Chapter 7

Cooperative Localization with Distributed State Estimation

7.1 Motivation

The motivation behind considering cooperative localization is explained in Chapters 1 and 5. These general points are briefly recapitulated before focusing on the specific scenario shown in Figure 1.4. For cooperative localization, a distributed filtering scheme is required. This has the benefit of being more robust to communication failures and outages of the central computing node. The network load is also greatly reduced because sensor nodes can compute their own local estimates without relying on constantly sending and receiving data from a central node. This can result in lower power consumption and network latency. If the actuators of a machine rely on this sensor data for functioning properly, the reliability of the system can be improved if local estimates are always present. These local estimates can be improved by being periodically fused with other estimates.

The cooperative scenario achieves this in certain ways. As explained in Chapter 1, the WSN described by the cooperative scenario includes sensor nodes that are landmarks, on top of vehicles and placed on persons. The vehicle anchor nodes are used to detect the persons present in the environment. These estimates can then be fused. The landmark nodes localize the vehicles in global coordinates. They do not detect the persons in this scenario, principally because the vehicle anchors are more likely to be in direct line-of-sight of the person and the latency of the localization system would suffer if the vehicle and person tags have to continuously range with the landmark nodes[1].

[1] A similar feature is already implemented by Linde [50]. The Linde Safety Guard consists of placing four anchor nodes on top of a forklift and equipping persons with a tag. The assistance function warns the forklift driver if a person is nearby. However, no cooperative localization is implemented as the vehicles merely detect persons in their local coordinates.

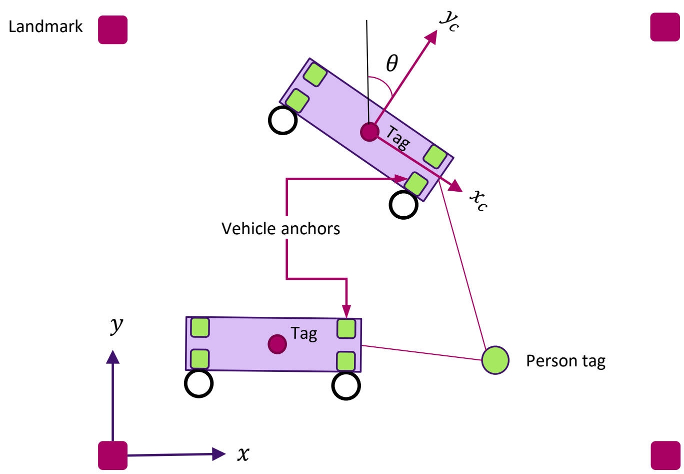

Figure 7.1: Cooperative scenario with two vehicles that detect the same person.

In order to do this, the WSN will have to operate two different channels. The channel depicted by the magenta nodes in Figure 7.1 operates with a lower data rate but offers longer range. The green nodes are operated with a higher data rate and thus with a shorter range. This relationship is also seen in real-world hardware. For example, Table 28 of the Decawave DW1000 Datasheet states that the highest range is provided when configuring a data rate of 110 Kbps [18]. Correspondingly, a shorter range is present when a channel is configured with a data rate of 6.8 Mbps.

Having both of these channels present results in two systems that complement each other well. A high data rate is better suited to react to possible collisions quickly. The measurements provided by the low data rate channel ensure that the global vehicle positions are also continuously available. The global person coordinates can also be made available as a vehicle can transfer the position of a person in its local coordinates to global coordinates.

If multiple vehicles detect the same person, their respective person estimates can be fused. As the vehicle anchors communicate using the same channel, they can also exchange estimates with each other. These estimates have to be in global coordinates because the position of the same person in different vehicle coordinates will vary. For transferring the person from local vehicle coordinates to global coordinates, the vehicle needs to have knowledge of its own position and of its orientation. This orientation is not treated as given but it can be observed using a state estimator. The next section describes a model that incorporates vehicle positions as well as orientation.

Only the EKF implementation of the collaborative localization scenario is complete. A UKF for just the vehicle model and the measurements received from the landmarks was implemented during this thesis. The results of comparing the EKF and UKF implementations, presented in Appendix D, do not show any benefits of using the UKF. Due to this reason, as well as time constraints, the EKF is chosen for the cooperative scenario. Therefore, the non-linear state and transition models of the vehicles, persons and joint states are linearised using EKF methods in the following sections.

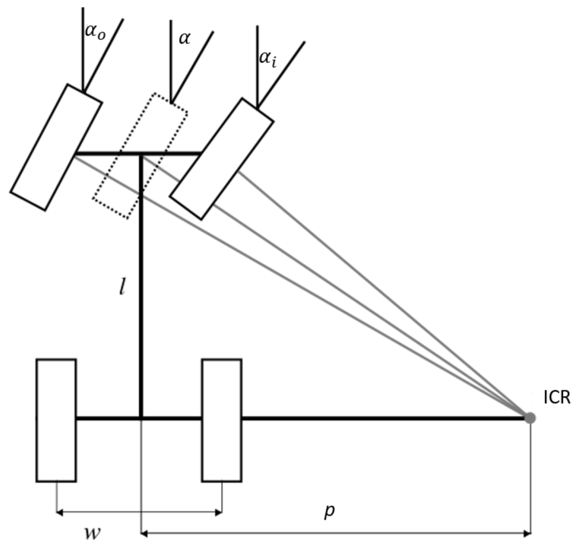

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Figure 7.2: Ackermann's relation for describing the steer angles of the inner and outer front wheels in relation to the instant centre of rotation (ICR). l is the distance between the rear and front axles, p is the distance between the midpoint of the rear angle and the ICR, and w is the distance between the rear wheels. α_o, α and α_i denote the steer angles of the outer wheel, the virtual centre wheel and the inner wheel. Adapted from [26].

7.2 Vehicle Model

As explained earlier, a vehicle needs to estimate its own orientation to properly transfer person estimates to global coordinates. As this chapter mainly focuses on simulation data and advanced vehicle modelling is outside the scope of this thesis, a single-track model with Ackermann steering is used. Ackermann's steer angles are described in Figure 7.2. In this case, the vehicle is treated as massless with two degrees of freedom. The vehicle can control the velocity of the rear tires and the steer angle of the front tire. The steer angles of the front tires are dependent on the instant centre of rotation (ICR). Their relation can be expressed using Ackermann's equation.

The relationship between these angles is described by the following equations, with

$$\tan \alpha = \frac{l}{p} \tag{7.1}$$

describing the tangent of the steer angle of the virtual centre wheel,

$$\tan \alpha_i = \frac{l}{p - w/2}, \tag{7.2}$$

describing the tangent of the steer angle of the inner wheel, and

$$\tan\alpha_o = \frac{l}{p + w/2} \tag{7.3}$$

describing the tangent of the steer angle of the outer wheel.

If the distance between the rear wheels w is constant, the individual steer angles of the front wheels can be described by a virtual centre wheel. As this is the case for the vehicles in the cooperative scenario, one centre wheel and one rear wheel are used for describing this vehicle model sufficiently. It is assumed that no states occur that would cause a wheel-lock, the wheel velocities are always in correct proportion to each other and that no wheel slippage occurs [65]. By applying Euler's velocity equation

$$|\dot{\theta}| = \frac{||\underline{v}||}{||\underline{p}||}, \tag{7.4}$$

(7.1) can be substituted into (7.4) to obtain

$$v = \frac{\dot{\theta} l}{\tan\alpha}. \tag{7.5}$$

To describe the state of the vehicle, a state vector $\underline{x}^v = [x^v, y^v, v^v, \theta^v]^{\mathrm{T}}$, where x^v and y^v describe the position, v^v describes the velocity, and θ^v describes the current orientation of the vehicle. These components are shown in Figure 7.3.

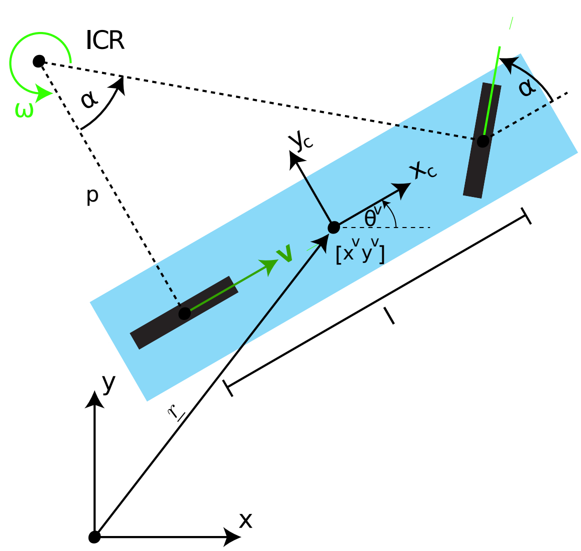

Figure 7.3: Single-track model with one front and one rear wheel. Adapted from [65].

7.2.1 State Transition Model

By using the model shown in Figure 7.3 and in Equation (7.5), a discrete-time state transition model can be defined for a vehicle state vector $\underline{x}^v = [x^v, y^v, v^v, \theta^v]^{\mathrm{T}}$ with the system input $\underline{u}_k^v = [u_k^v, \alpha_k^v]$. It is important to note that the vehicle position $[x^v, y^v]^{\mathrm{T}}$ are in global coordinates. Therefore, the orientation of the vehicle θ^v is required for transitioning to the next position $[x_{k+1}^v, y_{k+1}^v]^{\mathrm{T}}$ as seen in (7.6). The current orientation θ_k^v can be used with the acceleration input u_k^v in order to predict the next positions

$$\begin{aligned} x_{k+1}^v &= x_k^v + T v_k^v \cos\theta_k^v + \frac{T^2}{2} u_k^v \cos\theta_k^v \\ y_{k+1}^v &= y_k^v + T v_k^v \sin\theta_k^v + \frac{T^2}{2} u_k^v \sin\theta_k^v. \end{aligned} \tag{7.6}$$

The acceleration and velocity vectors u^v, v^v act directly upon the rear wheel, which is why the orientation of the vehicle is not required for predicting the velocity

$$v_{k+1}^v = v_k^v + T u_k. \tag{7.7}$$

Equation (7.4) can be used in order to predict the orientation of the vehicle

$$\theta_{k+1}^v = \theta_k^v + T \frac{v_k^v}{l} \tan\alpha_k^v. \tag{7.8}$$

In the context of state estimation, (7.6) is a non-linear state transition model

$$\underline{\boldsymbol{x}}_{k+1}^{\mathrm{p},v} = \underline{a}_k(\underline{\boldsymbol{x}}_k^{\mathrm{e},v}, \underline{\hat{u}}_k^v, \underline{\boldsymbol{w}}_k^v) \tag{7.9}$$

for estimating the random vehicle state $\underline{\boldsymbol{x}}_{k+1}^{\mathrm{p},v}$. The use of Kalman filter variants allows for the random vehicle state to be expressed with a mean $\underline{\hat{x}}_{k+1}^{\mathrm{p},v}$ and covariance $\mathbf{C}_{k+1}^{\mathrm{p},v}$. $\underline{\boldsymbol{w}}_k^v$ denotes the noise of the system input vector $\underline{\hat{u}}_k^v$. Due to the Gaussian assumption of zero-mean centred white noise, this process noise is described using the covariance matrix

$$\mathbf{C}^{w,v} = \begin{bmatrix} (\sigma_u^w)^2 & 0 \\ 0 & (\sigma_\alpha^w)^2 \end{bmatrix}. \tag{7.10}$$

The state transition model $\underline{a}_k(\,\cdot\,)$ finally has to be linearised for the EKF. This is calculated as

$$\begin{aligned} \mathbf{A}_k &= \left.\frac{\partial \underline{a}_k(\,\cdot\,)}{\partial \underline{x}_k}\right|_{\underline{x}_k = \underline{\hat{x}}_k^{\mathrm{e},v}, \underline{u}_k = \underline{\hat{u}}_k} \\ &= \begin{bmatrix} 1 & 0 & T\cos\theta_k^{\mathrm{e},v} & -T v_k^{\mathrm{e},v} \sin\theta_k^{\mathrm{e},v} - \frac{T^2}{2}\hat{u}_k^v \sin\theta_k^{\mathrm{e},v} \\ 0 & 1 & T\sin\theta_k^{\mathrm{e},v} & T v_k^{\mathrm{e},v} \cos\theta_k^{\mathrm{e},v} + \frac{T^2}{2}\hat{u}_k^v \cos\theta_k^{\mathrm{e},v} \\ 0 & 0 & 1 & 0 \\ 0 & 0 & \frac{T}{l}\tan\hat{\alpha}_k^v & 1 \end{bmatrix} \end{aligned} \tag{7.11}$$

and

$$
\begin{aligned}
\mathbf{B}_k &= \left.\frac{\partial \underline{a}_k(\cdot)}{\partial \underline{u}_k}\right|_{\underline{x}_k=\hat{\underline{x}}_k^{\mathrm{e},v},\underline{u}_k=\hat{\underline{u}}_k} \\
&= \begin{bmatrix} \frac{T^2}{2}\cos\theta_k^{\mathrm{e},v} & 0 \\ \frac{T^2}{2}\cos\theta_k^{\mathrm{e},v} & 0 \\ T & 0 \\ 0 & \frac{T}{l}\sec^2\hat{\alpha}_k^v \end{bmatrix}
\end{aligned} \tag{7.12}
$$

7.2.2 Measurement model

The measurement model of the tag placed on the car is identical to the measurement model in the centralized scenario. The only change is using L for the landmarks to avoid confusion. For the car state vector this is expressed as

$$
h_i(\underline{x}_k) = \sqrt{(L_i^x - x_k)^2 + (L_i^y - y_k)^2}, i = 1 \dots N, \tag{7.13}
$$

which can be linearised by the first-order Taylor approximation

$$
\begin{aligned}
\mathbf{H}_k &= \left.\frac{\partial h_k(\cdot)}{\partial \underline{x}_k}\right|_{\underline{x}_k=\hat{\underline{x}}_{k+1}^{\mathrm{p},v}} \\
&= \begin{bmatrix}
\frac{x_k-L_1^x}{\sqrt{(x_k-L_1^x)^2+(y_k-L_1^y)^2}} & \frac{y_k-L_1^y}{\sqrt{(x_k-L_1^x)^2+(y_k-L_1^y)^2}} & 0 & 0 & 0 & 0 \\
\frac{x_k-L_1^x}{\sqrt{(x_k-L_2^x)^2+(y_k-L_2^y)^2}} & \frac{y_k-L_2^y}{\sqrt{(x_k-L_2^x)^2+(y_k-L_2^y)^2}} & 0 & 0 & 0 & 0 \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
\frac{x_k-L_N^x}{\sqrt{(x_k-L_N^x)^2+(y_k-L_N^y)^2}} & \frac{y_k-L_N^y}{\sqrt{(x_k-L_N^x)^2+(y_k-L_N^y)^2}} & 0 & 0 & 0 & 0
\end{bmatrix},
\end{aligned} \tag{7.14}
$$

for N landmarks.

7.3 Person Model

The person model is very similar to the NCA acceleration model described in Chapter 4. The main difference is that the anchors detecting the persons are not static in global coordinates. They are, however, static in vehicle coordinates (x^c, y^c). A possible choice would be to track the person in vehicle coordinates due to the fact that the anchors are static in this case and transfer the person to global coordinates by using the orientation and position of the vehicle.

This choice is not made due to several reasons. Firstly, the movement of the person is, in reality, independent of the vehicle movement. If the vehicle were to move at a high speed, while the person is stationary, the tracked person would appear as a fast-moving object in vehicle coordinates. In this case, the NCA model would also depend on the acceleration