

# Vehicle-infrastructure localization based on the SME filter

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**Abstract**—Precise and accurate localization is important for safe autonomous driving. Given a traffic scenario with multiple vehicles equipped with proprioceptive sensors for self-localization and infrastructure equipped with exteroceptive sensors for car detection, vehicle-infrastructure communication can be used to improve the localization. However as the number of vehicles in a scenario increases, data association becomes increasingly challenging. We propose a solution utilizing the symmetric measurement equation filter (SME) for cooperative localization to address data association issues, as it does not require an enumeration of measurement-to-target associations. The key idea is to define a symmetric transformation which maps position measurements to a homogeneous function, thereby effectively addressing several challenges in vehicle-infrastructure scenarios such as bandwidth limitations, data association challenges and especially the configuration of the exteroceptive sensor. The approach works well even in the case that the location and orientation of the exteroceptive sensor are unknown. To the best of our knowledge, our proposed solution is among the first to address all these challenges of cooperative localization simultaneously, by utilizing the topology information of the vehicles.

A comparative study based on simulations demonstrates the reliability and the feasibility of the proposed approach in 2D coordinates.

## I. INTRODUCTION

Within the past few years, vehicle-infrastructure cooperative localization has become a hot issue in the intelligent transportation domain [1]. Not only can cooperative localization be used to improve perception performance, but it is also beneficial towards the goal of achieving optimal traffic flow.

Since GPS is susceptible to interference or even not fully available, for example in tunnels or underground, the localization task can be supported by utilizing both proprioceptive and exteroceptive sensors [2], [3]. Furthermore, with the development of Car-2-Car (C2C) and Car-2-Infrastructure (C2I) communication techniques, sharing information, like observations and state estimations, across the whole network becomes possible [4]. These new communication networks can be utilized to improve the perception performance, as cooperative localization can lead to better state estimates than separate self-localization by each individual vehicle [1]. Many methods have been proposed for the vehicle-infrastructure cooperative localization, e.g. Extended Kalman Filter [5], Markov Localization [6], Maximum Likelihood Estimation

[7] and Maximum A Posteriori Estimation [8]. However, challenges still existed:

- The bandwidth challenge.

The data-link utilized for exchanging information may have low bandwidth due to the network configuration. However, a high communication bandwidth is often required to transmit the states and the corresponding covariances. Specially, as the number of vehicles increases, the network might get overloaded and thus unusable.

- The uncertainty challenge.

Another important task for cooperative localization is called data association. The development of C2C and C2I techniques supports vehicles in localizing and identifying other traffic participants correctly. However, assuming there is no measurement-track association from the network, it is still a challenge to estimate the states correctly. Furthermore, measurements often contain clutters which increases the localization uncertainties.

- The coordinate transformation challenge.

Coordinate transformation plays an important role in cooperative localization. Measurements are acquired from proprioceptive and exteroceptive sensors to localize the positions. However, the proprioceptive sensor only provides the absolute location in 2D global coordinates whereas the exteroceptive sensor often provides the relative position in 2D local coordinates. This is still a challenge for cooperative localization in highly dynamic infrastructure environment, especially if the location and orientation of the exteroceptive sensor are unknown.

A method for vehicle-infrastructure cooperative localization based on the Symmetric Measurement Equation (SME) filter [9] is proposed in this paper. With the SME filter, a new type of symmetrical measurement transformation based on homogeneous symmetric functions has been introduced to combine measurements into a symmetric measurement equation [10]. The key idea is to convert measurement data with unknown association into a symmetrical measurement equation to estimate the corresponding states [11].

The work-flow of the proposed SME filter is as follows: Measurements from both proprioceptive and exteroceptive sensors are projected to a symmetrical equation as new observations whereas the SME filter recursively estimates the dynamic states.

The advantages of the SME filter are as follows:

First, the bandwidth challenge is addressed. Since the SME filter is a recursive centralized Bayes filter that only requires

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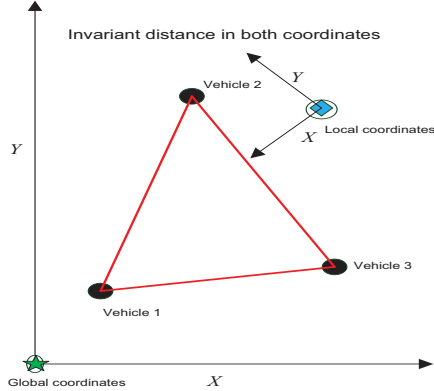


Figure 1. Topology of multiple vehicle cooperative localization system

the network to transmit observations, instead of additional covariance matrices, the amount of data that needs to be exchanged is reduced. In contrast to other methods, the proposed approach has especially small bandwidth requirements.

Second, the data association challenge is addressed. The SME filter provides a new solution to avoid the data association by using a symmetrical measurement equation to build up a pseudo-measurement space in which data association is unnecessary.

Third, the coordinate transformation challenge is addressed. Measurements are converted to a symmetrical measurement equation based on homogeneous symmetric functions, which avoids the transformation between different coordinates. Even if the configuration of the exteroceptive sensor is unknown, the proposed SME filter still works.

This paper is structured as follows: Sec. II briefly describes the scenario of the vehicle-infrastructure cooperative localization. Sec. III introduces more details about the SME filter with the implementation details. Sec. IV presents simulation results. Finally, the paper is concluded in Sec.V.

## II. BACKGROUND DESCRIPTION

As illustrated in Fig. 1, the vehicle-infrastructure cooperative localization scenario that we want to solve, described as follows:

- Each vehicle is able to localize itself according to an absolute reference. Here we assume that the measurements are given in a 2D global coordinate system and measured by the proprioceptive sensor.
- The infrastructure is able to measure the relative position of the vehicles. Here we assume that the measurements are given in a 2D local coordinate system and measured by the exteroceptive sensor.
- A communication network to exchange information between the cars and the infrastructure is available. Here we assume that there is no delay in the data-link and no

false detection originates from the vehicles, e.g. there is no clutter in the scenario.

- The communication method and protocol are not used to identify the individual vehicles. Furthermore, there is no prior information regarding to the configuration of the infrastructure. The location and orientation of the exteroceptive sensor are unknown.

Vehicle-infrastructure cooperative localization improves the precision of the position estimates. Assuming that the proprioceptive sensors provide measurements with large uncertainties, the localization may become imprecise. However, by cooperative localization, the precision is ensured with the help of the exteroceptive sensor.

Much work has been done for cooperative localization: centralized solution [5] and decentralized solution [12]. Regarding to the centralized localization, all vehicles are considered as a single system whereas the estimation is acquired by the Kalman filter. However, a data association process is required.

In contrast to the centralized architecture, a decentralized solution is proposed in which multiple fusion centers are used. Each fusion center handles parts of the local information. However, the computational demand is very high. Furthermore, it often exceeds network bandwidth limitations since each fusion center requires both the states and the corresponding covariances. Therefore communication and computation demand is a challenge in decentralized solutions.

None of the solutions consider the coordinate transformation issue during the localization process. Both centralized approaches and decentralized approaches assume that the transformation between the global measurement and the relative measurement is known. Cooperative localization only works under the condition that all measurements are exchanged in public coordinates. However, in highly dynamic environments, the configuration of the exteroceptive sensor is often unknown.

To the best of our knowledge, it is still a challenge to address the issues mentioned above simultaneously. In the next section, the SME filter is presented to take into account the issues in vehicle-infrastructure cooperative localization. This work is developed in cooperation with the SADA Project (BMW funded, 'IKT für Elektromobilität III') [13], to evaluate the performance of the cooperative localization between vehicle and infrastructure sensors.

## III. THE SYMMETRIC MEASUREMENT EQUATION FILTER

The SME filter based on homogeneous symmetric function is proposed because of its superior performance in multiple targets tracking.

### A. Overview on SME filter

A major challenge in multiple target tracking domain is data association since the association between the measurement and the track is unknown. In the past decades, various methods have been developed such as the Joint Probabilistic Data Association filter (JPDA) [14], the Probability Hypothesis Density filter (PHD) [15] and the Multi Hypothesis Tracking

filter (MHT)[16]. However, as the number of targets grows, the computation performance grows exponentially. Furthermore, the topology information between targets is not considered in above methods.

The Symmetric Measurement Equation (SME) filter is proposed to remove the data association by utilizing a symmetric transformation, which allows to bypass the combinatorial complexity of the association issue. Due to the symmetric measurement equation, the measurement-to-track association is unnecessary during the whole process. As a conclusion, the SME filter transforms the association issue into a nonlinear state estimation problem with non-additive Gaussian noise. In this way, one difficult problem is traded for another difficult, but quite different problem [17].

The first work on the SME filter was proposed by Kamen [9]. Furthermore, it was proposed to deal with the nonlinear conditions by the Unscented Kalman filter [17] and the Particle filter [18].

M. Baum [19] implemented the SME filter in the field of group targets tracking. The result illustrates that the SME filter is an effective solution for the multiple target tracking. In addition, it was shown that the SME filter is suitable for a large number of closely-spaced targets during the tracking phase.

This paper applies the SME filter to vehicle-infrastructure cooperative localization. Assuming the number of the vehicles is known and no missed detection or false measurements occur, the SME filter is utilized to localize the positions based on the symmetric measurement equations.

### B. Mathematic Background of the SME Filter

The idea of the SME filter is to generate 'pseudo-measurements' that consist of symmetric functions of the original measurement from targets.

#### • Problem formulation

For  $n$  dimension target state  $x_k^1, \dots, x_k^N$ , where  $k$  denotes the step and  $N$  is the number of the targets. The joint state in SME filter is represented as  $\mathbf{x}_k = [(x_k^1)^T, \dots, (x_k^N)^T]^T \in \mathbb{R}^{n \cdot N}$ .

1) *Measurement Model*: Assuming at each step the measurements are available, the following equation is acquired

$$y_k^{f_k(c)} = H_k^c(x_k^c) + v_k^c \quad (1)$$

where  $f_k \in \prod_N$  is a permutation in the symmetric group which specifies the unknown association assignment and  $v_k^c$  is considered as the additive zero-mean white noise. Combined with the joint SME state, the equations (1) can be composed as follows

$$\underbrace{\begin{bmatrix} y_k^{f_k(1)} \\ \vdots \\ y_k^{f_k(N)} \end{bmatrix}}_{\mathbf{y}_k} = \underbrace{\begin{bmatrix} H_k^1 & & \\ & \ddots & \\ & & H_k^N \end{bmatrix}}_{\mathbf{H}_k} \cdot \underbrace{\begin{bmatrix} x_k^1 \\ \vdots \\ x_k^N \end{bmatrix}}_{\mathbf{x}_k} + \underbrace{\begin{bmatrix} v_k^1 \\ \vdots \\ v_k^N \end{bmatrix}}_{\mathbf{v}_k} \quad (2)$$

where  $\mathbf{y}_k = [(y_k^{f_k(1)})^T, \dots, (y_k^{f_k(N)})^T]^T$  and  $f_k(\cdot)$  permutes the joint single measurement in the SME filter.

2) *Process Model*: With the same manner, the target system model in SME filter is represented as

$$x_{k+1}^c = A_k^c(x_k^c) + w_k^c \quad (3)$$

where  $A_k^c$  is the process matrix and  $w_k^c$  is the additive white noise. Equation (3) can also be composed as

$$\underbrace{\begin{bmatrix} x_{k+1}^1 \\ \vdots \\ x_{k+1}^N \end{bmatrix}}_{\mathbf{x}_{k+1}} = \underbrace{\begin{bmatrix} A_k^1 & & \\ & \ddots & \\ & & A_k^N \end{bmatrix}}_{\mathbf{A}_k} \cdot \underbrace{\begin{bmatrix} x_k^1 \\ \vdots \\ x_k^N \end{bmatrix}}_{\mathbf{x}_k} + \underbrace{\begin{bmatrix} w_k^1 \\ \vdots \\ w_k^N \end{bmatrix}}_{\mathbf{w}_k} \quad (4)$$

3) *Symmetric Transformation*: Since the SME filter is to remove the association uncertainty on the measurement equation (1), a symmetric transformation to the pseudo-measurement is required.

Two simple examples of how to construct the symmetric measurement equations for tracking three targets in one dimension are given as follows:

#### Example 1. Sum-of-product:

$$S_{prod} = \begin{bmatrix} m_1 + m_2 + m_3 \\ m_1 m_2 + m_2 m_3 + m_1 m_3 \\ m_1 m_2 m_3 \end{bmatrix} \quad (5)$$

#### Example 2. Sum-of-powers:

$$S_{pow} = \begin{bmatrix} m_1 + m_2 + m_3 \\ m_1^2 + m_2^2 + m_3^2 \\ m_1^3 + m_2^3 + m_3^3 \end{bmatrix} \quad (6)$$

The above two SME are called the sum of products and sum of powers. It is concluded that the original measurement  $m_i$  can be recovered uniquely from the pseudo-measurement  $S$ . Therefore, there is no information loss regarding to the new transformation. The SME approach turns the data association problem into an analytic nonlinearity and makes a measurement-to-track association unnecessary.

Based on the nonlinear Bayesian estimators such as Extended Kalman filter (EKF), Unscented Kalman filter (UKF) or Particle filter (PF), the joint single state is estimated in the SME filter.

### C. Implementation of SME filter

The mathematic background of the SME filter is briefly introduced in Sec. III-B. However, there are still open issues regarding to the implementation, e.g. how to utilize the SME filter in vehicle-infrastructure cooperative localization? How can configuration uncertainties of the exteroceptive sensor be addressed?

With the goal of utilization the SME filter, a homogeneous symmetric form of the converted measurements is constructed as follows:

For the process model, the joint single state of the vehicles  $\mathbf{x}_k = [p_{x,k}^1, \dot{p}_{x,k}^1, p_{y,k}^1, \dot{p}_{y,k}^1, \dots, p_{x,k}^N, \dot{p}_{x,k}^N, p_{y,k}^N, \dot{p}_{y,k}^N]^T$  consists of the positions  $(p_{x,k}, p_{y,k})$  and velocities  $(\dot{p}_{x,k}, \dot{p}_{y,k})$  of the vehicles.

Following the linear Gaussian dynamics, the evolution of the process models can be represented as:

$$A_k^1 = A_k^2 = \dots = A_k^N = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (7)$$

$$Q_k^1 = \dots = Q_k^N = \delta^2 \begin{bmatrix} T^2/4 & T^2/2 & 0 & 0 \\ T^2/2 & T & 0 & 0 \\ 0 & 0 & T^2/4 & T^2/2 \\ 0 & 0 & T^2/2 & T \end{bmatrix},$$

$$Q_k = \begin{bmatrix} Q_k^1 & & \\ & \ddots & \\ & & Q_k^N \end{bmatrix} \quad (8)$$

where  $Q_k$  denotes the covariance of the noise  $\mathbf{w}_k$  and  $\delta$  is the standard deviation of the process noise.

The transformation of the original measurements into the symmetric equation form needs to be done both for the proprioceptive and the exteroceptive sensor.

To map the state to the observation space, measurements from the proprioceptive sensors are converted as follows:

$$\mathbf{y}_{1k} = [\underline{\mathbf{y}}_{x,k}, \underline{\mathbf{y}}_{y,k}]^T \quad (9)$$

$$\underline{\mathbf{y}}_{x,k} = \left[ \sum_{i=1}^N p_{x,k}^i, \sum_{i=1}^N (p_{x,k}^i)^2, \dots, \sum_{i=1}^N (p_{x,k}^i)^N \right]^T$$

$$\underline{\mathbf{y}}_{y,k} = \left[ \sum_{i=1}^N p_{y,k}^i, \sum_{i=1}^N (p_{y,k}^i)^2, \dots, \sum_{i=1}^N (p_{y,k}^i)^N \right]^T$$

Since in the described scenario the configuration of the exteroceptive sensor is unknown (the orientation, location is not provided), the topology information (distance between vehicles) is therefore utilized as follows:

$$\mathbf{y}_{2k} = \left[ \sum_{i=1}^{N-1} \sum_{j=i+1}^N (p_{x,k}^i - p_{x,k}^j)^2 + \sum_{i=1}^{N-1} \sum_{j=i+1}^N (p_{y,k}^i - p_{y,k}^j)^2 \right]^T \quad (10)$$

No matter in which coordinate system, the global coordinate system or the local relative coordinate system, the distances between the vehicles are the same. Equation (10) is therefore considered as a new measurement to the SME filter, even if the configuration of the exteroceptive sensor is unknown. Furthermore, even if the exteroceptive sensor is moving a high speed, the topology information of the vehicles would still be equal in both coordinate systems. The joint measurement of the SME filter is therefore acquired as

$$\mathbf{y}_k = [\mathbf{y}_{1k}, \mathbf{y}_{2k}]^T \quad (11)$$

Based on the above procedure, the challenges in vehicle-infrastructure cooperative localization are addressed simultaneously. The state is estimated during the whole process by the pseudo-measurement. We would like to remind the reader that the new measurement noise covariance matrix is calculated with respect to the SME pseudo-measurement space, not in the original Cartesian measurement space. More details of the result can be found in [10], [17].

#### IV. SIMULATION RESULTS

The simulation was implemented with three vehicles on the ground plane. The performance of the SME filter is demonstrated with respect to the general Kalman filter.

In the simulation, vehicles are equipped with proprioceptive sensors to measure their global coordinates. The exteroceptive sensor also provides the positions, however, in the format of local coordinates whereas the transformation between the two coordinates is unknown.

The noise from proprioceptive sensor is assumed to be white Gaussian with zero mean and covariance  $\mathbf{diag}[50, 50]$ , whereas the exteroceptive sensor noise is zero mean and covariance  $\mathbf{diag}[10, 10]$ . The standard deviation of the process noise  $\delta$  is  $\frac{1}{2}$ . The joint single state is the  $[0, 80, 0, 0, 0, 45, 0, 45, 0, 0, 0, 80]$  whereas the step interval  $T$  is 1. It is also assumed that there is no false nor missed detections during the whole process. In order to evaluate the performance, vehicles are not able to identify the others through the vehicle-infrastructure communication system.

During the whole process, the SME filter is implemented based on an Extended Kalman filter. Regarding to the general Kalman filter, it is assumed that the data association is known from the proprioceptive sensors (only for the comparison purposes). However, since the configuration of the exteroceptive sensor is unknown, the information from exteroceptive sensor is therefore useless for the general Kalman filter.

Figure 2 exhibits the true trajectories and the corresponding estimations from different approaches: the SME filter and the Kalman filter. Regarding to the Kalman filter, although it is considered as the optimal estimation, the estimation is far from the true trajectories compared to the SME filter. The high performance of the SME filter results from the utilization of the topology information measured by the infrastructure sensor (the configuration is unknown). Furthermore, in contrast to the Kalman filter (KF), the SME operates on the pseudo-measurement space which avoids the data association issue.

Figure 3 analyzes the performances of both methods by calculating the RMSE (root mean square deviation) value. The total error is acquired by summing up the RMSE of each vehicle during the whole process:

$$Error = (x_{est} - x_{real})^2 + (y_{est} - y_{real})^2 \quad (12)$$

$$total\_error = \sqrt{\frac{\sum_{j=1}^n \sum_{i=1}^3 Error_i^j}{n}} \quad (13)$$

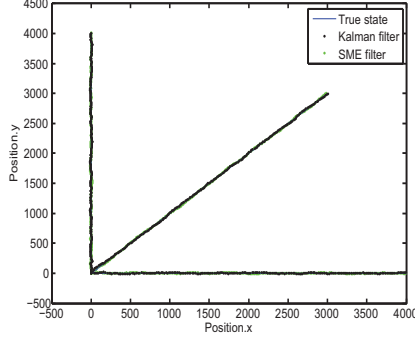


Figure 2. The vehicles' trajectories and estimation result

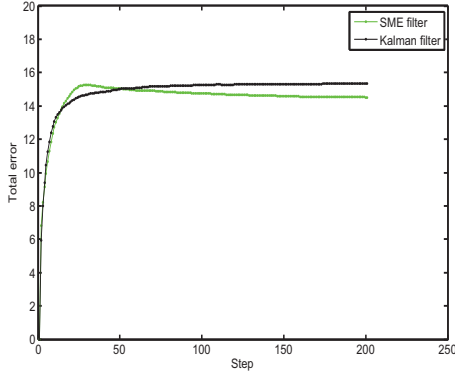


Figure 3. The performance of the estimation

where  $n$  is the time index. From Fig. 3 we can see that both the SME and the KF have a certain estimation error compared with the true trajectories. This error is caused by the uncertainties in the measurements. However, Fig. 3 illustrates that the overall performance of the SME filter is better than the performance of the Kalman filter.

Regarding to the bandwidth and computation issue, the SME filter is superior. As mentioned above, the SME filter is a predict and correct framework for recursive Bayes filtering which does not rely on each estimation and the corresponding covariance. Only measurements are transmitted on the network and the required communication bandwidth is therefore minimal. Assuming each location  $(p_x, p_y)$  takes two communication bits when transmission happens, the SME filter requires only  $2N$  bits bandwidth at each step (There is a total of  $N$  measurements acquired by exteroceptive sensor and  $N$  measurements acquired by proprioceptive sensor).

- **Discussion**

To study the robustness of the SME filter in real applications, the following issues need further discussion.

1) *False detection and missed detection*: In this paper, both proprioceptive and exteroceptive sensors are assumed to work in an ideal environment. However, in practice, the number of measurements  $M$  may not be equal to the number of vehicles  $N$ , which can be caused by false or missed detections (due to clutter). In order to address this challenge, the SME filter should be implemented in parallel, c.p. [20], [21]. However, these specific details are not the focus of this paper.

2) *Exteroceptive sensor estimation*: It is possible to jointly estimate the vehicles and the infrastructure configuration. In this case, the transformation between the coordinates is calculated. However, the challenge is the over-convergence problem. This is due to the stochastic interdependence between the estimations when sharing the information [3]. Another problem may also influence the localization: assuming the exteroceptive sensor is moving with high speed, the uncertainty of its estimation could become big and influence the transformation function calculation. It is reasonable that in such a situation the SME filter would only use the topology information of the vehicles.

As a conclusion, the benefits of the SME filter are as follows:

First, the communication bandwidth is addressed in vehicle-infrastructure cooperative localization. The inter-communication system only transmits the original measurements to the SME filter which results in minimal consumption requirements.

Second, data association is avoided. With the symmetric measurement equations, the data association issue is traded for another difficult, but quite different, problem. In this way, it is possible to estimate states without considering the association between measurements and targets.

Third, coordinate transformation is not required. By using the topology information from the whole vehicles, the coordinate transformation is avoided. Even if the configuration of the infrastructure is totally unknown, the vehicles' relative measurements can still be utilized by the SME filter with the goal of localization.

## V. CONCLUSION

In this paper, a recursive Bayesian solution for vehicle-infrastructure cooperative localization is proposed. The communication bandwidth issue, measurement-to-track association uncertainty and unknown coordinates transformation problem make cooperative localization complex and unfeasible. However, an SME filter solution is proposed to address all of the mentioned issues simultaneously. In comparison to the related work, all vehicles are considered as a joint single state which is updated with the symmetric measurement equations. The proposed method has been evaluated in simulations and the results demonstrate the high performance of the SME filter for cooperative localization.

Future work will focus on the evaluation of the proposed approach in cluttered environments.

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