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Cooperative Multi-Vehicle Localization Using Split Covariance Intersection Filter

Hao LI, Fawzi NASHASHIBI

Abstract—**Vehicle localization (ground vehicles) is an important task for intelligent vehicle systems and vehicle cooperation may bring benefits for this task. A new cooperative multi-vehicle localization method using split covariance intersection filter is proposed in this paper. In the proposed method, each vehicle maintains an estimate of a decomposed group state and this estimate is shared with neighboring vehicles; the estimate of the decomposed group state is updated with both the sensor data of the ego-vehicle and the estimates sent from other vehicles; the covariance intersection filter which yields consistent estimates even facing unknown degree of inter-estimate correlation has been used for data fusion. A comparative study based simulations demonstrate the effectiveness and the advantage of the proposed cooperative localization method.[1]**

I. INTRODUCTION

Vehicle localization (ground vehicles) is an important task for intelligent vehicle systems. Traditionally, for a vehicle, the localization process is only based on the data from its own sensors, such as GPS [1][2], cameras [3] or laser scanners [4][5] etc. On the other hand, the rapidly developed inter-vehicle communication technology [6] which enables information sharing among multiple vehicles stimulates research interests in cooperative multi-vehicle (robot) localization ("cooperative localization" for short) [7], where multiple vehicles perform localization task cooperatively by taking advantage of information sharing. It is believed that cooperative localization method will outperform traditional single-vehicle localization method. Different estimation methods such as Extended Kalman Filter [8] [9] [10], Particle Filter [11] [12], Maximum Likelihood Estimation [13], and Maximum *A Posteriori* Estimation [14] [15], have been used to perform cooperative localization.

If the size of a group of vehicles in cooperation is small, then **a centralized architecture**, in which only one fusion center maintains a single global state vector for the whole group, might be a possible solution. However, in real traffic scenarios, thousands of vehicles will operate in the same district at the same time. It is unlikely for a single fusion center to fulfill the task of cooperative localization, due to limited computational resources as well as limited vehicle communication ability. Instead of a centralized architecture, **a decentralized architecture**, where multiple fusion centers exist and each of them handles only local information, turns out to be a desirable solution, because of comparatively low computational burden for each fusion center and the flexibility for dealing with dynamic vehicle networks.

An important issue for decentralized architecture is how to handle inter-estimate correlation, i.e. the correlation (interdependency) among different estimate sources. Careless handling of this correlation will lead to circular reasoning [12] which further leads to the over-convergence problem, i.e. the estimates quickly converge to inaccurate values or even severely diverged values while extremely large confidence is given to these inaccurate values.

Since the over-convergence problem is due to inter-estimate correlation, a natural idea for avoiding this problem is to control inter-estimate correlation, which is realized by monitoring and controlling the data flow within vehicle networks. Many research works in literature adopt this idea. The authors in [12] propose a heuristic method based on a dependency tree which establishes for each distribution only one parent distribution and zero or more child distributions. A distribution can not be used to update its ancestors, but may be used to update its descendants. The relationship among these distributions may change according to the arrival of new observations. The authors in [11] propose some heuristic rules which function similarly with the idea of the dependency tree. The limitation of these heuristic methods is that they do not have complete monitoring or controlling of data flow and the risk of over-convergence may still exist. The authors in [17] propose an information transfer scheme which enables distributed robots to obtain delayed estimates that are comparable with centralized estimates; the delay length depends on the evolution of the communication graph over time. One undesirable aspect of this method is the uncertainty of the availability of the fused estimates; besides, the communication requirement of this method is demanding, due to the large pedigrees of data that have to be relayed within the networks. The authors in [10] [16] propose state exchange based method which only allows independent estimate (estimate maintained by each vehicle using its own sensor measurements) to be shared within vehicle networks; thus the risk of over-convergence can be removed. This method has two drawbacks: first, a vehicle can not benefit from other vehicles that are outside its directly visible neighborhood; second, one more set of estimate should be maintained by each vehicle.

Another possible idea for handling inter-estimate correlation is to use an estimation method that yields consistent estimates even facing unknown degree of inter-

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estimate correlation; the covariance intersection filter [18] [19] is such kind of estimation method. Compared with previous idea, this idea has several merits for implementing cooperative localization: First, the vehicles are exempted from complicated techniques of monitoring and controlling data flow within vehicle networks and the programming architecture for cooperative localization becomes simpler. Second, the risk of over-convergence can be essentially removed, because the risk is removed directly by the estimation method itself. Third, communication requirement are comparatively low, because no pedigree of information is needed to be explicitly relayed within vehicle networks.

Motivated by the merits of the second idea for handling inter-estimate correlation, a new cooperative multi-vehicle localization method using the split covariance intersection filter is proposed in this paper. The basic idea is: each vehicle maintains an estimate of a decomposed group state and this estimate is shared with neighboring vehicles; the estimate of the decomposed group state is updated with both the sensor data of the ego-vehicle and the estimates sent from other vehicles, based on the split covariance intersection filter.

Similar works can be found in [20] [21] which exploit the advantage of covariance intersection or split covariance intersection for cooperative localization in different tasks. Different from these existing works, the contribution of the proposed method is: it provides a solution of cooperative localization in the context of outdoor intelligent vehicle field. The advantage of the proposed method is demonstrated, especially through a performance comparison with an existing cooperative localization method [16].

This paper will be arranged as follows: covariance intersection filter (CIF) and split covariance intersection filter (SCIF) and their relationship with Kalman Filter (KF) or Extended Kalman Filter (EKF) will be briefly reviewed in section 2; the proposed cooperative localization method will be detailed in section 3; simulation based experiments will be presented in section 4, followed by the conclusion in section 5.

II. SPLIT COVARIANCE INTERSECTION FILTER

Given two estimates $\{\mathbf{X}_i, \mathbf{P}_i\}(i=1,2)$ to-be-fused; $\mathbf{X}_i$ denotes the estimated state vector and $\mathbf{P}_i$ denotes the estimated covariance matrix. The formula of the Kalman Filter to fuse both estimates can be written as:

$$\mathbf{P}^{-1} = \mathbf{P}_1^{-1} + \mathbf{P}_2^{-1}$$
$$\mathbf{X} = \mathbf{P}(\mathbf{P}_1^{-1}\mathbf{X}_1 + \mathbf{P}_2^{-1}\mathbf{X}_2)$$

The effectiveness of Kalman Filter is based on the assumption that the two estimates are independent of each other. If there is correlation between these two estimates, the Kalman Filter might yield inconsistent results, in other words, the fused result might be over-confident.

The authors in [18] propose a new data fusion method named covariance intersection, which takes a convex combination of the means and covariances of the estimate sources in the information space. The covariance intersection filter is theoretically guaranteed to yield consistent results. The formula of the covariance intersection filter can be written as:

$$\mathbf{P}^{-1} = (\mathbf{P}_1 / w)^{-1} + (\mathbf{P}_2 /(1-w))^{-1}$$
$$\mathbf{X} = \mathbf{P}[(\mathbf{P}_1 / w)^{-1}\mathbf{X}_1 + (\mathbf{P}_2 /(1-w))^{-1}\mathbf{X}_2]$$

This original covariance intersection filter (CIF) has a drawback of yielding pessimistic estimate, because it treats the estimates to-be-fused as being totally dependent and neglects possible independent information in them. In [19] the generalized form of the covariance intersection filter, i.e. the split covariance intersection filter (SCIF) is described, which provides the ability to incorporate and maintain known independent information in the estimates.

Given two estimates to-be fused: $\{\mathbf{X}_1, \mathbf{P}_{1d}+\mathbf{P}_{1i}\}$ and $\{\mathbf{X}_2, \mathbf{P}_{2d}+\mathbf{P}_{2i}\}$, where the covariance components $\mathbf{P}_{1d}$ and $\mathbf{P}_{2d}$ represent the maximum degree to which these estimates are possibly correlated with each other or others; the covariance components $\mathbf{P}_{1i}$ and $\mathbf{P}_{2i}$ represent the known degree of their absolute independence. Let the fused estimate be denoted as $\{\mathbf{X}, \mathbf{P}_d+\mathbf{P}_i\}$, also with its covariance separated as two parts: $\mathbf{P}_d$ and $\mathbf{P}_i$ respectively represent the correlated and the independent part. The formula of the split covariance intersection filter can be written as:

$$\mathbf{P}_1 = \mathbf{P}_{1d} / w + \mathbf{P}_{1i}$$
$$\mathbf{P}_2 = \mathbf{P}_{2d} /(1-w) + \mathbf{P}_{2i}$$
$$\mathbf{P}^{-1} = \mathbf{P}_1^{-1} + \mathbf{P}_2^{-1} \tag{1a}$$
$$\mathbf{X} = \mathbf{P}(\mathbf{P}_1^{-1}\mathbf{X}_1 + \mathbf{P}_2^{-1}\mathbf{X}_2) \tag{1b}$$
$$\mathbf{P}_i = \mathbf{P}(\mathbf{P}_1^{-1}\mathbf{P}_{1i}\mathbf{P}_1^{-1} + \mathbf{P}_2^{-1}\mathbf{P}_{2i}\mathbf{P}_2^{-1})\mathbf{P} \tag{1c}$$
$$\mathbf{P}_d = \mathbf{P} - \mathbf{P}_i \tag{1d}$$

Where w belongs to the interval [0, 1] and any choice of w in this interval guarantees the consistency of the fused result. In practice, w can be determined by optimizing an objective function in terms of w such as the trace or determinant of the new covariance [19]. In this paper, w is determined by minimizing the determinant of the new covariance. Notice that the split covariance intersection filter in (1) is compatible with the Kalman Filter: let the $\mathbf{P}_{1d}$ and $\mathbf{P}_{2d}$ be zero and (1) will become the same to the Kalman Filter.

Above formula forms of the Kalman filter, the original and the split covariance intersection filter are only for demonstrating the idea of these filters. In real implementations, the formula form could be different. For the two estimates $\{\mathbf{X}_1, \mathbf{P}_{1d}+\mathbf{P}_{1i}\}$ and $\{\mathbf{X}_2, \mathbf{P}_{2d}+\mathbf{P}_{2i}\}$ whose indications have been introduced above, suppose the $\mathbf{X}_1$ is complete measurement i.e. $\mathbf{X}_1=\mathbf{X}_{true}$, while the $\mathbf{X}_2$ is partial measurement i.e. $\mathbf{X}_2=\mathbf{H}\mathbf{X}_{true}$ ($\mathbf{H}$ is not of full rank). The split covariance intersection filter can be given as in (2):

$$\mathbf{P}_1 = \mathbf{P}_{1d} / w + \mathbf{P}_{1i}$$
$$\mathbf{P}_2 = \mathbf{P}_{2d} /(1-w) + \mathbf{P}_{2i}$$

$$\mathbf{K} = \mathbf{P}_1\mathbf{H}^T(\mathbf{H}\mathbf{P}_1\mathbf{H}^T + \mathbf{P}_2)^{-1}$$

$$\mathbf{X} = \mathbf{X}_1 + \mathbf{K}(\mathbf{X}_2 - \mathbf{H}\mathbf{X}_1) \quad (2a)$$

$$\mathbf{P} = (\mathbf{I} - \mathbf{K}\mathbf{H})\mathbf{P}_1 \quad (2b)$$

$$\mathbf{P}_i = (\mathbf{I} - \mathbf{K}\mathbf{H})\mathbf{P}_{1i}(\mathbf{I} - \mathbf{K}\mathbf{H})^T + \mathbf{K}\mathbf{P}_{2i}\mathbf{K}^T \quad (2c)$$

$$\mathbf{P}_d = \mathbf{P} - \mathbf{P}_i \quad (2d)$$

III. COOPERATIVE LOCALIZATION

Suppose there are multiple vehicles and the total number of vehicles is unknown. The following assumptions will be considered based on their feasibility in reality.

1) Absolute positioning function: each vehicle is able to obtain a measurement on its position in an absolute reference. Absolute positioning function can be realized in different ways, as mentioned at the beginning of this paper.

2) Relative positioning function: each vehicle is able to measure the relative position of neighbouring vehicles. Here, 'neighbour' indicates being within the perception range. In reality, perceptive sensors such as laser scanner can realize relative positioning function.

3) Motion monitoring function: each vehicle is equipped with motion sensors which output measurement on its velocity, yaw rate or other kinds of motion state.

4) Communication function: information can be shared among neighbouring vehicles. Effective communication range is usually larger than effective perception range; so the term 'neighbour' mentioned above has an additional meaning of being able to communicate with.

5) Timestamping function: the vehicles are able to timestamp their data according to an absolute time reference.

A. DECOMPOSED GROUP STATE

In the proposed method, the formalism for each vehicle is the same; therefore, the formalism will be described just from the perspective of one single vehicle (referred to as "ego-vehicle"). The ego-vehicle maintains an estimate of its group state $\mathbf{X}_G$ which consists of several sub-states:

$$\mathbf{X}_G = \{\mathbf{X}_E; \mathbf{X}_{O1}, \mathbf{X}_{O2}, ..., \mathbf{X}_{Om}\}$$

where sub-state $\mathbf{X}_E=[x_e;y_e;\theta_e;v_e]^T$ denotes the state of the ego-vehicle; sub-state $\mathbf{X}_{Oi}=[x_{oi};y_{oi};\theta_{oi};v_{oi}]^T$ (i=1,2,…,m) denotes the state of neighboring vehicles observed by the ego-vehicle; '(x,y)' and 'θ' respectively denote the position and the heading angle of the vehicle in the absolute reference; 'v' denotes vehicle velocity. The term *group state* here is similar to but is different from that in [16]: the group state in our method (only one estimate for the group state) can be updated with the estimates sent from other vehicles and can also be shared with other vehicles. In [16], each vehicle maintains two estimates for its group state: one estimate, which is updated only using the sensor data of the ego-vehicle, can be shared with other vehicles but can not be updated with the estimates sent from other vehicles; the other one can be updated with the estimates sent from other vehicles but can not be further shared with other vehicles.

There is another difference: in [16], a large global covariance matrix is maintained for the whole group state; on the other hand, in our method, the covariance matrix for the group state is decomposed into a group of small covariance matrices, each of which corresponds to a sub-state in the group state; any pair of sub-states is assumed to have no correlation. In other words, the group state in our method is a decomposed group state, denoted as:

$$\mathbf{E}_G = \{\mathbf{X}_G, \mathbf{P}_G\} = \{\{\mathbf{X}_E, \mathbf{P}_E\}; \{\mathbf{X}_{O1}, \mathbf{P}_{O1}\}, ..., \{\mathbf{X}_{Om}, \mathbf{P}_{Om}\}\} =$$
$$\{\{\mathbf{X}_E, \mathbf{P}_{dE} + \mathbf{P}_{iE}\}; \{\mathbf{X}_{O1}, \mathbf{P}_{dO1} + \mathbf{P}_{iO1}\}, ..., \{\mathbf{X}_{Om}, \mathbf{P}_{dOm} + \mathbf{P}_{iOm}\}\}$$
$$\mathbf{P}_G = \{\mathbf{P}_E; \mathbf{P}_{O1}, \mathbf{P}_{O2}, ..., \mathbf{P}_{Om}\}$$

where the subscript d and i denote respectively the correlated and independent component of the covariance. Thanks to the decomposed representation, computational burden is reduced.

B. GROUP STATE EVOLUTION

The motion of the vehicles can be modelled according to kinematic bicycle model (denoted as function G):

$$\mathbf{X}_{E(k)} = G(\mathbf{X}_{E(k-1)}, \mathbf{u}_{E(k)}) \quad (3a)$$

$$\mathbf{X}_{Oj(k)} = G(\mathbf{X}_{Oj(k-1)}, \mathbf{u}_{Oj(k)}) \quad (3b)$$

where j=1,…,m; the '$\mathbf{u}_E$(k)' denotes the measurement on the motion state of the ego-vehicle; the error affecting this measurement is assumed to follow the Guassian distribution N($\mathbf{0}$,$\mathbf{\Sigma}_u$). The '$\mathbf{u}_{Oi(k)}$' denotes the measurement on the motion state of observed vehicles; this measurement is not available in reality, so it is imaginarily obtained based on the assumption that the motion state of observed vehicles is temporarily constant. The evolution of the sub-state covariance matrices is given as:

$$\mathbf{P}_{E(k)} = \mathbf{G}_{\mathbf{X}e}(\mathbf{P}_{E(k-1)} + \mathbf{R}_{E(k)})\mathbf{G}_{\mathbf{X}e}{}^T + \mathbf{G}_\mathbf{u}\mathbf{\Sigma}_\mathbf{u}\mathbf{G}_\mathbf{u}{}^T \quad (4a)$$

$$\mathbf{P}_{Oj(k)} = \mathbf{G}_{\mathbf{X}oj}(\mathbf{P}_{Oj(k-1)} + \mathbf{R}_{Oj(k)})\mathbf{G}_{\mathbf{X}oj}{}^T \quad (4b)$$

$$\mathbf{P}_{iE(k)} = \mathbf{G}_{\mathbf{X}e}(\mathbf{P}_{iE(k-1)} + \mathbf{R}_{E(k)})\mathbf{G}_{\mathbf{X}e}{}^T + \mathbf{G}_\mathbf{u}\mathbf{\Sigma}_\mathbf{u}\mathbf{G}_\mathbf{u}{}^T \quad (4c)$$

$$\mathbf{P}_{iOj(k)} = \mathbf{G}_{\mathbf{X}oj}(\mathbf{P}_{iOj(k-1)} + \mathbf{R}_{Oj(k)})\mathbf{G}_{\mathbf{X}oj}{}^T \quad (4d)$$

The '$\mathbf{G}_{Xe}$', '$\mathbf{G}_u$' and '$\mathbf{G}_{Xoj}$' are respectively the Jacobian matrices of the function 'G' with respect to the '$\mathbf{X}_E$', '$\mathbf{u}_E$' and '$\mathbf{X}_{Oj}$'; the '$\mathbf{R}_{E(k)}$' and '$\mathbf{R}_{Oi(k)}$' are the covariance matrices of the model error. Since the split covariance intersection filter is used in the proposed method, not only the total covariance ($\mathbf{P}_{E(k)}$ and $\mathbf{P}_{Oj(k)}$) but also the independent part ($\mathbf{P}_{iE(k)}$ and $\mathbf{P}_{iOj(k)}$) are evolved.

C. GROUP STATE UPDATE USING SENSOR DATA OF THE EGO-VEHICLE

The ego-vehicle can obtain both absolute positioning measurement and relative positioning measurement. The absolute positioning measurement is used only to update the state estimate of the ego-vehicle, i.e. the sub-state '$\mathbf{X}_E$'; the relative positioning measurement, together with the estimate for '$\mathbf{X}_E$', is used to update the state estimate of observed vehicles, i.e. sub-states '$\mathbf{X}_{Oj}$'.

1) Update with absolute positioning measurement

Let the absolute positioning measurement for the ego-vehicle be denoted as $\mathbf{Z}_A=(x_A,y_A)$. The measurement model can be described as (at time k):

$$\mathbf{Z}_{A(k)} = \mathbf{H}_{A(2\times4)}\mathbf{X}_{E(k)} + \mathbf{R}_A$$

where $\mathbf{H}_A=[\mathbf{I}_{2x2}\ \mathbf{0}_{2x2}]$; the measurement error $\mathbf{R}_A$ is assumed to follow the Gaussian distribution $N(\mathbf{0},\mathbf{\Sigma}_A)$. Notice that the absolute positioning measurement is completely independent of any existing estimates or any other measurements, the split covariance intersection filter is carried out as follows:

$$\mathbf{K} = \mathbf{P}_{E(k)}\mathbf{H}_A{}^T(\mathbf{H}_A\mathbf{P}_{E(k)}\mathbf{H}_A{}^T + \mathbf{\Sigma}_A)^{-1}$$
$$\mathbf{X}_{E(k)} = \mathbf{X}_{E(k)} + \mathbf{K}(\mathbf{Z}_{A(k)} - \mathbf{H}_A\mathbf{X}_{E(k)})$$
$$\mathbf{P}_{E(k)} = (\mathbf{I} - \mathbf{K}\mathbf{H}_A)\mathbf{P}_{E(k)}$$
$$\mathbf{P}_{iE(k)} = (\mathbf{I} - \mathbf{K}\mathbf{H}_A)\mathbf{P}_{iE(k)}(\mathbf{I} - \mathbf{K}\mathbf{H}_A)^T + \mathbf{K}\mathbf{\Sigma}_A\mathbf{K}^T$$
$$\mathbf{P}_{dE(k)} = \mathbf{P}_{E(k)} - \mathbf{P}_{iE(k)}$$

2) Update with relative positioning measurement

The relative positioning measurement, together with the ego-vehicle state estimate, will be used to update the state estimates of the observed vehicles. Let the relative positioning measurement be denoted as $\mathbf{Z}_R=\{\mathbf{Z}_{Rj}=(\Delta x_{Rj};\Delta y_{Rj};\Delta\theta_{Rj})^T|j=1,2,\ldots,n\}$ where n is the number of the vehicles observed by the ego-vehicle; the error that affects each $\mathbf{Z}_{Rj}$ is assumed to follow Gaussian distribution $N(\mathbf{0},\mathbf{\Sigma}_R)$. Let absolute positioning inference for the observed vehicles be denoted as $\mathbf{Z}_{OA}=\{\mathbf{Z}_{OAj}=(x_{OAj};y_{OAj};\Delta\theta_{OAj})^T|j=1,2,\ldots,n\}$.

In [20], the relative positioning measurement between two space vehicles directly represents their position difference in an absolute reference; the position of one space vehicle can be inferred simply by adding the relative positioning measurement to the position of the other space vehicle, i.e. $\mathbf{Z}_{OAj(k)}=\mathbf{Z}_{Rj(k)}+\mathbf{H}_R\mathbf{X}_{E(k)}$ where $\mathbf{H}_R=[\mathbf{I}_{3x3}\ \mathbf{0}_{3x1}]$. This kind of relative positioning measurement model is not suitable for ground vehicles where an ego vehicle can only measure the position of other vehicles in the reference of this ego vehicle. The relative positioning measurement model is given by a nonlinear transformation of translation and rotation 'T' which is related to the pose of the observing vehicle:

$$\mathbf{Z}_{OAj(k)} = \mathbf{T}(\mathbf{Z}_{Rj(k)},\mathbf{H}_R\mathbf{X}_{E(k)})$$

Let the covariance matrices corresponding to '$\mathbf{Z}_{OA}$' be denoted as $\mathbf{P}_{OA}=\{\mathbf{P}_{OAj}|j=1,2,\ldots,n\}$, then:

$$\mathbf{P}_{OAj} = (\mathbf{T}_{HrXe}\mathbf{H}_R)\mathbf{P}_{E(k)}(\mathbf{T}_{HrXe}\mathbf{H}_R)^T + \mathbf{T}_{Zrj}\mathbf{\Sigma}_R\mathbf{T}_{Zrj}{}^T$$

The '$\mathbf{T}_{HrXe}$' and '$\mathbf{T}_{Zrj}$' are respectively the Jacobian matrices of the function 'T' with respect to the '$\mathbf{H}_R\mathbf{X}_{E(k)}$' and '$\mathbf{Z}_{Rj(k)}$'.

Suppose the measurement '$\mathbf{Z}_{OAj(k)}$' corresponds to the sub-state '$\mathbf{X}_{Oi(k)}$' and is used to update '$\mathbf{X}_{Oi(k)}$' using the split covariance intersection filter as follows:

$$\mathbf{P}_1 = \mathbf{P}_{dOi(k)}/w + \mathbf{P}_{iOi(k)}$$
$$\mathbf{P}_2 = (\mathbf{T}_{HrXe}\mathbf{H}_R)\mathbf{P}_{E(k)}(\mathbf{T}_{HrXe}\mathbf{H}_R)^T/(1-w) + \mathbf{T}_{Zrj}\mathbf{\Sigma}_R\mathbf{T}_{Zrj}{}^T$$
$$\mathbf{K} = \mathbf{P}_1\mathbf{H}_R{}^T(\mathbf{H}_R\mathbf{P}_1\mathbf{H}_R{}^T + \mathbf{P}_2)^{-1}$$
$$\mathbf{X}_{Oi(k)} = \mathbf{X}_{Oi(k)} + \mathbf{K}(\mathbf{Z}_{OAj(k)} - \mathbf{H}_R\mathbf{X}_{Oi(k)})$$
$$\mathbf{P}_{Oi(k)} = (\mathbf{I} - \mathbf{K}\mathbf{H}_R)\mathbf{P}_1$$
$$\mathbf{P}_{iOi(k)} = (\mathbf{I} - \mathbf{K}\mathbf{H}_R)\mathbf{P}_{iOi(k)}(\mathbf{I} - \mathbf{K}\mathbf{H}_R)^T + \mathbf{K}\mathbf{T}_{Zrj}\mathbf{\Sigma}_R\mathbf{T}_{Zrj}\mathbf{K}^T$$
$$\mathbf{P}_{dOi(k)} = \mathbf{P}_{Oi(k)} - \mathbf{P}_{iOi(k)}$$

where the w is determined by minimizing the determinant of the new covariance.

D. GROUP STATE UPDATE USING THE ESTIMATES FROM OTHER VEHICLES

The ego-vehicle shares its group state estimate with its neighboring vehicles via inter-vehicle communication device; besides, it can also receive the group state estimates of its neighboring vehicles. Without loss of generality, let the group state shared by a neighboring vehicle (referred to as 'communicated ego-vehicle') be donted as:

$$\begin{aligned}\mathbf{E}_{CG} &= \{\mathbf{X}_{CG},\mathbf{P}_{CG}\} = \{\{\mathbf{X}_{CE},\mathbf{P}_{CE}\};\{\mathbf{X}_{COj},\mathbf{P}_{COj}\}\mid j=1,\ldots,m_c\}\\ &= \{\{\mathbf{X}_{CE},\mathbf{P}_{dCE}+\mathbf{P}_{iCE}\};\{\mathbf{X}_{COj},\mathbf{P}_{dCOj}+\mathbf{P}_{iCOj}\}\mid j=1,\ldots,m_c\}\end{aligned}$$

Where the '$\mathbf{X}_{CE}$' denotes the sub-state of the 'ego-vehicle' and the '$\mathbf{X}_{COj}$' denotes the sub-states of 'observed vehicles' from the perspective of the communicated ego-vehicle. In fact, the sub-state '$\mathbf{X}_{CE}$' is not needed to be shared. The subscript d and i denote respectively the correlated and independent component of the covariance.

If none of the sub-states '$\mathbf{X}_{COj}$' can be associated with the '$\mathbf{X}_E$', it means that the ego-vehicle can not be observed by the communicated ego-vehicle. Otherwise, the ego-vehicle can be observed, and let the sub-state associated with the '$\mathbf{X}_E$' be denoted as $\{\mathbf{X}_{COe}, \mathbf{P}_{dCOe}+\mathbf{P}_{iCOe}\}$.

The '$\mathbf{X}_E$' and the '$\mathbf{X}_{COe}$' are both state estimates of the ego-vehicle, the former is maintained by the ego-vehicle itself and the latter is maintained by the communicated ego-vehicle. These two estimates are fused by the split covariance intersection filter as follows:

$$\mathbf{P}_1 = \mathbf{P}_{dE(k)}/w + \mathbf{P}_{iE(k)}$$
$$\mathbf{P}_2 = \mathbf{P}_{dCOe(k)}/(1-w) + \mathbf{P}_{iCOe(k)}$$
$$\mathbf{K} = \mathbf{P}_1(\mathbf{P}_1 + \mathbf{P}_2)^{-1}$$
$$\mathbf{X}_{E(k)} = \mathbf{X}_{E(k)} + \mathbf{K}(\mathbf{X}_{COe(k)} - \mathbf{X}_{E(k)})$$
$$\mathbf{P}_{E(k)} = (\mathbf{I} - \mathbf{K})\mathbf{P}_1$$
$$\mathbf{P}_{iE(k)} = (\mathbf{I} - \mathbf{K})\mathbf{P}_{iE(k)}(\mathbf{I} - \mathbf{K})^T + \mathbf{K}\mathbf{P}_{iCOe(k)}\mathbf{K}^T$$
$$\mathbf{P}_{dE(k)} = \mathbf{P}_{E(k)} - \mathbf{P}_{iE(k)}$$

IV. SIMULATIONS

The proposed cooperative multi-vehicle localization method is tested in simulation. The simulation condition has been set according to the assumptions specified in previous section. The perception range and the communication range are both set to be constantly 50 meters (though the communication range is considerably larger than this value). The absolute position measurement is set to have a standard deviation of 7 meters; the absolute positioning measurement is available every one second. The error of motion state measurement is modeled according to the data collected during field tests on single vehicle localization.

As the experiments are carried out in simulation, a comparative study could be more meaningful than only demonstrating the performance of the proposed method. Therefore, the proposed cooperative localization method and several other methods are executed simultaneously on the same synthetic data and their respective performances are compared. The methods under tests are as follows:

1) Single vehicle localization method [2] (SL):

As for each ego-vehicle, the localization is performed only using its own sensor data; the EKF is used for data fusion.

2) Naïve cooperative localization method (NCL):

Each ego-vehicle treats the estimates sent from other vehicles simply as new measurement; the EKF is used for data fusion.

3) State exchange based cooperative localization method [16] (SECL):

Each ego-vehicle maintains two estimates for its group state: one estimate, which is updated only using the sensor data of the ego-vehicle, can be shared with other vehicles but can not be updated with the estimates sent from other vehicles; the other one can be updated with the estimates sent from other vehicles but can not be further shared with other vehicles.

4) The proposed cooperative localization method using the split covariance intersection filter (SCIFCL):

Details of the method are described previously.

A. EXPERIMENTAL SCENARIO

A main scenario for comparative study is designed based on abstraction of real traffic scenarios and is as follows:

A chain of vehicles (8 vehicles) move on the same road in the same direction; the velocity of each vehicle is around 50 km/s and may vary. Each vehicle is only able to observe its immediate neighbouring vehicles, i.e. its immediate front vehicle and its immediate following vehicle.

B. RESULTS

The simulation is carried out in the following way: at the first stage, each vehicle only uses the SL method until its own state estimate converges; then at the second stage, the SL method, the NCL method, the SECL method and the SCIFCL method are executed simultaneously and vehicle localization errors associated respectively with all these methods are collected for comparison.

The localization error of one round of test is demonstrated in Fig.1 as an example. For a vehicle in simulation, its localization error associated with each method is displayed in the same sub-figure of Fig.1, where the vertical coordinates indicates the localization error and the horizontal coordinates indicates the time sequence. As we can see, the estimate obtained by the NCL method severely diverges, which shows that careless handling of the inter-estimate correlation in cooperative localization will easily incur the over-convergence problem.

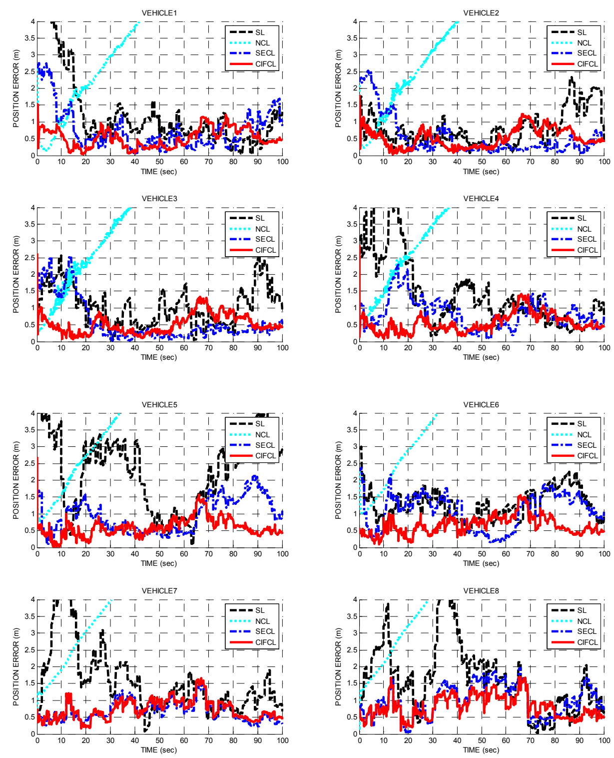

Fig 1 the performance of the SL method, the NCL method, the SECL method and the SCIFCL method

On the other hand, both the SECL method and the SCIFCL method achieve better performance than the SL method on the whole, which shows that cooperative localization methods, if well designed, can considerably improve the performance of vehicle localization.

The result shown in Fig.1 gives an intuitive comparison among the performance of the methods. Furthermore, a large number of tests (totally fifty rounds of test) have been carried out to have a quantitative comparison among the methods. In every round of test, the RMS (Root Mean Square) of the localization error of the vehicles, associated with each of the SL method, the SECL method and the SCIFCL method (the NCL method is excluded for comparison because it usually leads to severely diverged result), is computed. The result is demonstrated in Fig.2, where the vertical coordinates indicates the computed RMS and the horizontal coordinates indicates the index of the round of test.

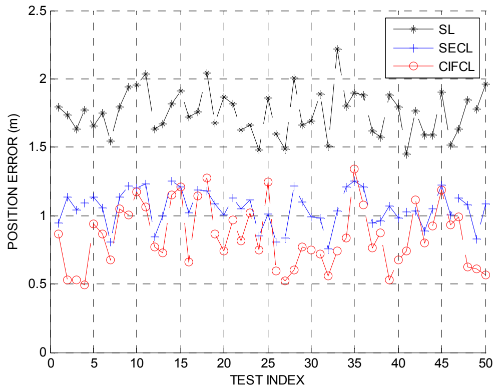

Fig 2 the RMS of the localization error associated with the SL method, the SECL method and the SCIFCL method

As we can see in Fig.2, the SECL method and the SCIFCL method always outperform the SL method, which shows the advantage of cooperative localization over single vehicle localization. The SCIFCL method also outperforms slightly the SECL method (the RMS errors of the 50 rounds of test for the SCIFCL and SECL method are respectively 0.88m and 1.06m), which shows the effectiveness and advantage of the proposed method in realizing cooperative localization. Besides, it is worthy noting again that (as mentioned in previous section) the SCIFCL method is computationally more efficient than the SECL method because each vehicle using the SCIFCL method only needs to maintain a decomposed group state.

V. CONCLUSION

A new cooperative multi-vehicle localization method using covariance intersection filter is proposed in this paper. In the proposed method, each vehicle maintains an estimate of a decomposed group state and this estimate is shared with neighboring vehicles; the estimate of the decomposed group state is updated with both the sensor data of the ego-vehicle and the estimates sent from other vehicles; the split covariance intersection filter has been used for data fusion.

The proposed cooperative localization method has been tested in simulation and a comparative study (among the single vehicle localization method, the naïve cooperative localization method, the state exchange based cooperative localization method and the proposed method) has been carried out. Experiment results demonstrate the effectiveness and advantage of the proposed cooperative localization method.

The proposed cooperative localization method whose promising performance has been shown in the simulation based comparative study, is a valuable guide for implementing cooperative localization in reality, which will be the future work.

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