3 – Motion control

Advanced Methods for Mapping and Self-localization in Robotics (MPC-MAP)

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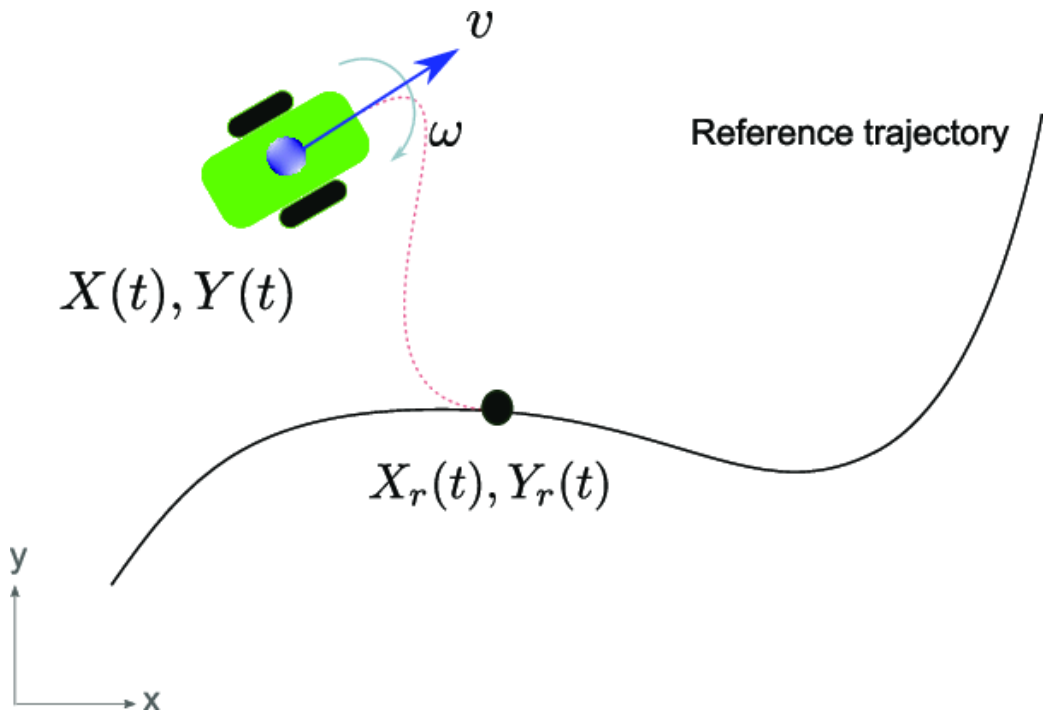
Motivation

What is motion control for?

- Following known trajectory
- Kinematic model is required – a relation between the wheels speed and the robot motion
- Are there any constraints?
- How to model motion?



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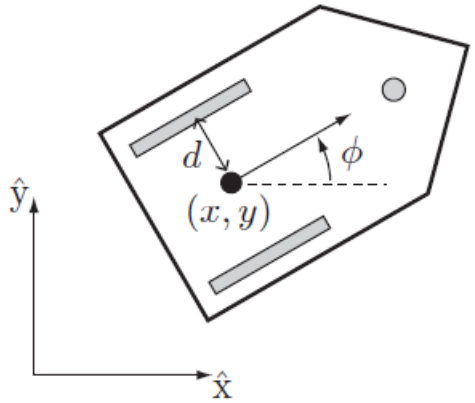
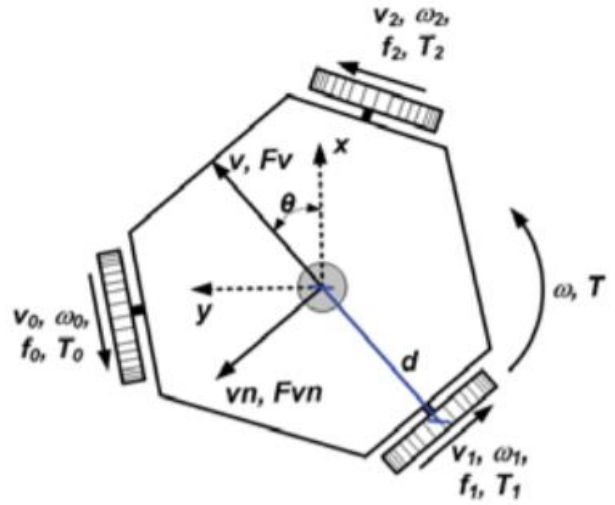
[1] ABDELWAHAB, Mohamed et al. Trajectory Tracking of Wheeled Mobile Robots Using Z-Number Based Fuzzy Logic. *IEEE Access* [online]. 2020, **8**, 18426-18441 [cit. 2022-02-10]. DOI: 10.1109/ACCESS.2020.2968421

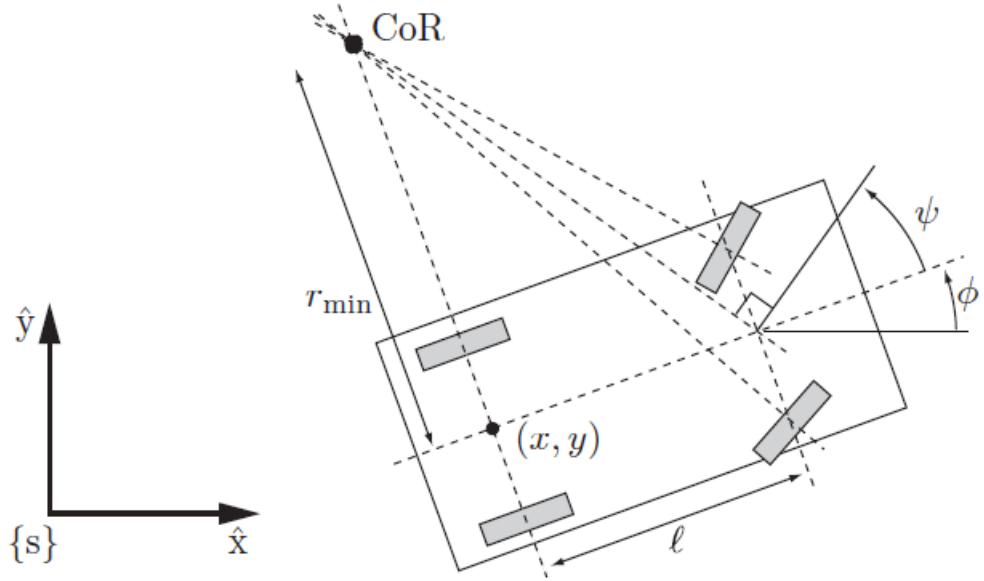
Types of drive:
- Differential
- Ackermann
- Omnidirectional
- Others …

Kinematics
- „Geometry of motion“
- Relation (acceleration –) velocity – position
- Cause of motion is not analyzed

Dynamics
- Focuses on „why is object moving“
- Forces, torques, mass, etc.







[1]

[1] Electronics and Robotics Club. The ERC Handbook: Drive Mechanism [online]. BITS Goa, 2020 [cit. 2022-02-14]. Available at: https://erc-bpgc.github.io/handbook/mechanical/drive_mechanism/

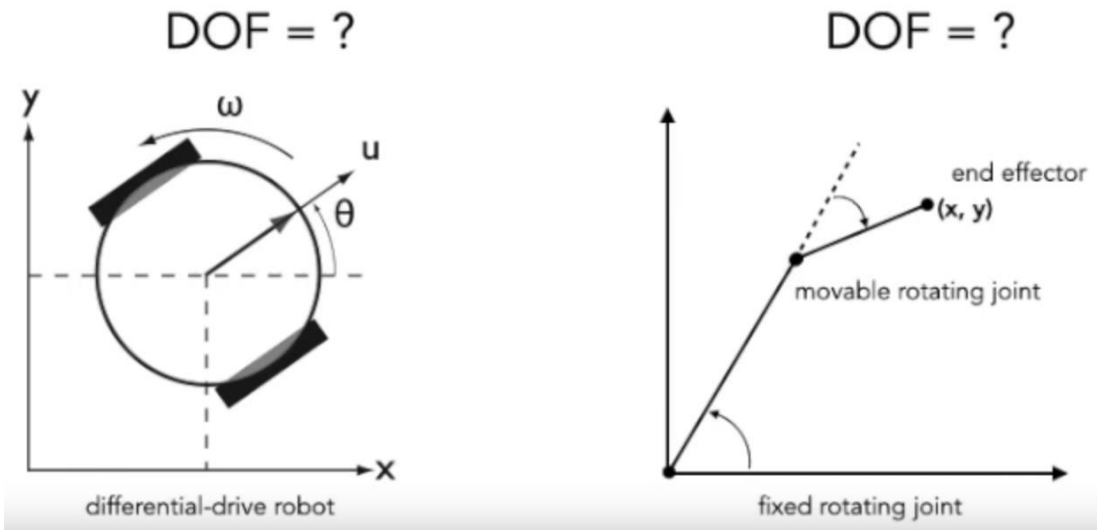
Holonomic vs. non-holonomic

Degrees of freedom (DOFs)

- Minimum number of real numbers to represent the robot‘s configuration
- Most actuators control a single DOF
- Either translational or rotational
- Depends on the type of robot

Degrees of motion (DOMs)

- = Differentiable DOFs (DDOFs)
- Number of DOFs that can be directly accessed by the actuators
- Also number of independent motion velocities
  - Unicycle = 2, Bicycle = 1



[1]

[1] PROROK, Amanda. Mobile Robot Systems, Lecture 3: Robot Motion & Control. In: *YouTube* [online]. 2021 [cit. 2022-02-16]. Available at: https://youtu.be/tocxlukOa-I

Holonomic vs. non-holonomic

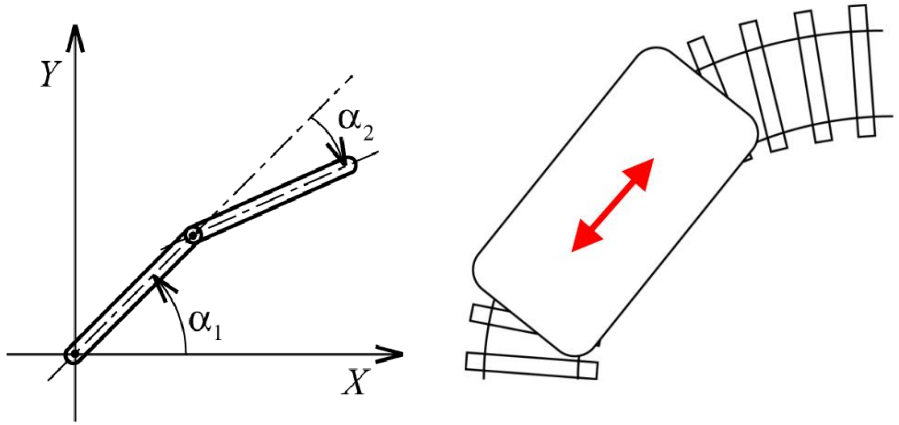
Constraints
- Constrain position = holonomic
- Constrain velocity = non-holonomic

Integrability of constraints
- $f(\boldsymbol{q}, t)$ – depends only on position = integrable = holonomic
- $f(\boldsymbol{q}, \dot{\boldsymbol{q}}, t)$ – depends also on velocity = is not integrable = non-holonomic

Holonomic robot
- DOF = DOM (= DDOF)
- All constraints are holonomic

Non-holonomic robot
- DOF > DOM
- Position depends on the order of control inputs!

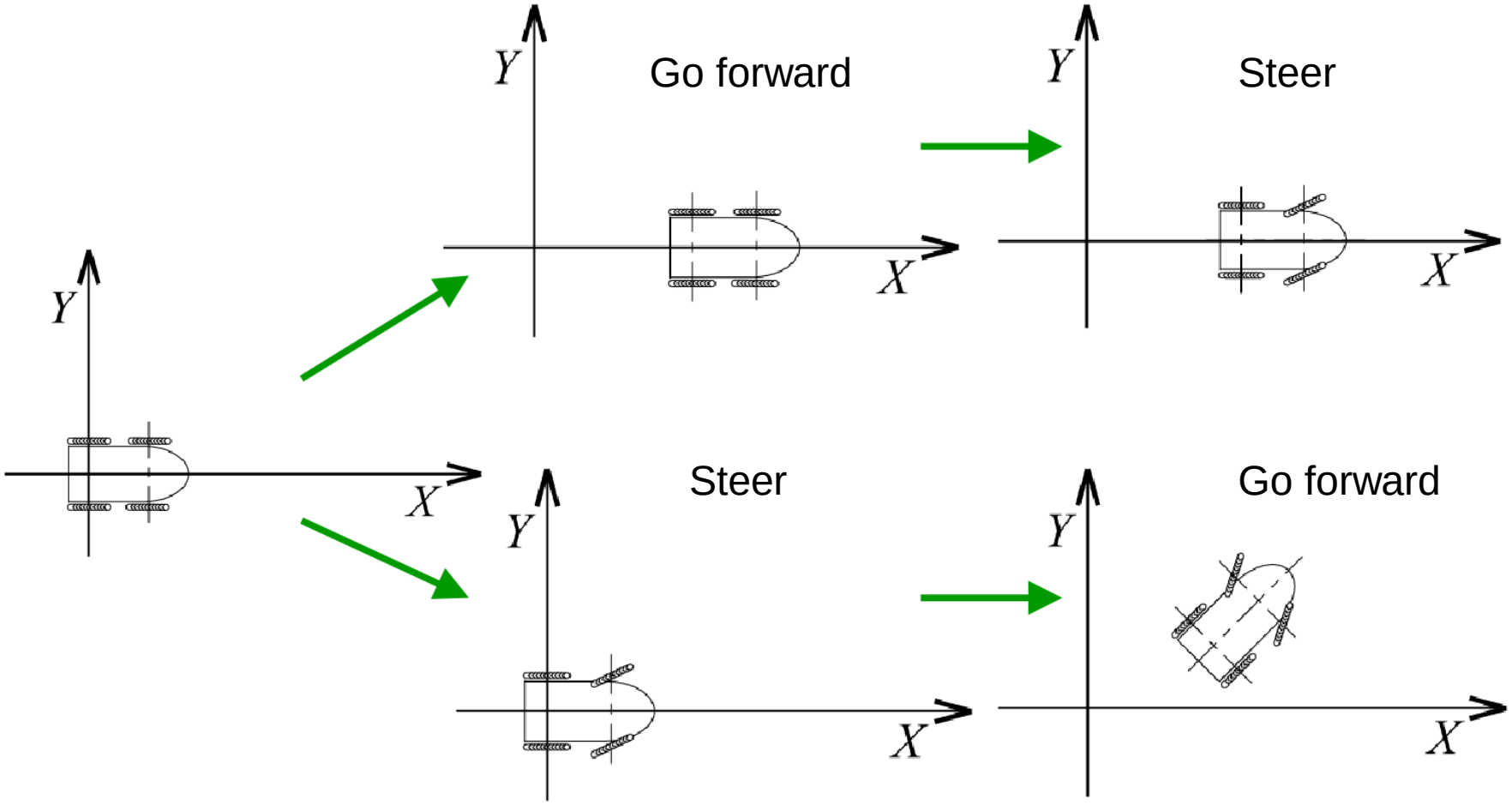
Examples of holonomic systems:



[1]

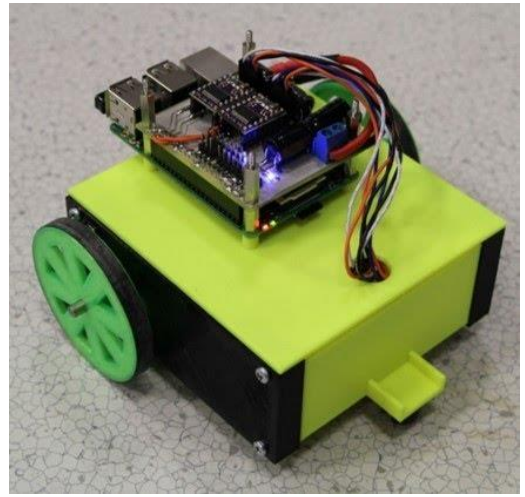
[1] Robotics Lab [online]. Nairi-Tech, 2014 [cit. 2021-02-28]. Available at: http://nairi-tech.com/products/view/robotics-lab.html

Holonomic vs. non-holonomic



Depends on the order!

Differential drive = non-holonomic



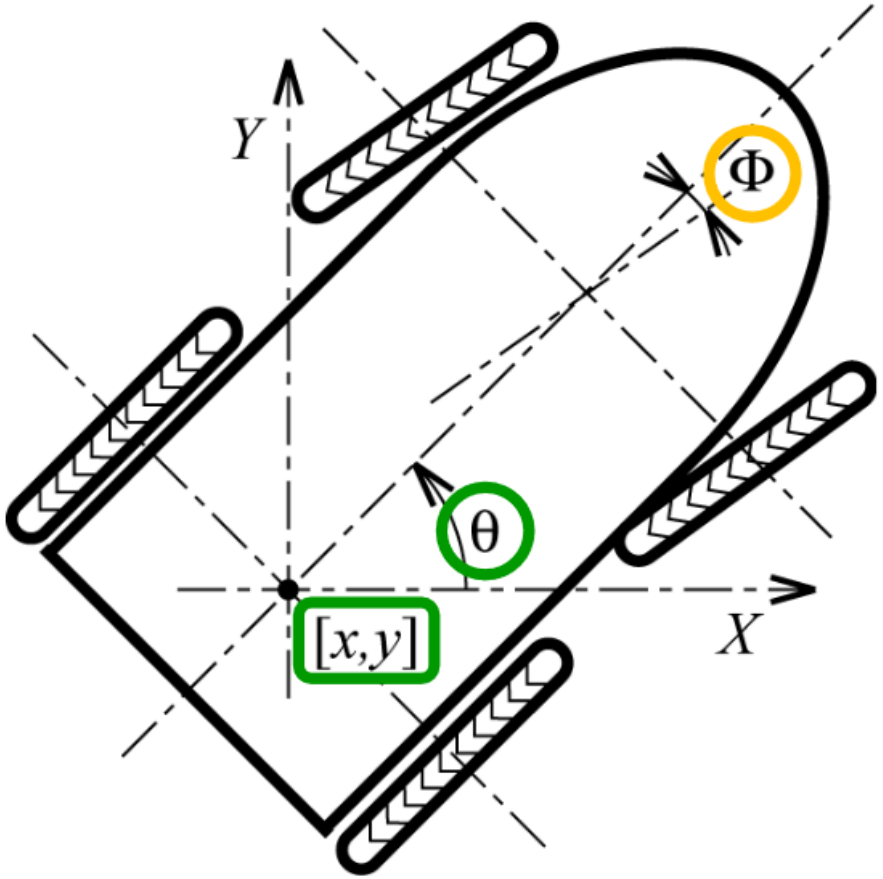
State of the robot in 2D

State

- Position of the reference point in the world frame – x, y
- Orientation – θ
- Describes configuration of the robot body
- $\boldsymbol{x} = (x, y, \theta)$

Extended state

- State + additional parameters
- E. g., steering angle Φ in Ackermann drive
- $\boldsymbol{x}_{\mathrm{Ack}} = (x, y, \theta, \Phi)$



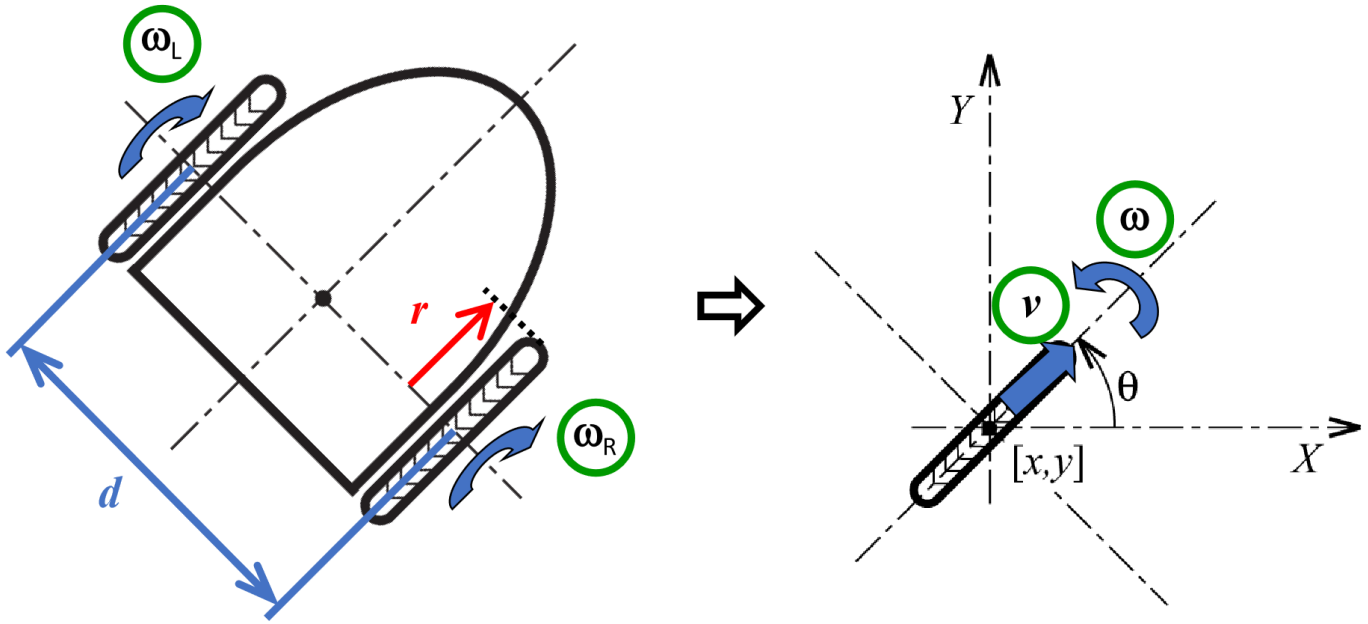
Differential drive

Parameters of the chassis
- Wheel radius r
- Distance between wheels d

Control inputs
- Speed of wheels ω_R, ω_L

Simplification to unicycle
- Forward velocity v
- Angular velocity ω

$$v = \omega R$$



$$v = \frac{r(\omega_R + \omega_L)}{2}$$

$$\omega = \frac{r(\omega_R - \omega_L)}{d}$$

$$\omega_R = \frac{2v + \omega d}{2r}$$

$$\omega_L = \frac{2v - \omega d}{2r}$$

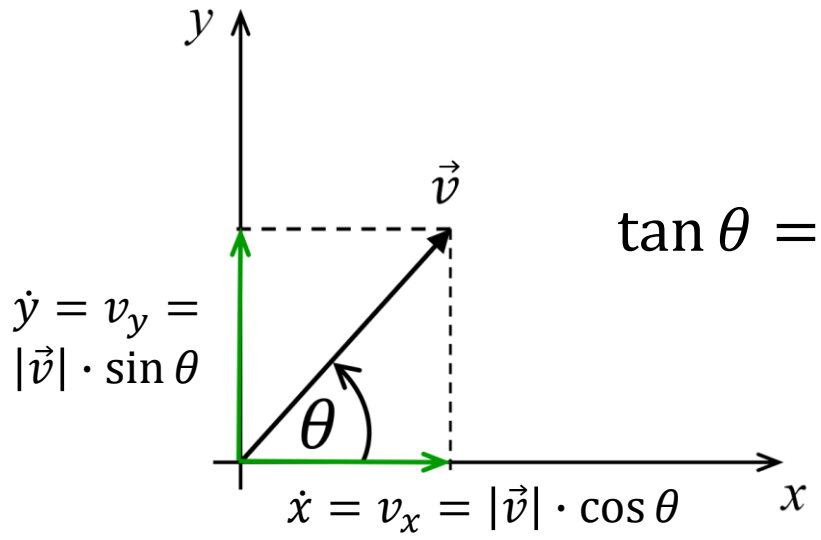
[1] BORENSTEIN, J. and Y. KOREN. The vector field histogram-fast obstacle avoidance for mobile robots. *IEEE Transactions on Robotics and Automation* [online]. **7**(3), [cit. 2021-02-28]. DOI: 10.1109/70.88137
[2] SVEGLIATO, Justin. How does a robot plan a path using RRT? In: *Towards Data Science* [online]. 2020 [cit. 2021-02-28]. Available at: https://towardsdatascience.com/how-does-a-robot-plan-a-path-in-its-environment-b8e9519c738b

State equations

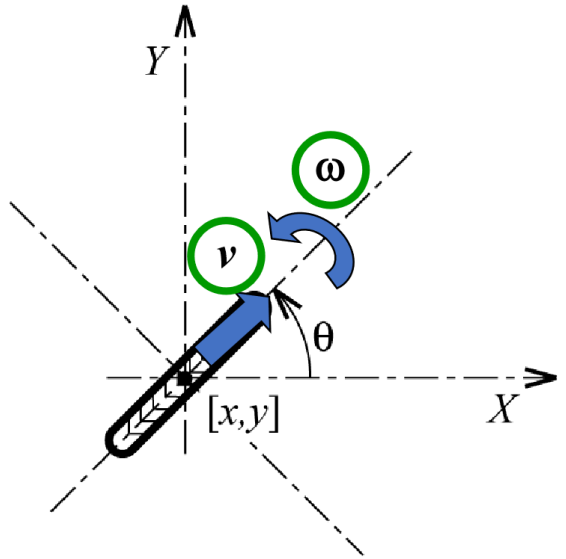
- 3 states
- 2 control inputs

$$\begin{pmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{pmatrix} = \begin{pmatrix} \cos\theta \\ \sin\theta \\ 0 \end{pmatrix} v + \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} \omega$$

- Constraint: $\dot{x}\sin\theta = \dot{y}\cos\theta$



$$\tan\theta = \frac{\dot{y}}{\dot{x}}$$



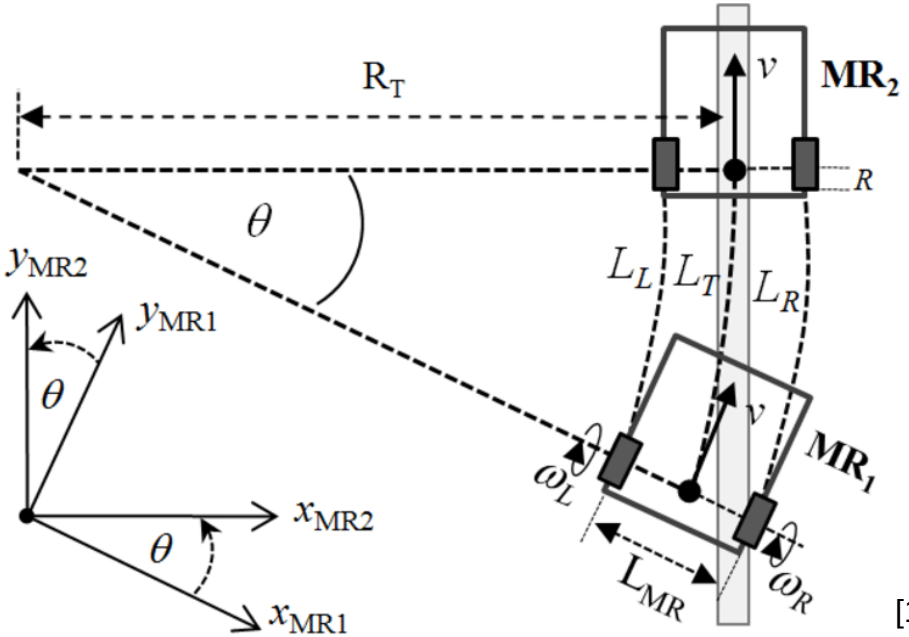
$$\dot{\theta} = \omega$$

Differential drive

Forward kinematics
- Initial state and control inputs are known
- What is the final state of the robot?
- Straightforward task

Inverse kinematics
- Initial and final states are known
- What are the control inputs?
- Problematic in case of non-holonomic platforms
- Singular points

Instantaneous center of curvature (rotation)
- Each wheel must rotate along its *y*-axis
- Wheels move along circular ($R < \infty$) or straight trajectories



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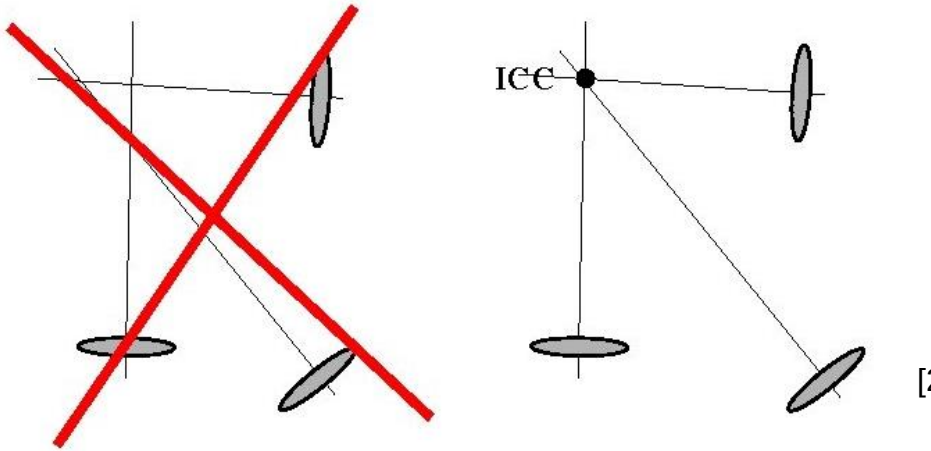


[2]

[1] MAULANA, Eka, M. Aziz MUSLIM a Akhmad ZAINURI. Inverse kinematics of a two-wheeled differential drive an autonomous mobile robot. In: *2014 Electrical Power, Electronics, Communicatons, Control and Informatics Seminar (EECCIS)* [online]. IEEE, 2014 [cit. 2022-02-14]. ISBN 978-1-4799-6947-0. DOI: 10.1109/EECCIS.2014.7003726
[2] BURGARD, Wolfram et al. Probabilistic Robotics: Wheeled Locomotion. Uni Freiburg, 2005.

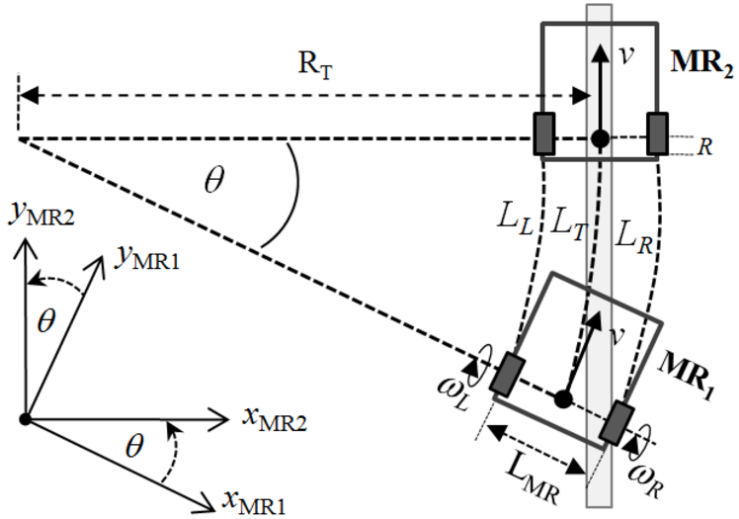
Differential drive – forward kinematics

- Turning radius

$$R = \frac{v}{\omega} = \frac{\frac{r(\omega_R + \omega_L)}{2}}{\frac{r(\omega_R - \omega_L)}{d}} = \frac{d(\omega_R + \omega_L)}{2(\omega_R - \omega_L)}$$

- ICC

$$\begin{pmatrix} ICC_x \\ ICC_y \end{pmatrix} = \begin{pmatrix} x + R\cos(\theta + \pi/2) \\ y + R\sin(\theta + \pi/2) \end{pmatrix} = \begin{pmatrix} x - R\sin\theta \\ y + R\cos\theta \end{pmatrix}$$

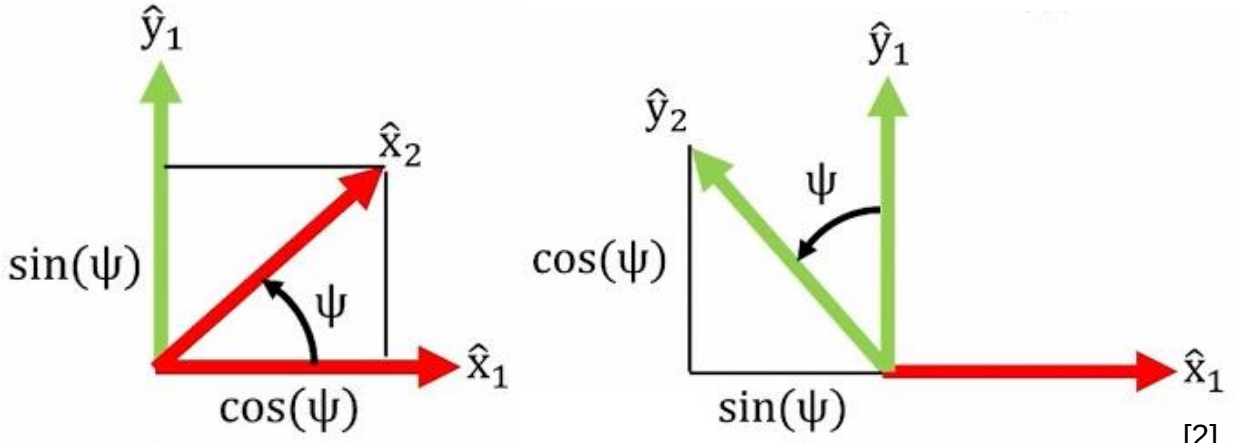


[1]

- Rotation matrix

$$\begin{pmatrix} \widehat{x_1} \\ \widehat{y_1} \\ 1 \end{pmatrix} = \begin{pmatrix} \cos\psi & -\sin\psi & 0 \\ \sin\psi & \cos\psi & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \widehat{x_2} \\ \widehat{y_2} \\ 1 \end{pmatrix}$$

$$\begin{pmatrix} \widehat{x_2} \\ \widehat{y_2} \\ 1 \end{pmatrix} = \begin{pmatrix} \cos\psi & \sin\psi & 0 \\ -\sin\psi & \cos\psi & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \widehat{x_1} \\ \widehat{y_1} \\ 1 \end{pmatrix}$$



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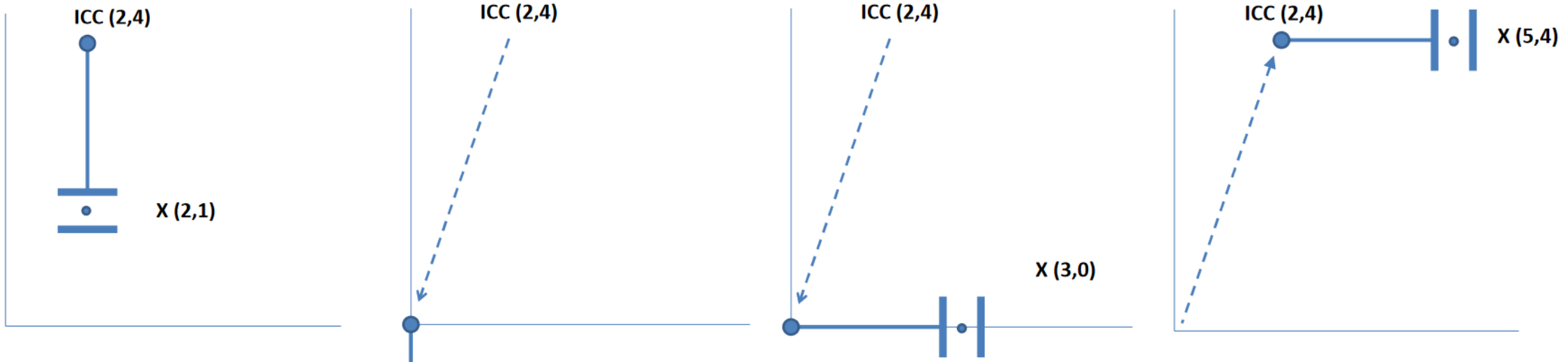
[2] WOOLFREY, Jon. 2.2 Rotation Matrices. In: *YouTube* [online]. 2018 [cit. 2022-02-15]. Available at: https://youtu.be/4srS0s1d9Yw

Differential drive – forward kinematics



[1]

1. Translate the ICC to origin
2. Rotate about z-axis
3. Translate back to the original ICC

$$\begin{pmatrix} x' \\ y' \\ \theta' \end{pmatrix} = \begin{pmatrix} \cos(\omega\Delta t) & -\sin(\omega\Delta t) & 0 \\ \sin(\omega\Delta t) & \cos(\omega\Delta t) & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x - ICC_x \\ y - ICC_y \\ \theta \end{pmatrix} + \begin{pmatrix} ICC_x \\ ICC_y \\ \omega\Delta t \end{pmatrix} = \begin{pmatrix} x \\ y \\ \theta \end{pmatrix} + \begin{pmatrix} -R\sin\theta + R\sin(\theta + \omega\Delta t) \\ R\cos\theta - R\cos(\theta + \omega\Delta t) \\ \omega\Delta t \end{pmatrix}$$

[1] ALLEN, Peter K. Notes – Differential Drive Robots [online]. Columbia University, 2017 [cit. 2022-02-15]. Available at: http://www.cs.columbia.edu/~allen/F17/NOTES/icckinematics.pdf

Differential drive – inverse kinematics

- We can express the state equations using the rotation matrix

World frame

Robot frame

$$\begin{pmatrix}\dot{x}\\ \dot{y}\\ \dot{\theta}\end{pmatrix} = \begin{pmatrix}\cos\theta & -\sin\theta & 0\\ \sin\theta & \cos\theta & 0\\ 0 & 0 & 1\end{pmatrix}\begin{pmatrix}\dot{x}_R\\ \dot{y}_R\\ \dot{\theta}_R\end{pmatrix} = \begin{pmatrix}\cos\theta & -\sin\theta & 0\\ \sin\theta & \cos\theta & 0\\ 0 & 0 & 1\end{pmatrix}\begin{pmatrix}v\\ 0\\ \omega\end{pmatrix}$$

$$= \boldsymbol{R}(\theta)$$

- Let us invert the equations

$$\begin{pmatrix}v\\ 0\\ \omega\end{pmatrix} = \boldsymbol{R}^{-1}(\theta)\begin{pmatrix}\dot{x}\\ \dot{y}\\ \dot{\theta}\end{pmatrix} = \boldsymbol{R}^{\mathsf{T}}(\theta)\begin{pmatrix}\dot{x}\\ \dot{y}\\ \dot{\theta}\end{pmatrix} = \begin{pmatrix}\cos\theta & \sin\theta & 0\\ -\sin\theta & \cos\theta & 0\\ 0 & 0 & 1\end{pmatrix}\begin{pmatrix}\dot{x}\\ \dot{y}\\ \dot{\theta}\end{pmatrix}$$

$$v = \dot{x}\cos\theta + \dot{y}\sin\theta$$

$$\omega = \dot{\theta}$$

- Ideally, we would set

$$\begin{pmatrix}\dot{x}\\ \dot{y}\\ \dot{\theta}\end{pmatrix} = K\begin{pmatrix}x_G - x\\ y_G - y\\ \theta_G - \theta\end{pmatrix}$$

Goal = (x_G, y_G, θ_G)

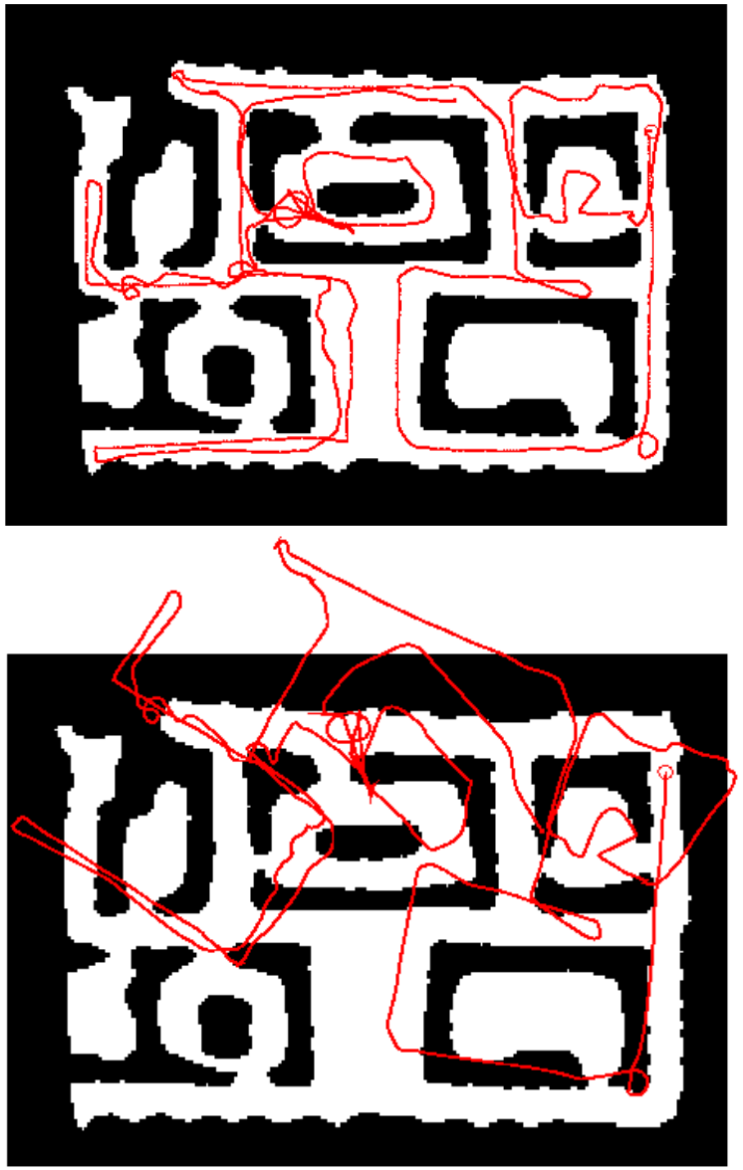
- But we have to follow the non-holonomic constraint $\dot{x}\sin\theta = \dot{y}\cos\theta$

Probabilistic motion model

- Motion is inherently uncertain – how to model it?
- *Probabilistic* models are needed

- To implement Bayes filters (particle, Kalman, …) we need to know the posterior probability $p(x_t|x_{t-1}, u_t)$
  = what is the probability that action u_t takes the system from state x_{t-1} to state x_t

- Two major types of motion models:
  - odometry-based
  - velocity-based (dead reckoning)



[1] BURGARD, Wolfram et al. Probabilistic Motion Models [online]. Uni Freiburg, 2011 [cit. 2022-02-16]. Available at: http://ais.informatik.uni-freiburg.de/teaching/ss11/robotics/slides/06-motion-models.pdf

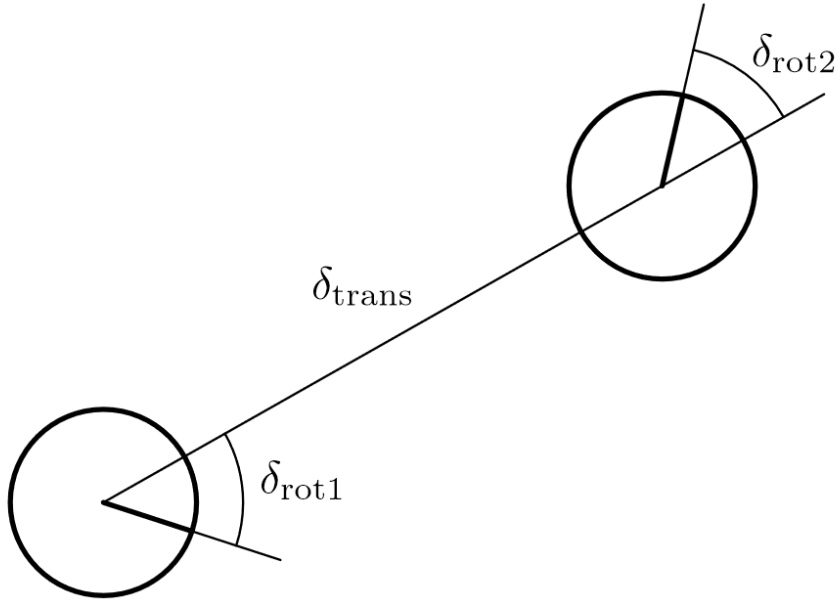
[1]

Probabilistic motion model

Odometry-based models:

- Systems equipped with wheel encoders
- Suitable for estimation
- Generally more accurate
- $u_t = \begin{pmatrix} \bar{x}_{t-1} \\ \bar{x}_t \end{pmatrix} \rightarrow (\delta_{\text{rot1}}, \delta_{\text{trans}}, \delta_{\text{rot2}})$

  (decomposition to rotation-translation-rotation)



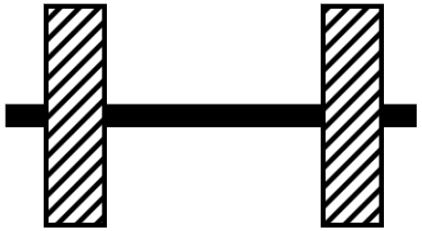
[1]

Velocity-based models:

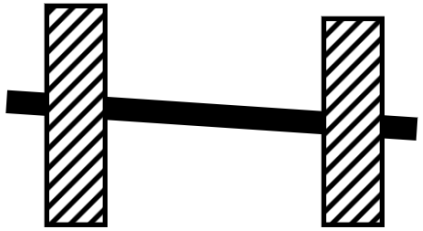
- New pose is calculated from velocities and time elapsed
- Dead reckoning = deduced reckoning
- Suitable for prediction
- $u_t = \begin{pmatrix} v_t \\ \omega_t \end{pmatrix}$

[1] THRUN, Sebastian, Wolfram BURGARD a Dieter FOX. *Probabilistic robotics*. Massachusetts: MIT Press, 2006. ISBN 978-0-262-20162-9.

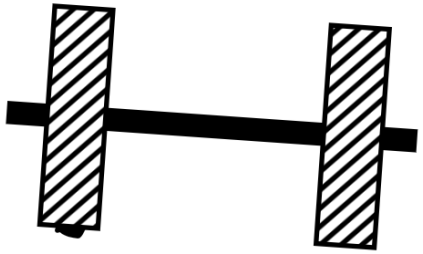
Reasons for motion errors



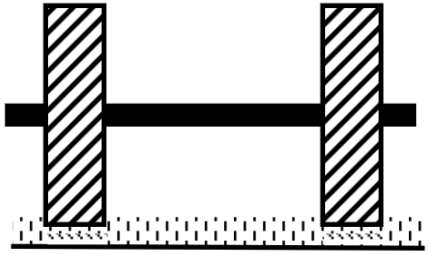
ideal case



different wheel diameters



bump



carpet

and many more ...

[1]

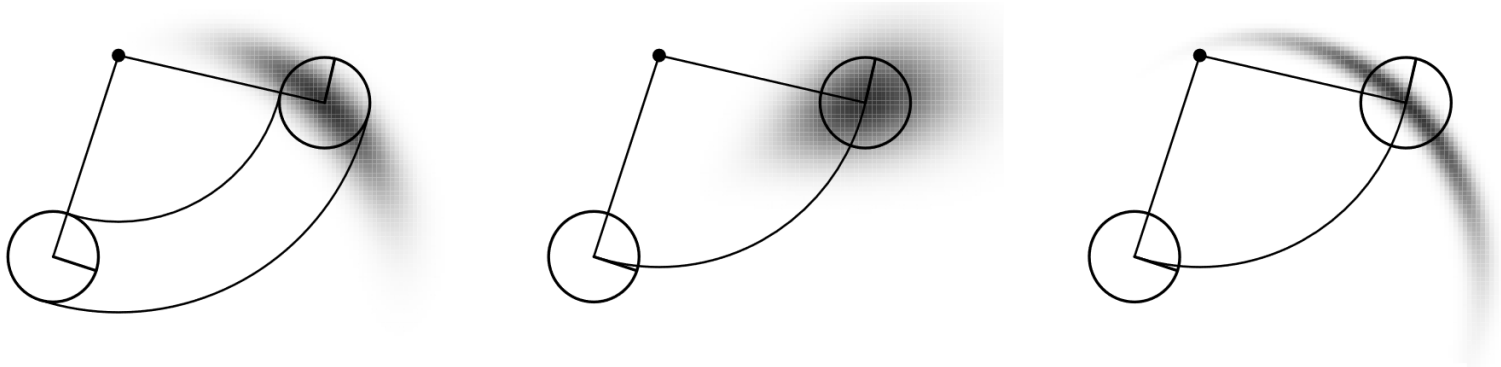
[1] BURGARD, Wolfram et al. Probabilistic Motion Models [online]. Uni Freiburg, 2011 [cit. 2022-02-16]. Available at: http://ais.informatik.uni-freiburg.de/teaching/ss11/robotics/slides/06-motion-models.pdf

Velocity-based model

- We are looking for $p(x_t|x_{t-1}, u_t)$ for a differential drive
- Naive approach: Normal distribution (3D) centered in x_t = not very realistic
- Let us assume that actual control inputs consist of desired velocities and a noise:

$$\begin{pmatrix} \hat{v} \\ \hat{\omega} \end{pmatrix} = \begin{pmatrix} v \\ \omega \end{pmatrix} + \begin{pmatrix} \varepsilon_{\alpha_1 v^2 + \alpha_2 \omega^2} \\ \varepsilon_{\alpha_3 v^2 + \alpha_4 \omega^2} \end{pmatrix}$$

where ε_{b^2} is a zero-mean error variable with variance b^2, parameters α_i are robot-specific error coefficients

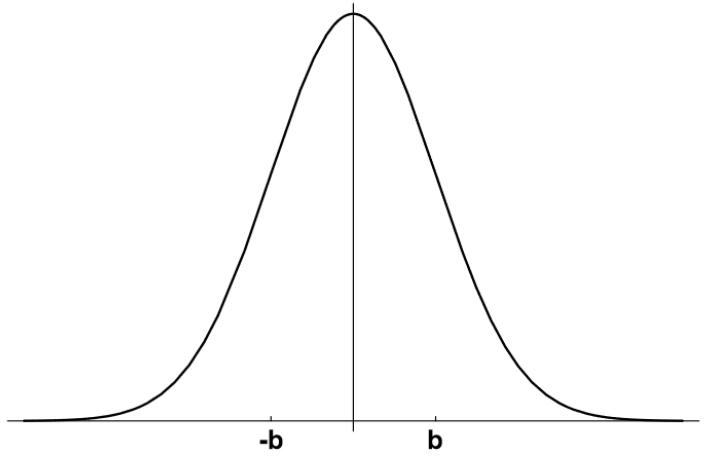


[1]

[1] THRUN, Sebastian, Wolfram BURGARD a Dieter FOX. *Probabilistic robotics*. Massachusetts: MIT Press, 2006. ISBN 978-0-262-20162-9.

Velocity-based model

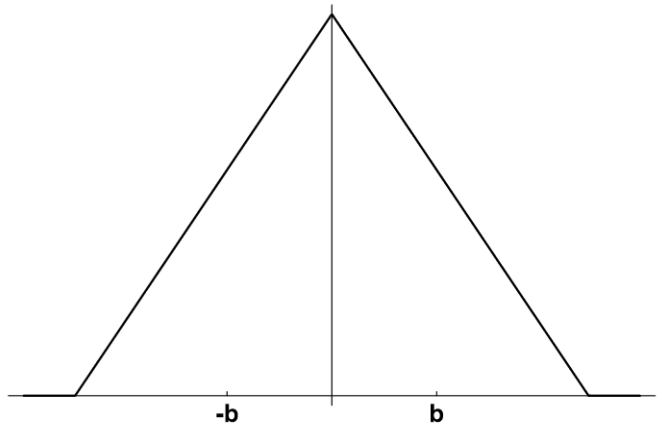
- Possible error distibutions:
  - Normal $\varepsilon_{b^2}(a) = \frac{1}{\sqrt{2\pi b^2}} e^{-\frac{1a^2}{2b^2}}$
  - Triangular $\varepsilon_{b^2}(a) = \max\left\{0, \frac{1}{\sqrt{6}b} - \frac{|a|}{6b^2}\right\}$



Normal distribution

- Assuming $x_{t-1} = (x, y, \theta)$, $x_t = (x', y', \theta')$, we have:

$$\begin{pmatrix} x' \\ y' \\ \theta' \end{pmatrix} = \begin{pmatrix} x \\ y \\ \theta \end{pmatrix} + \begin{pmatrix} -\hat{v}/\hat{\omega} \sin\theta + \hat{v}/\hat{\omega} \sin(\theta + \hat{\omega}\Delta t) \\ \hat{v}/\hat{\omega} \cos\theta - \hat{v}/\hat{\omega} \cos(\theta + \hat{\omega}\Delta t) \\ \hat{\omega}\Delta t \end{pmatrix}$$



[1]

Triangular distribution

[1] THRUN, Sebastian, Wolfram BURGARD a Dieter FOX. *Probabilistic robotics*. Massachusetts: MIT Press, 2006. ISBN 978-0-262-20162-9.

Velocity-based model

- 2 velocities control 3 states → all posterior poses are located on a 2D manifold within a 3D space → degeneracy of the motion model
- We need to add third variable, a final rotation $\hat{\gamma}$

$$\theta' = \theta + \hat{\omega}\Delta t + \hat{\gamma}\Delta t \qquad \hat{\gamma} = \varepsilon_{\alpha_5 v^2 + \alpha_6 \omega^2}$$

- Resulting motion model:

$$\begin{pmatrix} x' \\ y' \\ \theta' \end{pmatrix} = \begin{pmatrix} x \\ y \\ \theta \end{pmatrix} + \begin{pmatrix} -\hat{v}/\hat{\omega}\sin\theta + \hat{v}/\hat{\omega}\sin(\theta + \hat{\omega}\Delta t) \\ \hat{v}/\hat{\omega}\cos\theta - \hat{v}/\hat{\omega}\cos(\theta + \hat{\omega}\Delta t) \\ \hat{\omega}\Delta t + \hat{\gamma}\Delta t \end{pmatrix}$$

[1]

[1] THRUN, Sebastian, Wolfram BURGARD a Dieter FOX. *Probabilistic robotics*. Massachusetts: MIT Press, 2006. ISBN 978-0-262-20162-9.

Velocity-based model

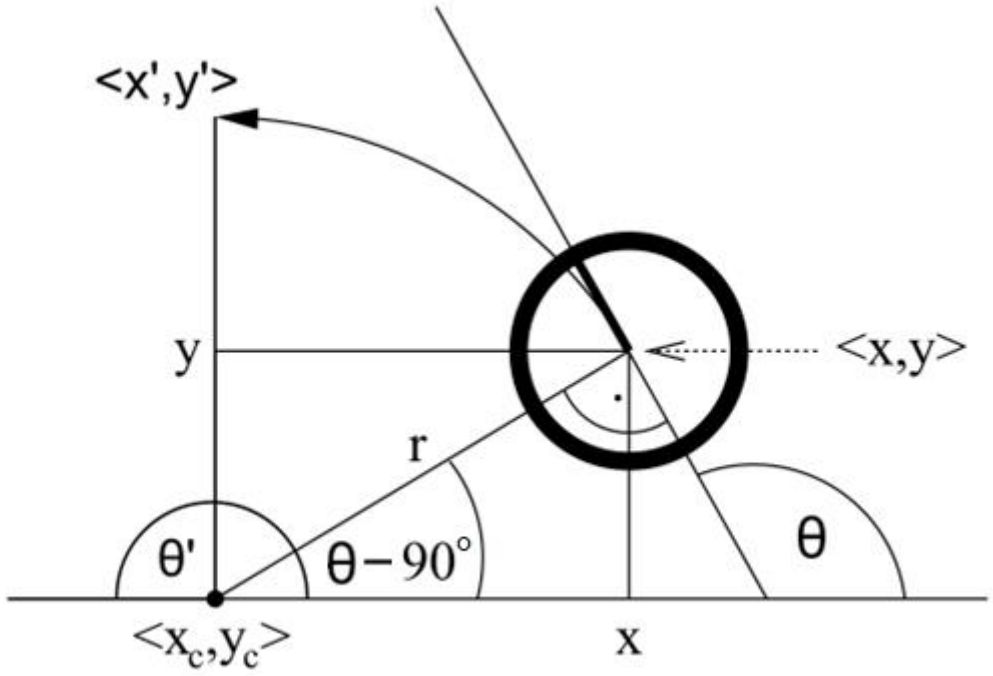
- To compute value $p(x_t|x_{t-1}, u_t)$ for arbitrary combination of arguments, we need an *inverse motion model*

$$\begin{pmatrix} x_c \\ y_c \end{pmatrix} = \begin{pmatrix} x \\ y \end{pmatrix} + \begin{pmatrix} -\lambda \sin\theta \\ \lambda \cos\theta \end{pmatrix} = \begin{pmatrix} \frac{x + x'}{2} + \mu(y - y') \\ \frac{y + y'}{2} + \mu(x' - x) \end{pmatrix}$$

$$\mu = \frac{1}{2} \frac{(x - x')\cos\theta + (y - y')\sin\theta}{(y - y')\cos\theta - (x - x')\sin\theta}$$

$$r = \sqrt{(x - x_c)^2 + (y - y_c)^2} = \sqrt{(x' - x_c)^2 + (y' - y_c)^2}$$

$$\Delta\theta = \text{atan2}(y' - y_c, x' - x_c) - \text{atan2}(y - y_c, x - x_c)$$



[1]

[1] THRUN, Sebastian, Wolfram BURGARD a Dieter FOX. *Probabilistic robotics*. Massachusetts: MIT Press, 2006. ISBN 978-0-262-20162-9.

Velocity-based model

- Inverse motion model – continuation

$$\begin{pmatrix} \hat{v} \\ \hat{\omega} \end{pmatrix} = \Delta t^{-1} \begin{pmatrix} r \cdot \Delta\theta \\ \Delta\theta \end{pmatrix}$$

$$\hat{\gamma} = \Delta t^{-1}(\theta' - \theta) - \hat{\omega}$$

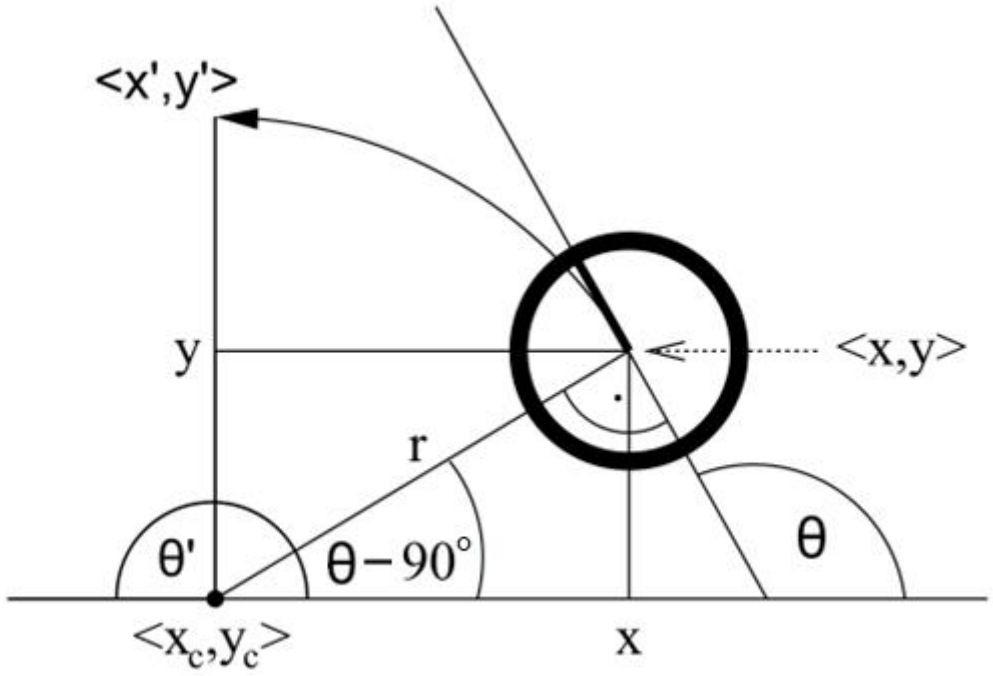
$$\varepsilon_1 = \varepsilon_{\alpha_1 v^2 + \alpha_2 \omega^2}(v - \hat{v})$$

$$\varepsilon_2 = \varepsilon_{\alpha_3 v^2 + \alpha_4 \omega^2}(\omega - \hat{\omega})$$

$$\varepsilon_3 = \varepsilon_{\alpha_5 v^2 + \alpha_6 \omega^2}(\hat{\gamma})$$

- Finally:

$$p(x_t | x_{t-1}, u_t) = \varepsilon_1 \cdot \varepsilon_2 \cdot \varepsilon_3$$



[1]

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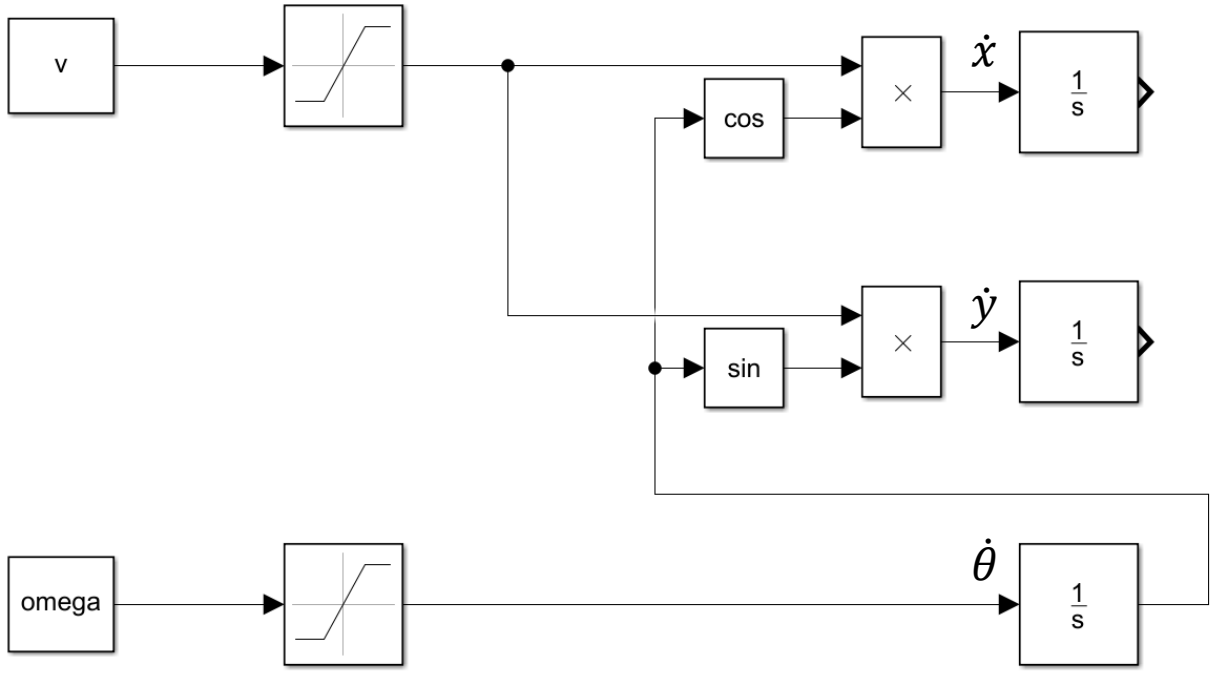
Trajectory following

- Trajectory description
  - Closed-form expression
    - E. g., Bézier curves
  - Sequence of waypoints
    - Equidistant vs. adaptive spacing

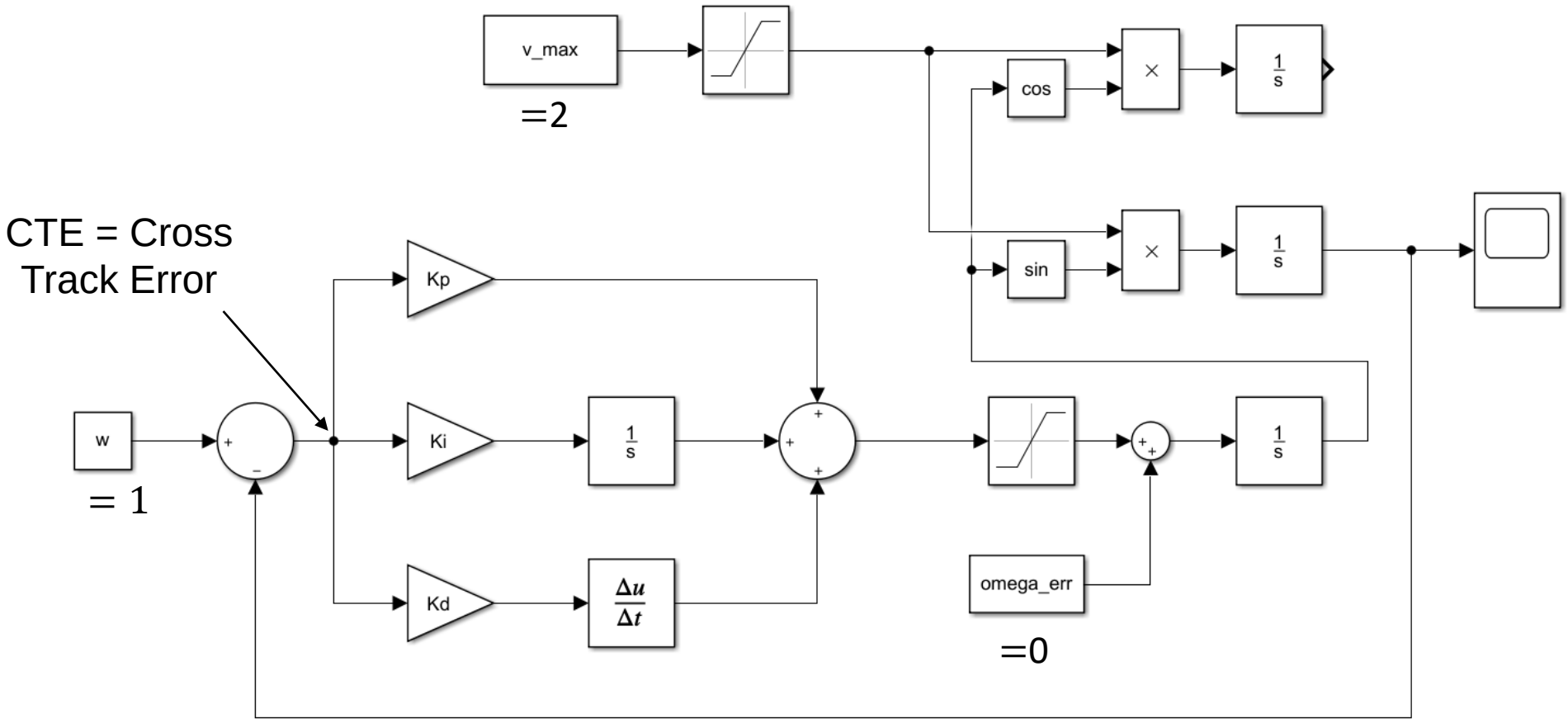
- Global planning
  - Optimal path to goal
  - Outlined in Lecture 6 – Path planning

- **Local planning**
  - *Navigate* robot to the pre-planned path
  - Do not hit any obstacles!
  - Inputs: (estimated) pose, desired path, sensor readings
  - Parameters: kinematic model of the robot
  - Outputs: robot control = velocities

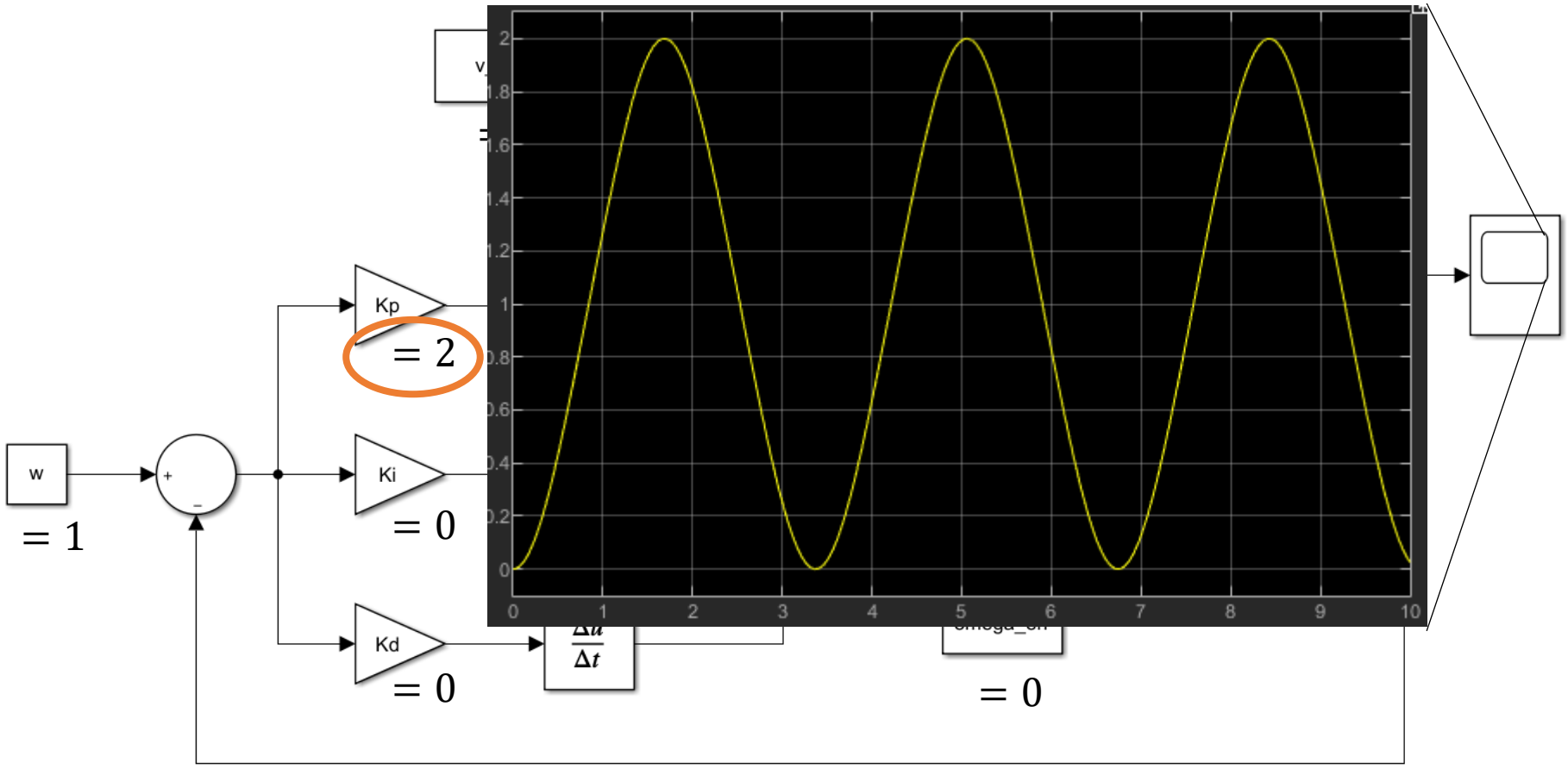
- State model of the differential drive:



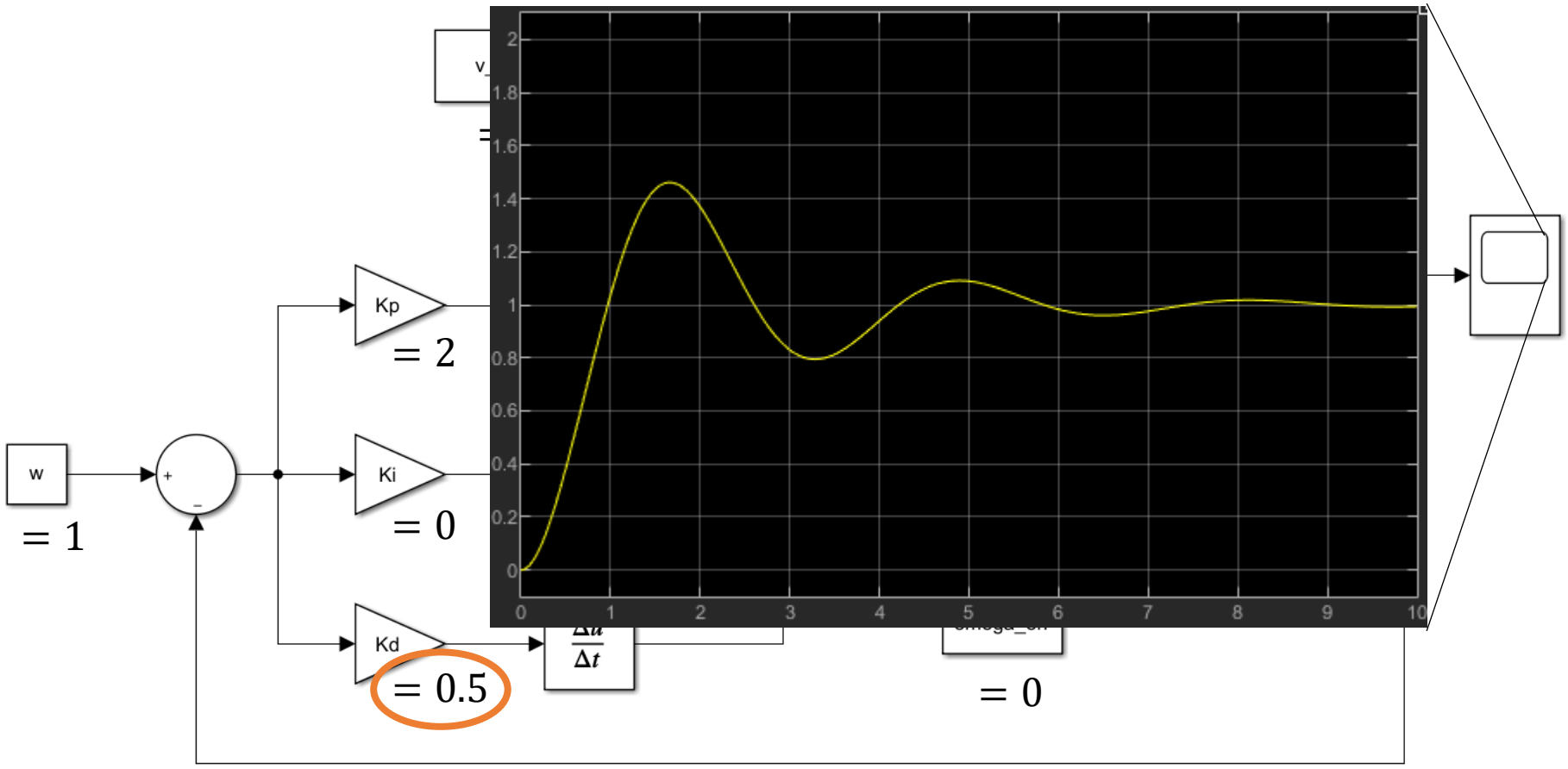
- Let us add a PID structure to control the y state



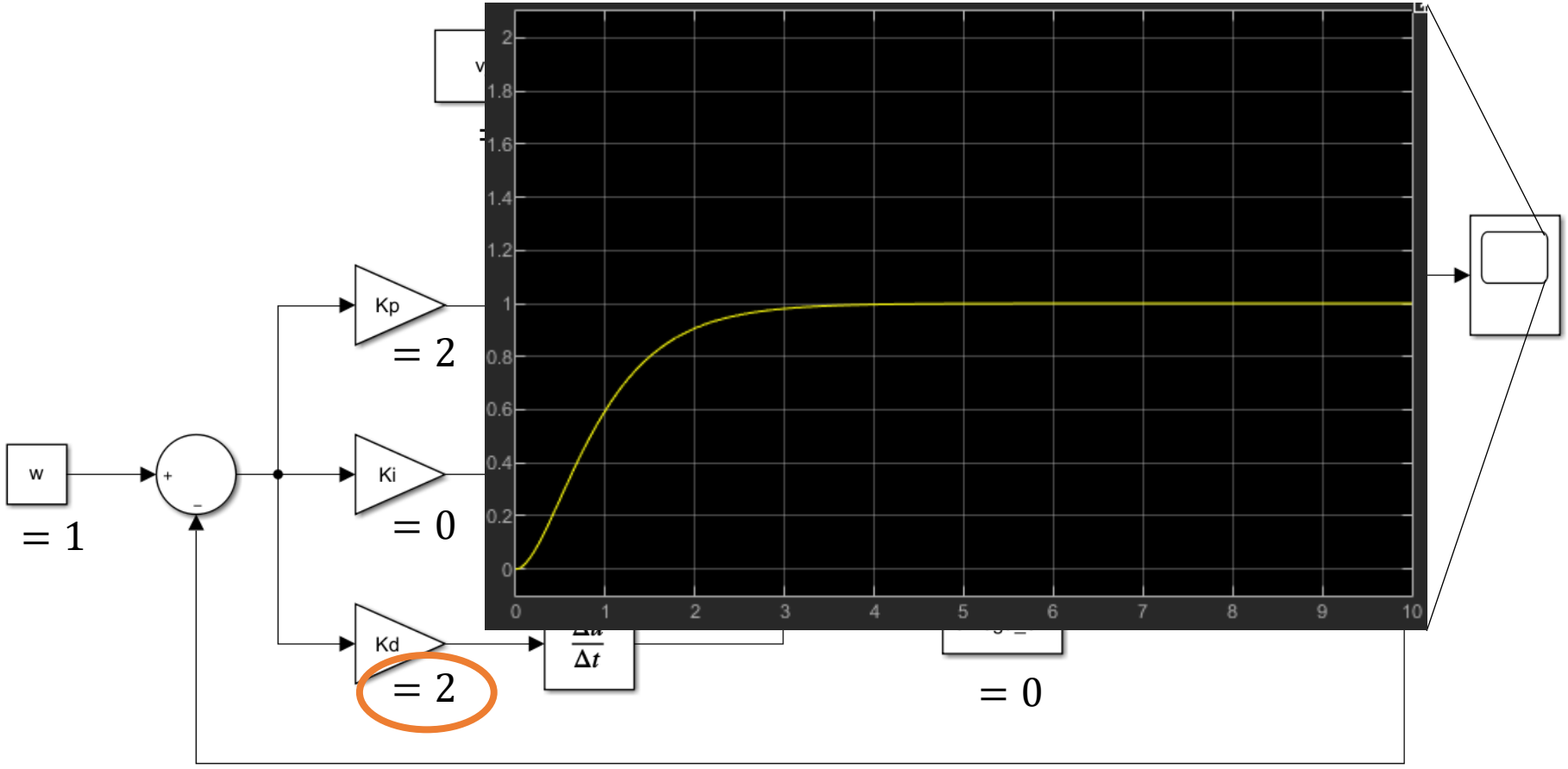
- P controller



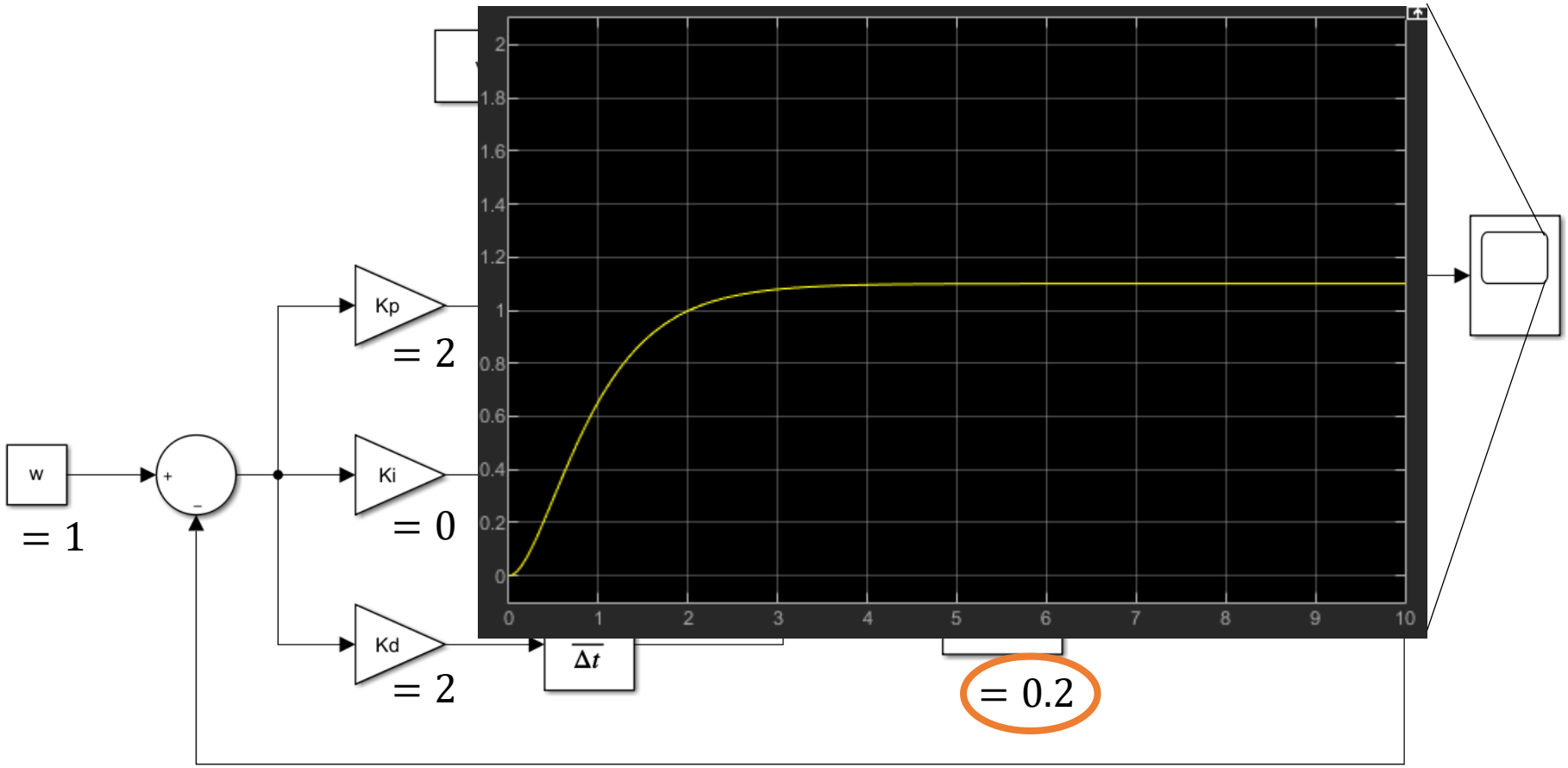
- PD controller



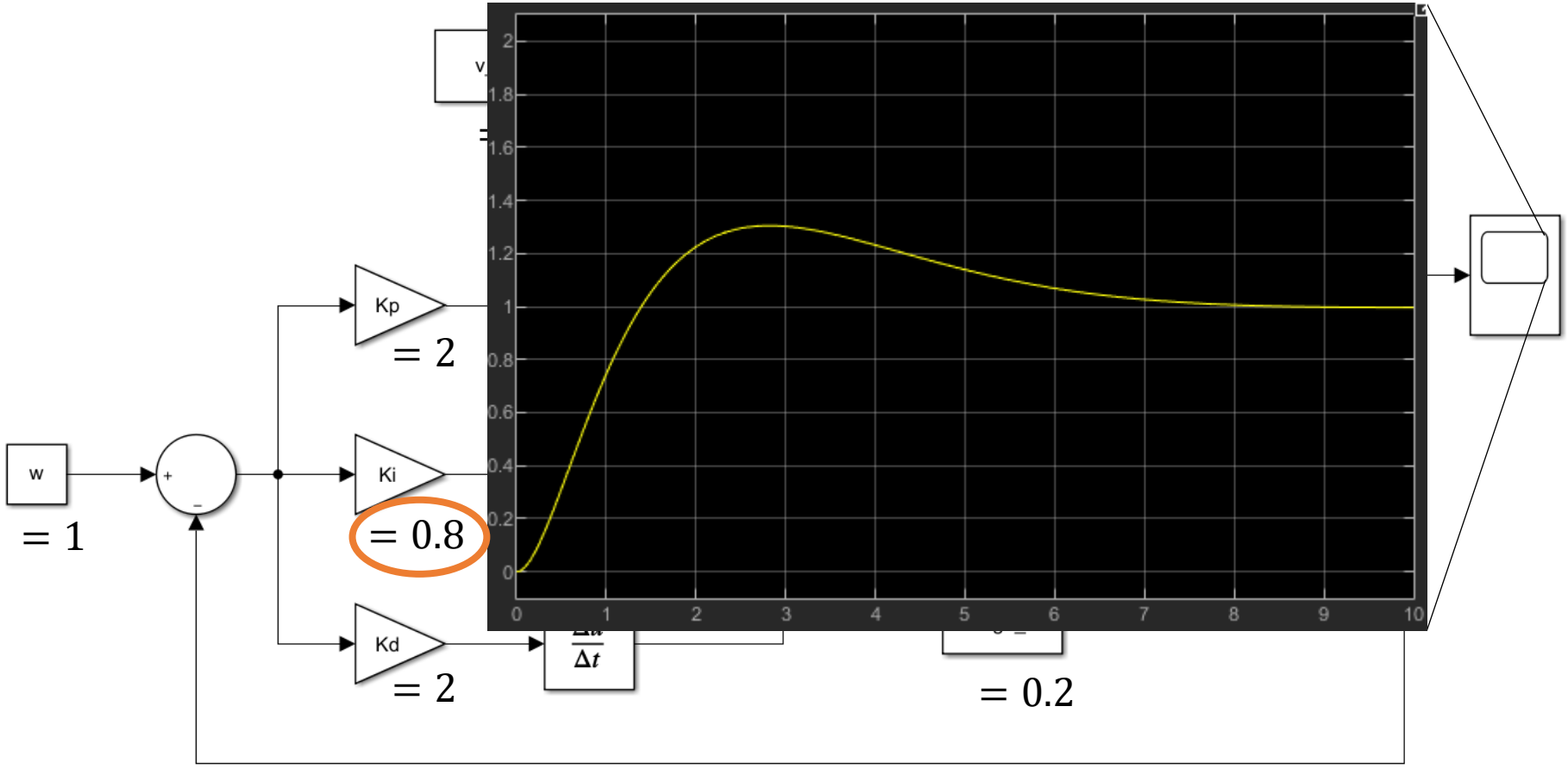
- PD controller – **higher D gain**



- PD controller – **with added error**

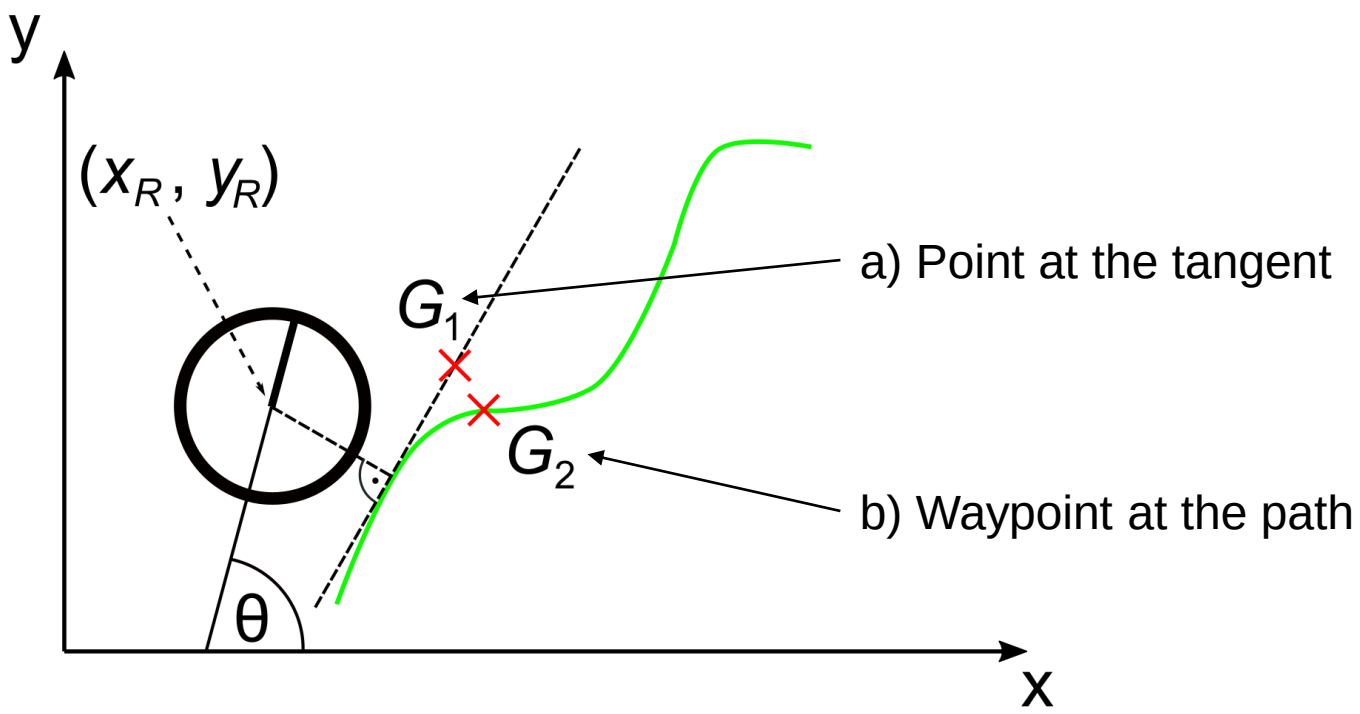


- PID controller – with added error



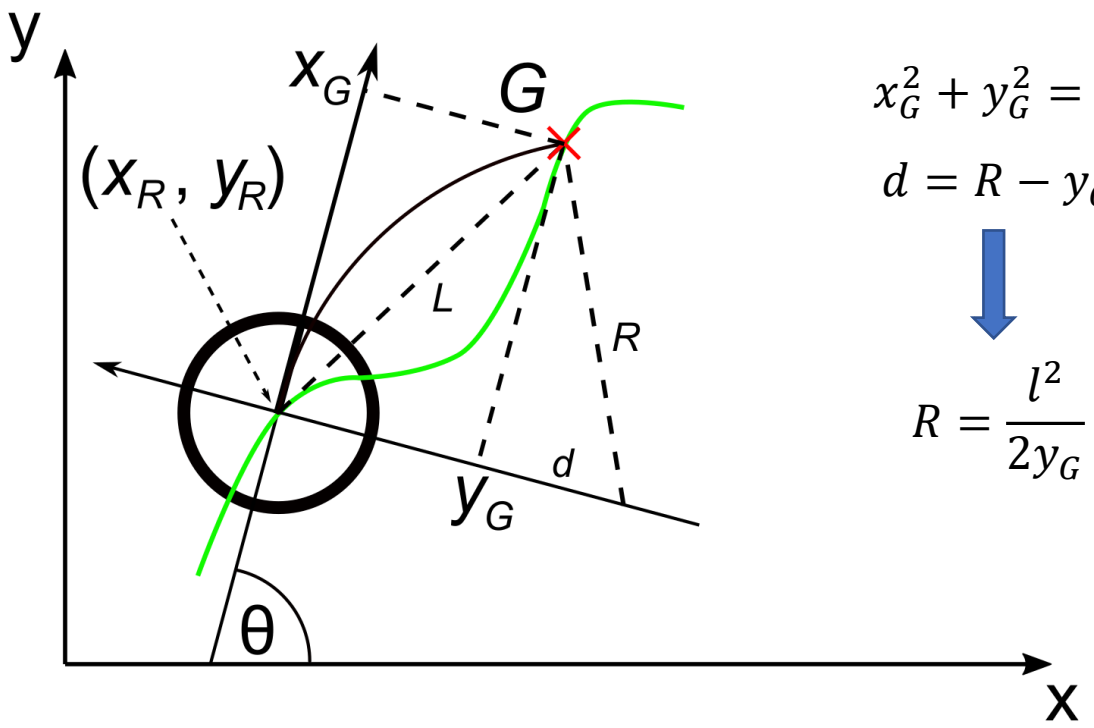
- How to navigate to trajectory in 2D?
- We will introduce two simple algorithms
  - Pure pursuit path tracking
  - Feedback linearization

- It is necessary to identify target/goal coordinates (x_G, y_G)



Pure pursuit path tracking

- Determine the curvature that will drive the vehicle to the chosen target
- The target is at *lookahead distance* l from the robot
- Constraints: $v_{\max}, \omega_{\max}, R_{\min}$ (minimal turning radius)



$$x_G^2 + y_G^2 = l^2$$

$$d = R - y_G$$

$$R = \frac{l^2}{2y_G}$$

Ideal case →

a) $|R| > R_{\min}$

$v = v_{\max}$ OR $|\omega| = \omega_{\max}$

$\omega = \frac{v}{R}$ OR $v = |R| \cdot \omega_{\max}$

b) $|R| \leq R_{\min}$

$|\omega| = \omega_{\max}$ OR $v = v_{\max}$

$v = R_{\min} \cdot \omega_{\max}$ OR $|\omega| = \frac{v_{\max}}{R_{\min}}$

The goal *is not* reached

Pure pursuit path tracking

- The effect of changing the lookahead distance
- Similar to second order dynamic system (l acts as a damping factor)

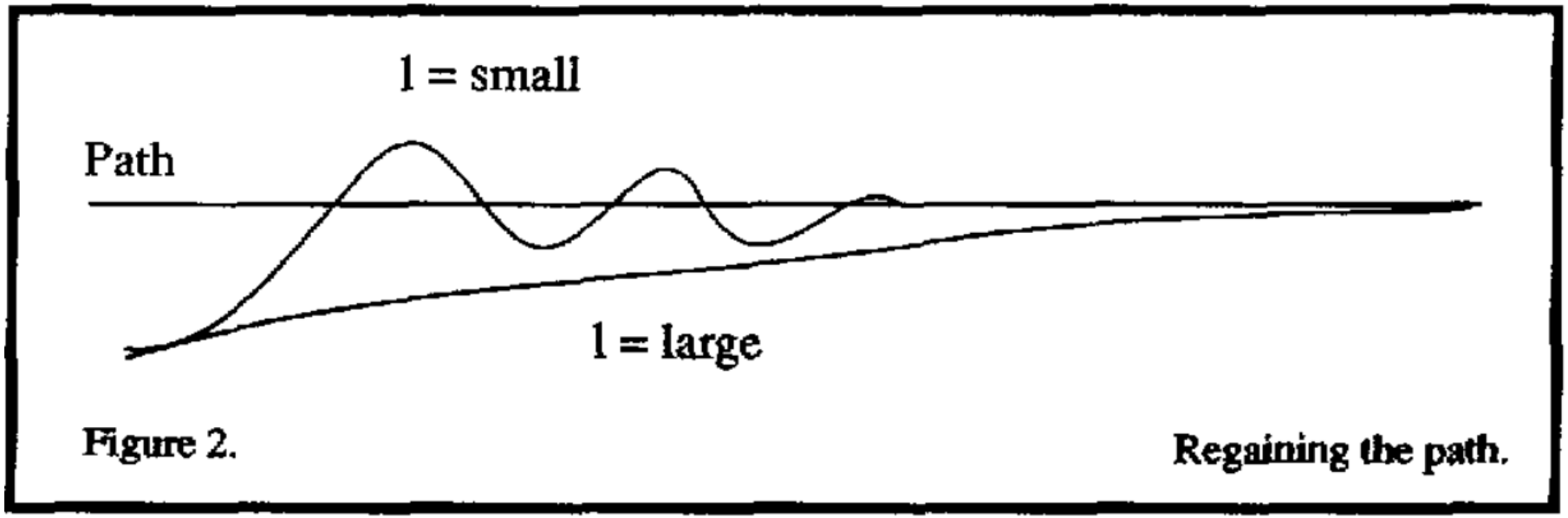


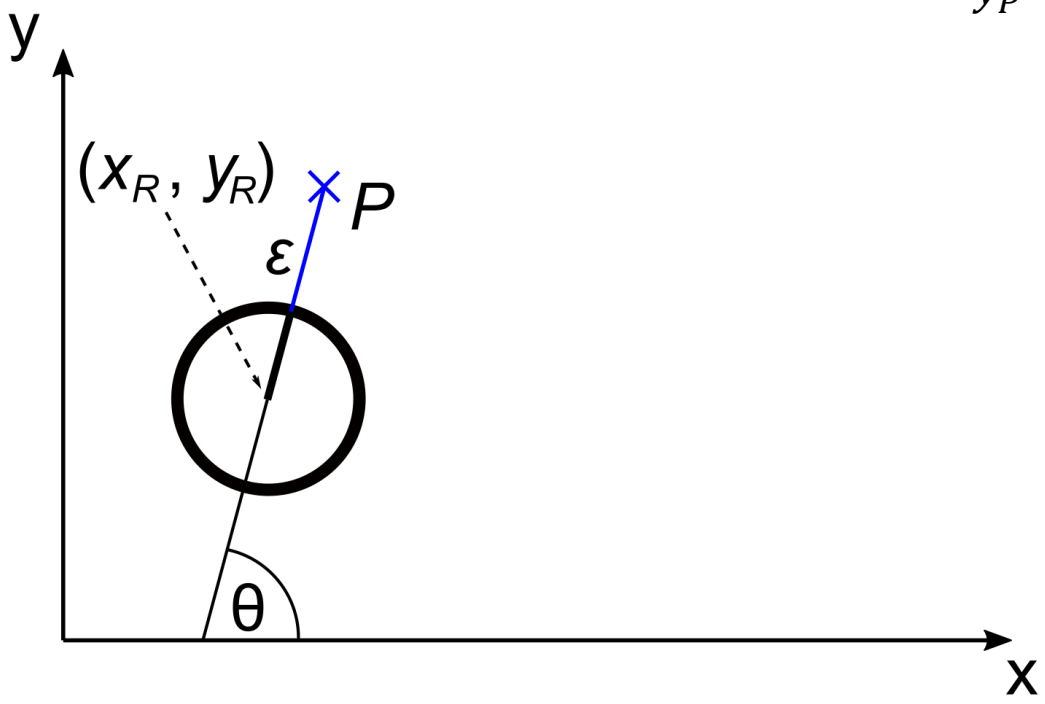
Figure 2. Regaining the path.

[1]

[1] COULTER, R. Craig. Implementation of the Pure Pursuit Path Tracking Algorithm [online]. The Robotics Institute, Carnegie Mellon University: 1992 [cit. 2022-02-18]. Available at: https://www.ri.cmu.edu/pub_files/pub3/coulter_r_craig_1992_1/coulter_r_craig_1992_1.pdf

Feedback linearization

- Linear control of holonomic point *P* to control a non-holonomic robot
- Rigid connection of the robot and *P*
- Key idea: $\begin{pmatrix} v \\ \omega \end{pmatrix} = f(\dot{x}_P, \dot{y}_P)$



$$x_P = x_R + \varepsilon \cos\theta \qquad y_P = y_R + \varepsilon \sin\theta$$

$$\xrightarrow{\frac{\mathrm{d}}{\mathrm{d}t}}$$

$$\dot{x}_P = \dot{x}_R + \varepsilon(-\dot{\theta}\sin\theta) \qquad \dot{y}_P = \dot{y}_R + \varepsilon(\dot{\theta}\cos\theta)$$

$$\downarrow$$

$$\begin{pmatrix} \dot{x}_P \\ \dot{y}_P \end{pmatrix} = v \begin{pmatrix} \cos\theta \\ \sin\theta \end{pmatrix} + \varepsilon\omega \begin{pmatrix} -\sin\theta \\ \cos\theta \end{pmatrix}$$

$$\downarrow$$

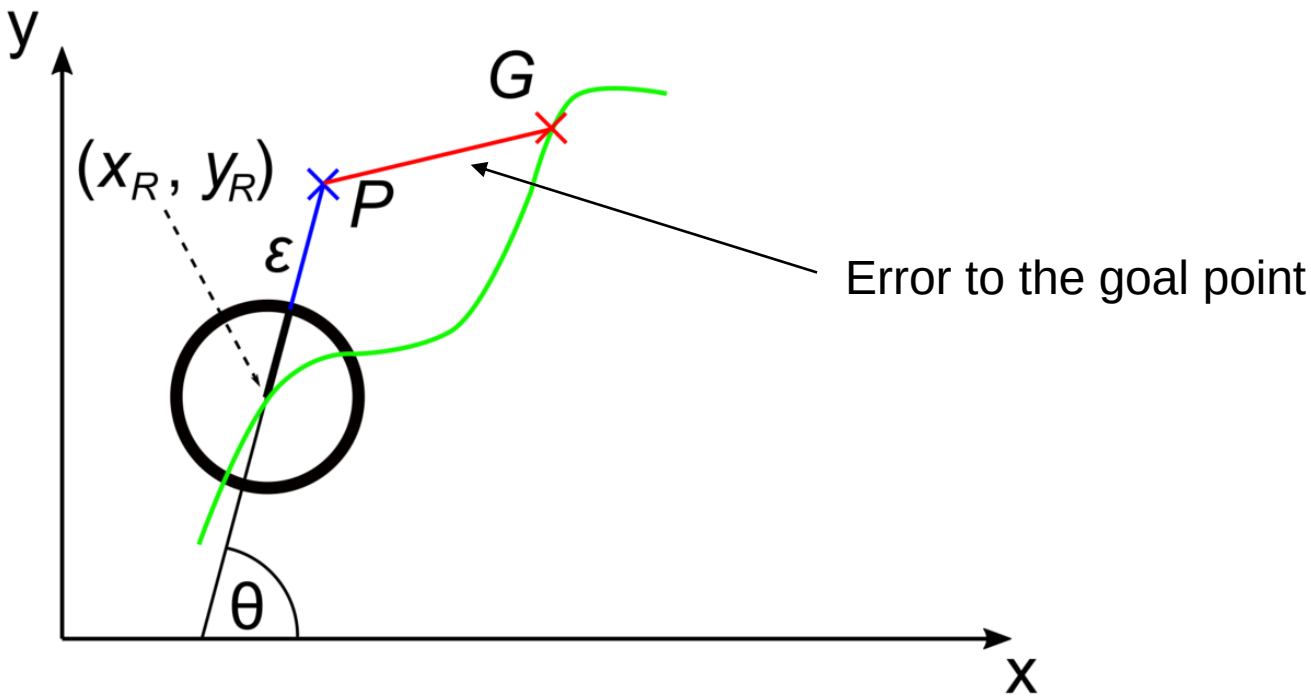
$$v = \dot{x}_P \cos\theta + \dot{y}_P \sin\theta$$

$$\omega = \frac{1}{\varepsilon}(-\dot{x}_P \sin\theta + \dot{y}_P \cos\theta)$$

Feedback linearization

$$\begin{pmatrix}\dot{x}_P\\ \dot{y}_P\end{pmatrix} = \kappa \begin{pmatrix}x_G - x_P\\ y_G - y_P\end{pmatrix} + \begin{pmatrix}\dot{x}_G\\ \dot{y}_G\end{pmatrix}$$

If goal is not stationary



Error to the goal point

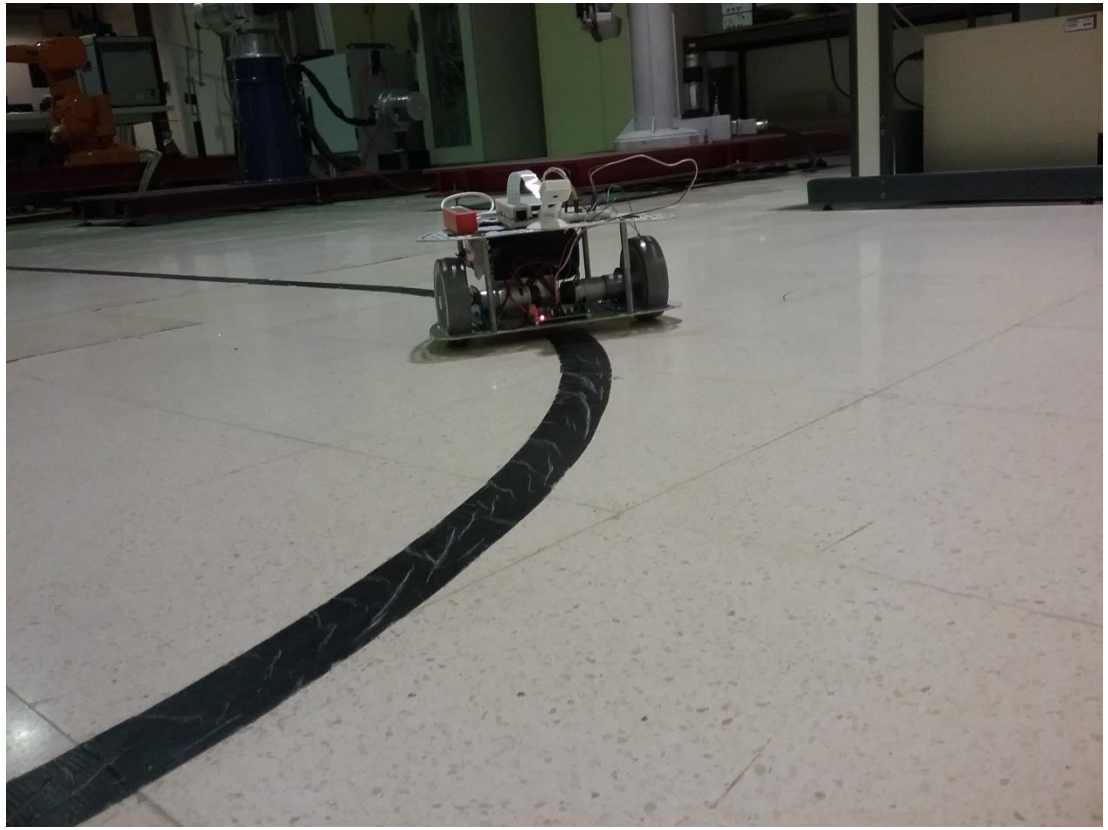
Summary

Kinematics

- Types of drive: differential, Ackermann, omnidirectional, …
- Holomomic vs. non-holonomic systems/constraints
- Computing forward and angular velocity from speed of wheels (and vice versa)
- Forward and inverse kinematics
- Probabilistic motion models

Following trajectory

- Trajectory description
- Selection of target point
- PID controller
- Pure pursuit tracking algorithm
- Feedback linearization



[1]

[1] SAHA, Anup. Path following robot woth artificial neural network [online]. 2015 [cit. 2022-02-19]. Available at: https://anupmec.wordpress.com/project/hands-on-robot/path-following-robot-with-artificial-neural-network/

Profile

Tomas Lazna

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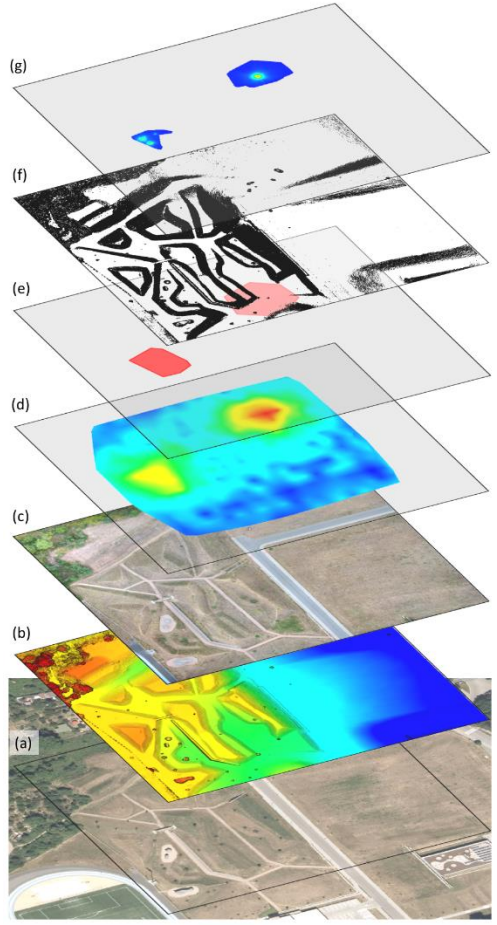

Background:

- Motion planning in mobile robotics
- Radiation data processing
- Cooperation of UASs and UGVs
- Estimation problems

Hobbies and interests:

- Star Wars & science fiction
- LEGO
- Politics

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