φ_p and φ_g parameters

For each particle i:

- initialise position $\mathbf{x}_i$ (uniformly distributed random vector of size d),
- initialise particle velocities $\mathbf{v}_i$ for each $\mathbf{x}_i$ vector element,
- remember current particle position as the best known particle position $\mathbf{p}_i=\mathbf{x}_i$.

Find the particle with the best value of <u>fitness function</u> $f(\boldsymbol{x}_i)$ and remember its position as the best known global position $\mathbf{g}=\mathbf{x}_i$.

For each particle i, repeat until the stop criterion is met:

- for each dimension d of $\mathbf{x}_i$ generate random numbers $r_{p,d}$ and $r_{g,d}$ ($\in$ <0;1>, uniform distribution),
- update particle's velocity:

$$v_{i,d} = \omega\, v_{i,d} + \varphi_p\, r_{p,d}\, (p_{i,d}-x_{i,d}) + \varphi_g\, r_{g,d}\, (g_d-x_{i,d}),$$

- update particle's position:

$$\mathbf{x}_i = \mathbf{x}_i + \mathbf{v}_i,$$

- if $f(\mathbf{x}_i)$ has a better value than $f(\mathbf{p}_i)$ update the best particle position $\mathbf{p}_i=\mathbf{x}_i$

dal identification with PSO

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nitial idea

- Search for modal parameters of all modes at once using PSO
  - One particle contains information about all of the modes
- Problem
  - Usually only dominant mode was estimated properly
    - » Other modes „overshadowed” by the dominant one
  - Slow algorithm convergence for other modes
- Problem reasons
  - Estimating many modes is a multiobjective problem
  - PSO is not well suited for multiobjective problems

al identification with miPSO

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1st STAGE

nitialisation of particles for one mode (pts 1…3 of the basic PSO)

Each particle consists of parameters that allow idetification of one mode only - each mode is identified independently

$f_m \in <0; f_s/2>$, random

where f_s is sampling frequency of vibration measurement signal A

$\xi_m \in <0.0001; 0.95>$, random

$Y_{0m} \in <0; 2*Y_{max}>$, random

where: Y_{max} is a maximum value of measured impact test signal

initial velocities, random

but do not exceed 2% of a parameter values' range

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One mode identification using PSO algorithm (PSO pt. 4)

Modified parameters: Y_{0m}, f_m, ξ_m

Fitness function:

$$f(\mathbf{x}_i) = \sum_{n=0}^{n_{fFFT}} \left(FFT_t(n) - FFT_x(n)\right)^4$$

FFT_t - FFT amplitude spectrum of an impact test signal,
FFT_x - FFT amplitude spectrum of the impulse response generated for x_i particle,
n_{fFFT} - number of FFT samples,
n - sample number.

At the end of 1st stage:

- f_m is usually identified with little error
- Y_{0m} and ξ_m are rarely correct

Suplementary particle repositioning

Once per 5 iterations, the worst particle (having the highest value of fitness function) is repositioned

New parameters are copied from the best particle (having the lowest value of fitness function) and additionally its ξ_m and Y_{0m} are reduced by 50%

- Y_{0m} corrected to keep the spectrum peak values before and after ξ_m modification at the same level

Improving algorithm convergence

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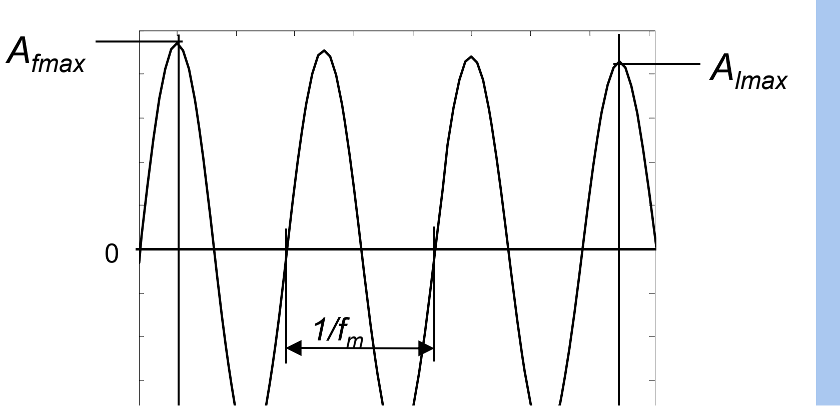
Band-pass filtering (<$0.8 \cdot f_m$; $1.2 \cdot f_m$>) of the measured signal to select one mode.

Calculation of the preliminary corrected value of ξ_m :

$$\xi_{mc} = \frac{\log\left(\frac{|A_{fmax}|}{|A_{lmax}|}\right)}{2\pi f_m \left(t_{lmax} - t_{fmax}\right)}$$

where:

- A_{fmax} – maximum amplitude of the first sine signal period in the selected time range,
- A_{lmax} – maximum amplitude of the last sine signal period in the selected time range,
- t_{fmax} – time of A_{fmax},
- t_{lmax} – time of A_{lmax}.



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Spectrum modification

The spectrum of impact test signal is modified by applying stop-band filter with cut-off frequencies set to $<0.8 \cdot f_m; 1.2 \cdot f_m>$. This eliminates already identified modes from further identification

Additionally, during identification of the next mode, the cut-off spectrum fragment is not taken into consideration for the fitness function calculation

dentification of the next mode

Point 1-5 repeated for each mode independently

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2nd STAGE

nitialisation of particles for the 2nd stage of identification

Each particle consists of parameters for all of the modes

1st particle - combined from best solutions obtained in pt. 2 (unmodified solutions), velocities set to 0

2nd particle - combined from best solutions obtained in pt. 2, but $\xi_m = \xi_{mc}$ (estimated in pt. 3) , velocities set to 0

other particles are initialised in a standard way, but in a narrower range:

- $f_m \in \pm 25\%$ of f_m estimated in pt. 2
- $\xi_m \in \pm 25\%$ of ξ_{mc} estimated in pt. 3
- $Y_{0m} \in \pm 25\%$ of Y_{0m} estimated in pt. 2

2nd stage of the identification using PSO algorithm (PSO pt. 4)

Identification of all modes using PSO algorithm

All modes are used for signal and FFT_x calculation

Example 1A

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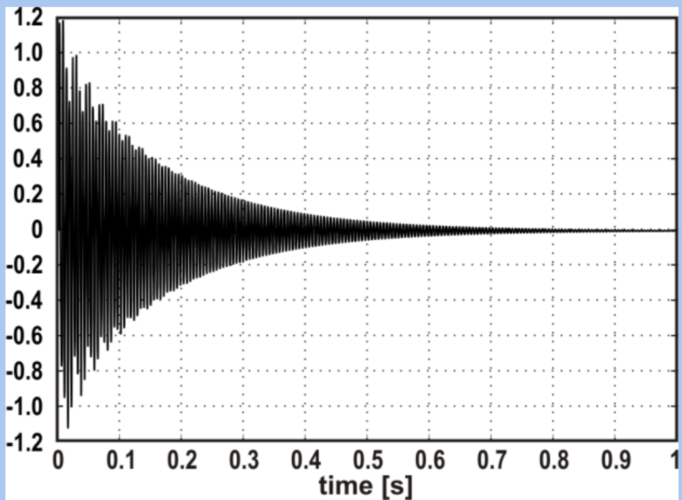
Simulated data

– 2 modes: 200 and 350 Hz



Generated signal

Average results from 20 runs

Mode number m	1	2
Y_{0m}		
- reference	1.000	0.300
- identified	0.993	0.287
error	0.71%	4.33%
f_m		
- reference	200.00	350.00
- identified	200.00	350.09
error	0.00%	0.03%
ξ_m		
- reference	0.005000	0.010000
- identified	0.005114	0.009664
error	2.27%	3.36%

Algorithm properly estimated modal parameters

Example 1B

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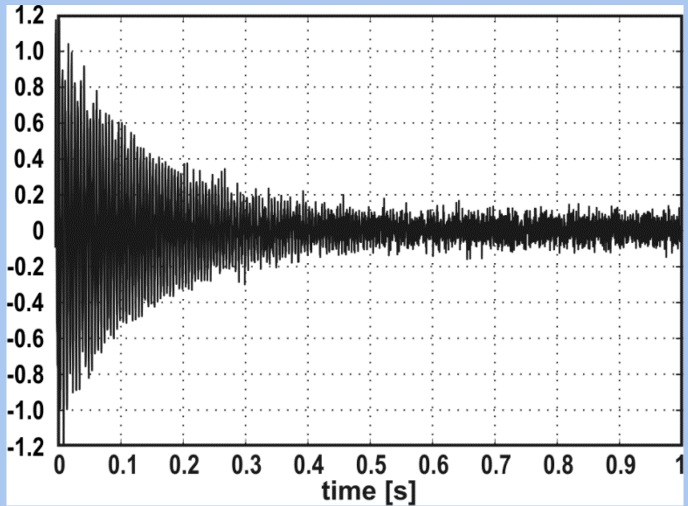
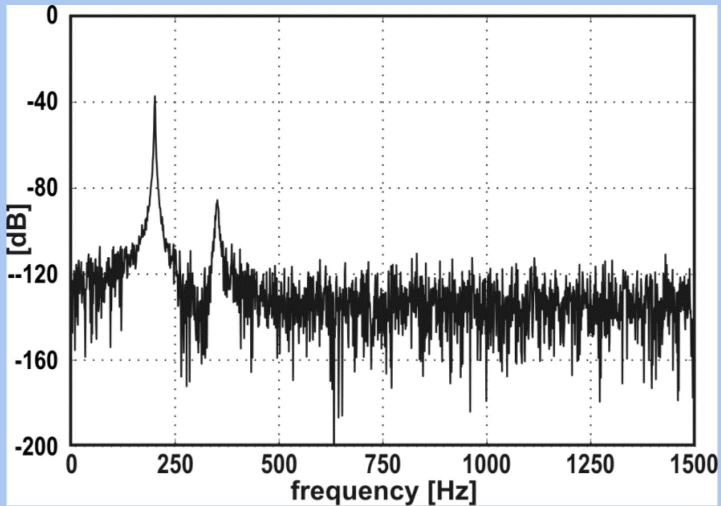
Simulated data

– 2 modes (as in 1A) + gausian noise



Generated signal



Signal spectrum

std. dev. σ_n = 0.0500

ode std. dev. σ_{m1} = 0.1995

d mode std. dev. σ_{m2} = 0.0320

Example 1B

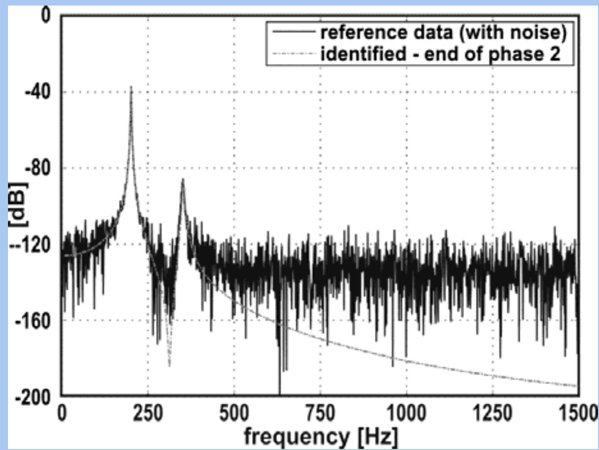
Results comparison

e number *m*	1	2
erence	1.000	0.300
PSO	0.983 (1.71%)	0.272 (9.23%)
erence	200.00	350.00
A	199,75 (0.13%)	350,53 (0.15%)
SCF(d)	200,02 (0.01%)	--
)	194,59 (2.71%)	--
ny	199,95 (0.03%)	350,01 (0.00%)
PSO	200.00 (0.00%)	350.22 (0.06%)
erence	0.005000	0.010000
A	0.002342 (53.2%)	0.016943 (69.4%)
SCF(d)	0.003631 (27.4%)	--
)	0.007303 (46.1%)	--
ny	0,004981 (0.38%)	0,013343 (33.4%)
PSO	0.005102 (2.04%)	0.008999 (10.0%)

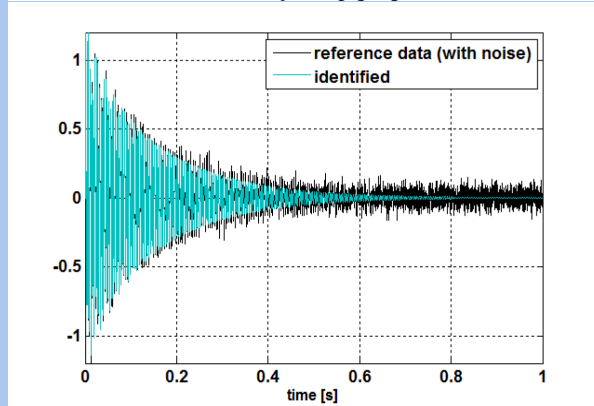
For miPSO - average results from 20 runs

Results for selected run

Spectrum plots



Time plot



Conclusion

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roposed 2-stage algorithm allowed achieving:

- proper identification results in multi-objective problem
- Identification results compaprable or better than for other methods, especialy in case of noisy signal

niPSO algorithm may by successfully utilised for simple modal identification asks

rawbacks and limitations

- At current stage – suitable only for SISO objects with clearly separated modes (due to the need of pass/stop-band filtering)

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Dziękuję za uwagę

Thank you for your attention

Vielen Dank für Ihre Aufmerksamkeit