

# MECH5170M

## Connected and Autonomous Vehicles Systems

Localisation of AV

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- Localisation
- Global navigation satellite system (GNSS)
- LiDAR and High-Definition Maps,
- Visual Odometry,
- Internal vehicle sensors



# Localisation

For autonomous vehicles, one of the most critical tasks is localisation, i.e., the accurate and real-time determination of the vehicle's position.

- Global navigation satellite system (GNSS),
- LiDAR and High-Definition Maps,
- Visual Odometry,
- Dead Reckoning (“deduced reckoning”) sensors.

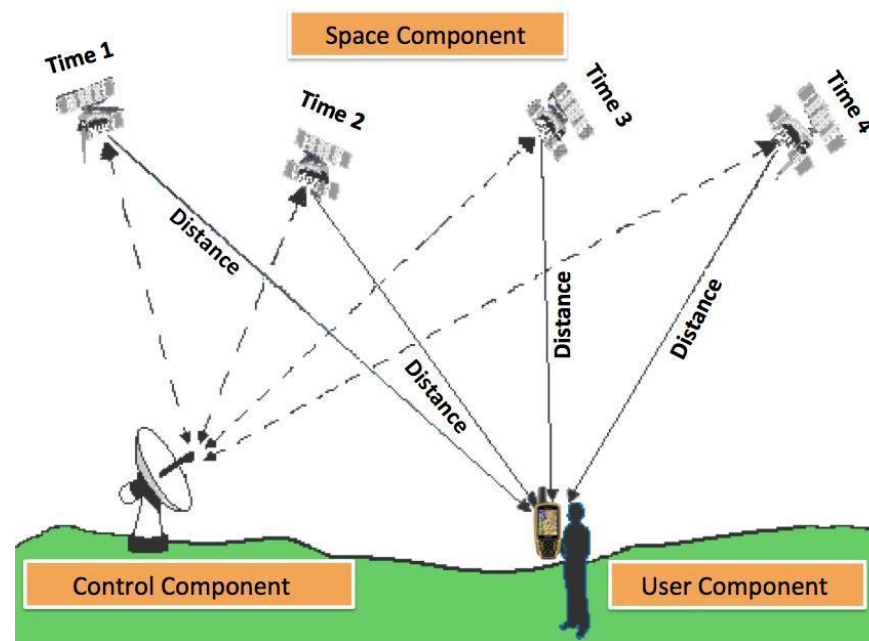
How often signals from each sensor is updated?

For autonomous vehicles, one of the most critical tasks is localisation, i.e., the accurate and real-time determination of the vehicle's position.

- Global navigation satellite system (GNSS) (1-5 Hz),
- LiDAR and High-Definition Maps (5-20 Hz),
- Visual Odometry (30-100 Hz),
- Dead Reckoning (“deduced reckoning”) sensors (1kHz).

## Global Positioning System

### System components



- Time stamped signal
- Difference in time provide position

- Global navigation satellite system (GNSS)
  - GPS (US),
  - GLONASS (Russia),
  - Galileo (EU),
  - BeiDou (China).
- Accuracy in meters
- Low frequency update
- Coverage area is limited

For  $n$  satellites, the equations to satisfy are:

$$d_i = (\tilde{t}_i - b - s_i) c, \quad i = 1, 2, \dots, n$$

where  $d_i$  is the geometric distance or range between receiver,  $\tilde{t}_i$  is on-board receiver clock,  $b$  is the receiver's clock bias,  $s_i$  is the satellite time and satellite  $i$  (the values without subscripts are the  $x$ ,  $y$ , and  $z$  components of receiver position):

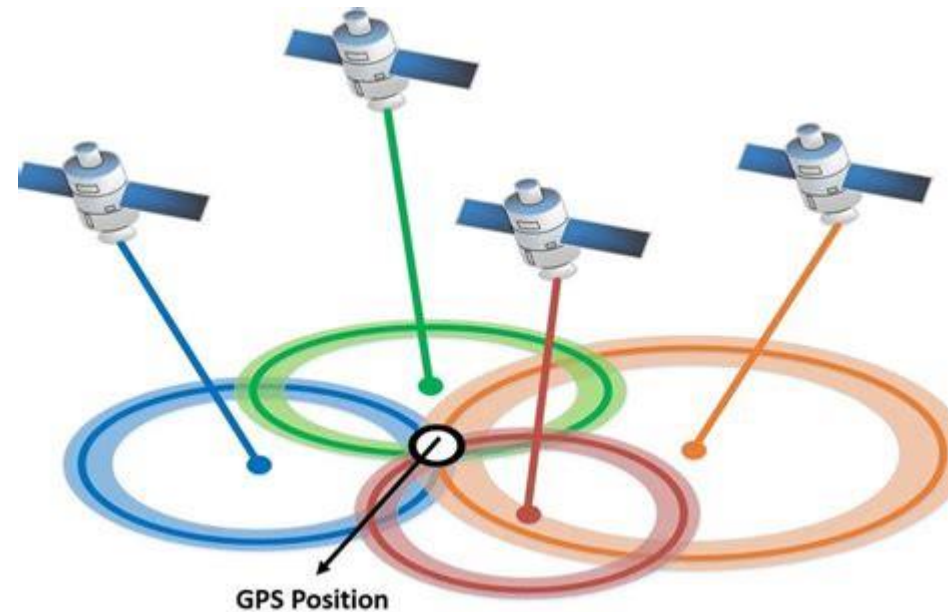
$$d_i = \sqrt{(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2}$$

## Global Positioning System

### Precision positioning

Precision of positioning depends on the number of satellites:

- More satellites signal will be available, more accurate positioning can be achieved.





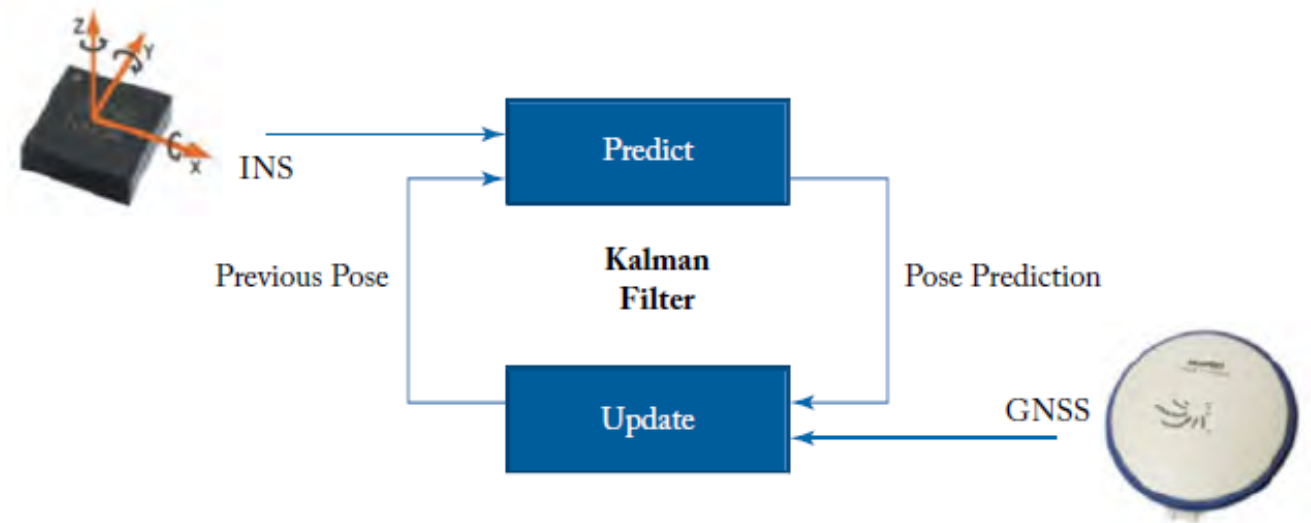
- **Satellite Clocks:** Any tiny amount of inaccuracy of the atomic clocks in the GNSS satellites can result in a significant error in the position calculated by the receiver. Roughly, 10 ns of clock error results in 3 m of position error.
- **Orbit Errors:** GNSS satellites travel in very precise, well-known orbits. However, like the satellite clock, the orbits do vary a small amount. When the satellite orbit changes, the ground control system sends a correction to the satellites and the satellite ephemeris (trajectory) is updated. Even with the corrections from the GNSS ground control system, there are still small errors in the orbit that can result in up to  $\pm 2.5$  m of position error.
- **Tropospheric** (<80km), **Ionospheric** (>80-600km), **Delay:** These ions delay the satellite signals and can cause a significant amount of satellite position error (typically  $\pm 5$  m). Errors can be caused by humidity, temperature and atmospheric pressure in the troposphere.

Contributing Source	Error Range
Satellite Clocks	$\pm 2$ m
Orbit Errors	$\pm 2.5$ m
Ionospheric Delays	$\pm 5$ m
Tropospheric Delays	$\pm 0.5$ m
Receiver Noise	$\pm 0.3$ m
Multipath	$\pm 1$ m

Inertial Navigation System (INS) uses rotation and acceleration information from an Inertial Measurement Unit (IMU) to compute a relative position over time.

Typically, INS systems run at a rate of 1 KHz, providing very frequent position updates.

INS, allowing it to minimize the localisation errors using a mathematical filter, such as a Kalman Filter.



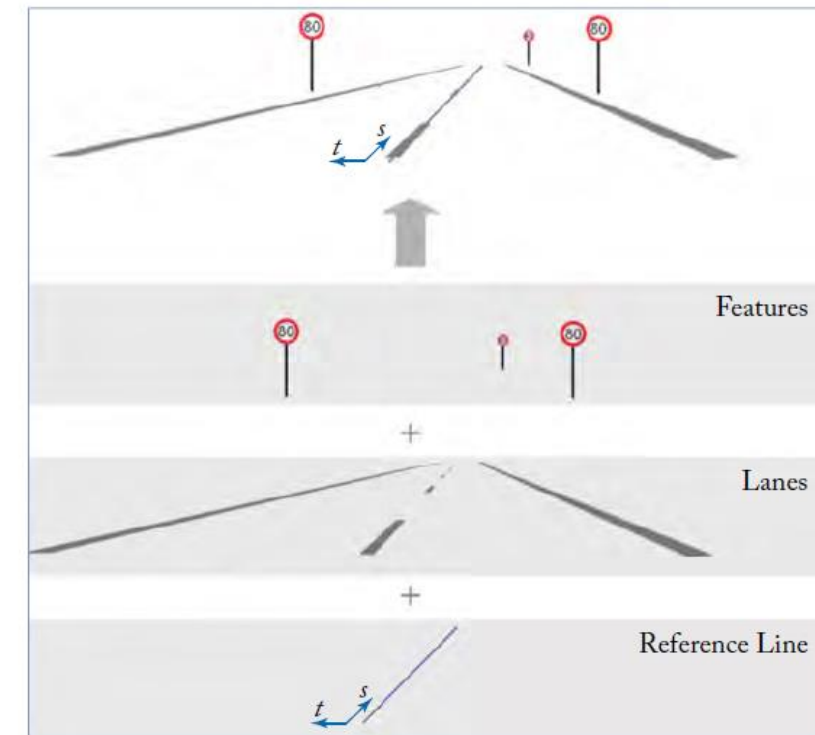
Most commercial autonomous vehicles prototypes, including Waymo, Baidu, BMW, etc., rely on LiDAR and HD Maps for Localisation.

HD maps make routes familiar to autonomous vehicles.

We need to localise a vehicle in real-time against the HD map.

**Kalman filtering** was the standard method for solving state space models. Can be applied to optimally solve a linear Gaussian state space model.

The standard approach to achieve this is through **particle filter**, based on Monte Carlo simulation. Can handle non Gaussian data.



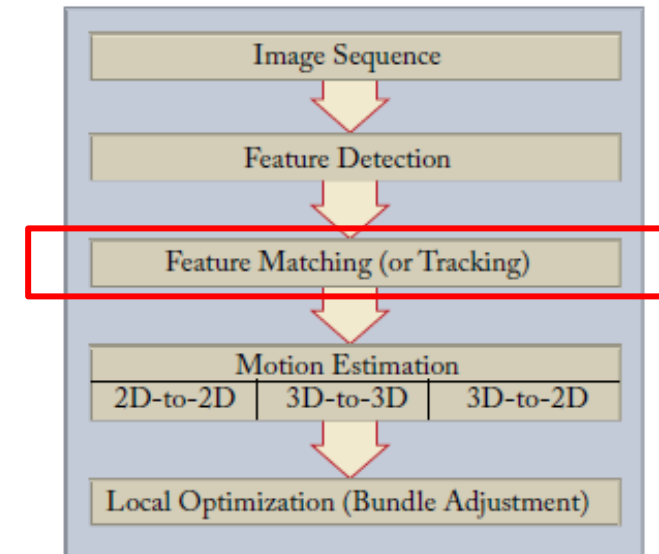
Semantic layers of HD maps

Visual odometry (VO) is the process of estimating the motion of a vehicle using only the input of one or more cameras.

The main task in VO is to compute the relative transformations between images and then to utilise the transformations to recover the full trajectory of the vehicle.

- Monocular visual odometry
- Stereo visual odometry

Less precise than LIDAR but can provide complimentary data for Sensor Fusion.



Name derived from “deduced reckoning” of old sailing days.

Simple mathematical procedure for **determining the present location** of a vehicle by **advancing some previous position** through **known course and velocity** information **over** a given length of **time**.

## WHEEL ENCODERS

Wheel odometry uses encoders to measure wheel rotation and/or steering orientation. Provides good short-term accuracy, is inexpensive, and allows very high sampling rates.

Over longer period of time can lead to accumulation of errors.

# Speed measurement with encoders



14

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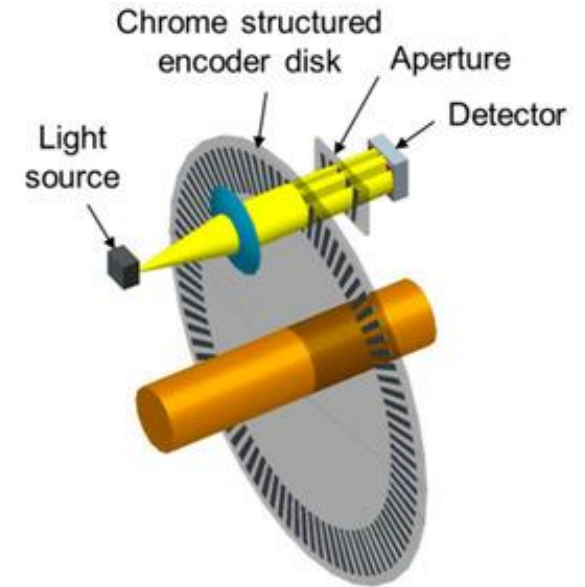
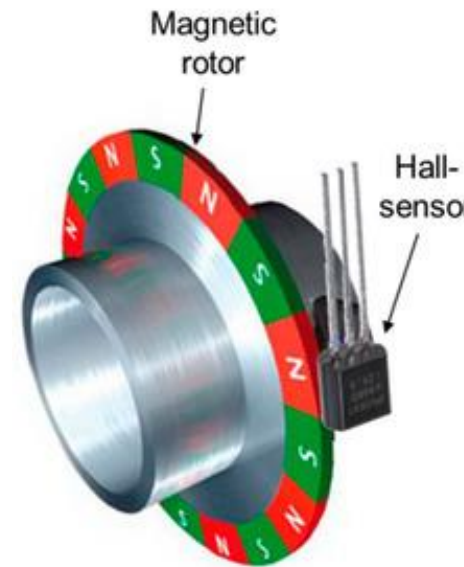
Rotary encoders are widely used to detect the rotation angle of motors and gear shafts.

Main types of encoders operate on principle of:

- Potentiometric,
- Capacitive,
- Magnetic,
- Optical.

Encoders can be used to measure the speed, due to relation between an encoder's pulse frequency and its rotational velocity.

Encoder speed can be determined by two methods:  
**pulse counting or pulse timing.**



[Appl. Sci. 2019, 9(3), 452; <https://doi.org/10.3390/app9030452>]

## Pulse counting

Pulse counting uses a sampling period ( $t$ ) and the number of pulses ( $n$ ) that are counted over the sampling period to determine the average time for one pulse ( $t/n$ ). Knowing the number of pulses per revolution ( $N$ ) for the encoder, the speed can be calculated.

$$\omega = \frac{2\pi n}{Nt}$$

Where:

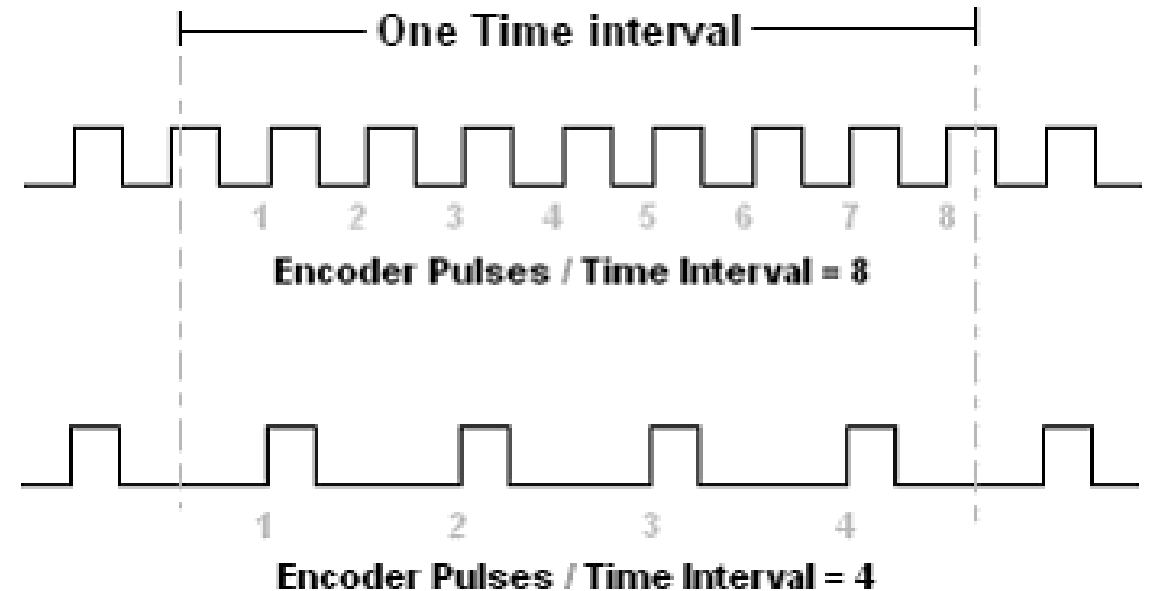
$\omega$  = angular speed (rad/s)

$n$  = number of pulses

$t$  = sampling period (s)

$N$  = pulses per rotation

At low speeds, the resolution of pulse counting is poor, so this method is best applied in high speed applications.



## Pulse timing

With the pulse timing method, a high-frequency clock signal is counted during **one encoder period** (the pitch, or interval between two adjacent lines or windows). The number of cycles of the clock signal ( $m$ ), divided by the clock frequency ( $f$ ), gives the time for the encoder period (the time for the encoder to rotate through one pitch). If the encoder PPR is denoted by  $N$ , the angular speed of the encoder is given by:

$$\omega = \frac{2\pi f}{Nm}$$

Where:

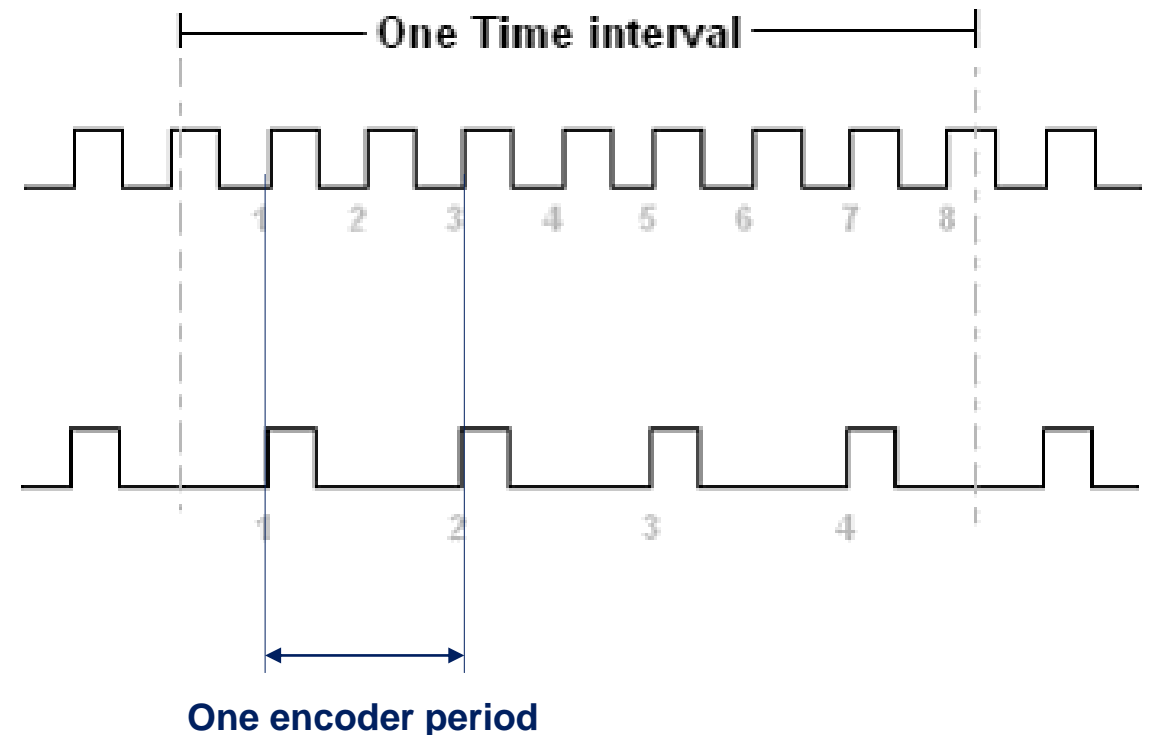
$\omega$  = angular speed (rad/s)

$f$  = clock frequency (Hz)

$m$  = number of clock cycles

$N$  = pulses per rotation

At high speeds, there may be too little time between pulses for pulse timing (also referred to as pulse frequency) to accurately measure clock cycles, so this method is best for low speed applications.



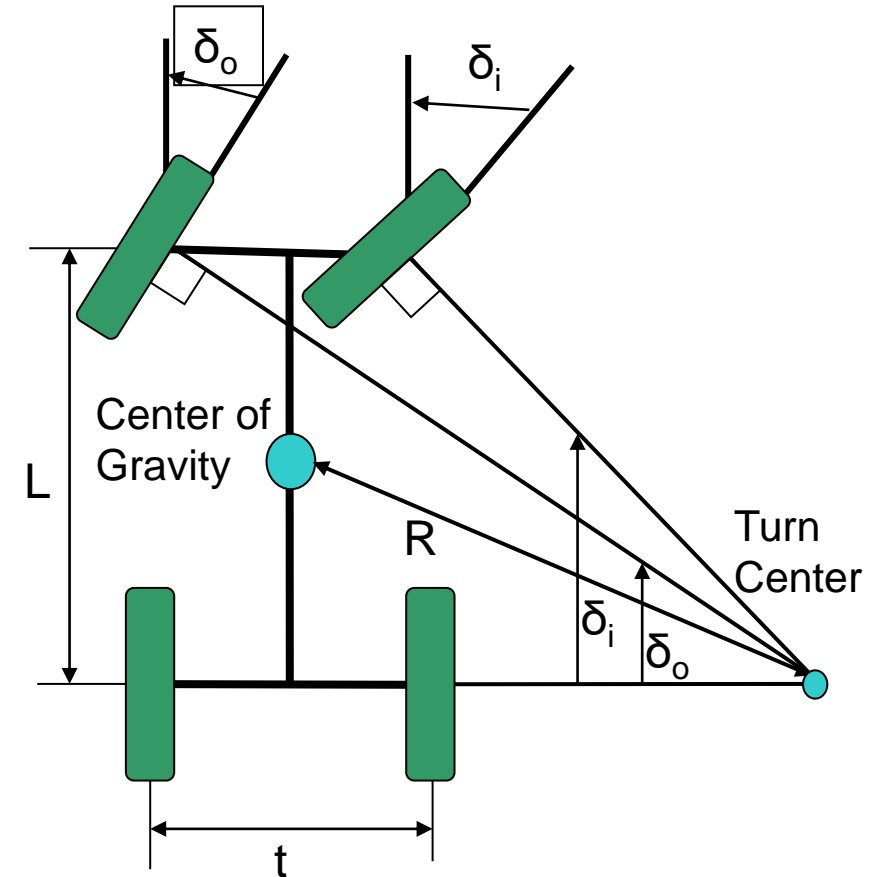


**Systematic errors** include: unequal wheel diameters, average of actual wheel diameters differs from nominal wheel diameter, actual wheelbase differs from nominal wheelbase, misalignment of wheels, finite encoder resolution, as well as finite encoder sampling rate.

**Non-systematic errors** include travel over uneven floors, travel over unexpected objects on the floor, wheel-slippage due to slippery road, wheel-slippage due to over-acceleration, fast turning (skidding), external forces (interaction with external bodies), internal forces (castor wheels), as well as non-point wheel contact with the floor.

**Instrument errors** include both mechanical imperfections in the encoder and errors in the pattern on the code disc.

**Quantization error** stems from the fact that there is no information between pulses or readings. In other words, quadrature encoders only read the *edges* of the signals.



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1. Shaoshan, Engineering Autonomous Vehicles and Robots, 2020
2. Shaoshan, Creating autonomous vehicle systems, 2018
3. J. Seybold et al. Miniaturized Optical Encoder with Micro Structured Encoder Disc, *Appl. Sci.* **2019**, 9(3), 452, MDPI.

ANY QUESTIONS  
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