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Localization of a Group of Communicating Vehicles by State Exchange

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***Abstract*— This paper considers the problem of cooperative localization of an heterogeneous group of road vehicles. Each vehicle can be equipped with proprioceptive and exteroceptive sensors enabling it to localize itself in its environment and also to localize (but not to identify) the other members of the group. Localization information can be exchanged between the vehicles through a wireless communication device. Every member of the group maintains (if possible) an estimation of the state of its environment and transmits it (if possible) to its neighbors. The global state of the environment is obtained by fusing the environment states of the vehicles. This fusion is based on Extended Kalman Filter where the poses of the detected vehicles are represented by a single system. The proposed approach takes into account the sensor constraints such as data unavailability and delays.**

I. INTRODUCTION

Inter vehicle communication has opened up new prospects to improve the existing driver assistance systems [1], this topic has attracted the interest of many research in the last years such as intersection assistance in [2], environmental perception enhancing [3] and implementation of high speed mobile network [4].

Localization is one of the most important tasks of driver assistance systems. In the case of a single vehicle system this is usually performed by fusing the proprioceptive data (which describes the motion of the vehicle) and exteroceptive data (which provides a perception of the environment) as presented in [5]. In multi-vehicle systems, Kurazume *et. al* [6] and Roumeliotis *et. al* [7] have demonstrated that the communication of relative poses information leads to the reduction of the localization uncertainty. Cooperative collective localization is obtained by fusing proprioceptive and exteroceptive data of each vehicle with information received from the other members of the group. Various algorithms such as Extended Kalman Filter [7], Bayesian formalism [8], Markov localization [9] or Maximum Likelihood approach [10] and sensors such as vision sensors [11], acoustic sensors [12] or Global Positioning System [13] where proposed for the collective localization.

The main problem of collective localization system is that the vehicles are not necessarily equipped with the same sensors. Fusing the sensor data, in order to perform the collective localization, requires to take into account for example the nature of the sensor which measured the information.

II. RELATED WORK

Roumeliotis *et. al* introduce in [7] a distributed approach for collective localization based on a centralized extended Kalman filter. The state of the group of robots is viewed as a single system. The collective localization is obtained by integrating the proprioceptive and exteroceptive measurements collected and exchanged by different robots of the group. The most significant result is the reduction of the uncertainty regarding the estimated pose (position and orientation) of each individual member of the group. This reduction is due to the exchange of the relative positioning information (relative position and orientation) among the group. Madhavan *et. al* present in [13] a similar approach which was experimented with an heterogeneous group of mobile robots in an outdoor environment. Martinelli *et. al* in [14] extend the approach introduced in [7] by considering the observation of the relative bearing.

These approaches are based on sensor information exchange. Every mobile shares its observations with the other members of the group. The collective localization is obtained by updating the global state of the group with the collected observations. The disadvantage of a such approach is the large quantity of transmitted information on the communication network. This quantity is even larger in the case of an heterogeneous group of vehicles. In order to use the incoming information for the update of the group state, the vehicles must exchange not only the sensor data but also the error model for instance.

The second idea is to exchange the updated global state. This approach can reduce the quantity of transmitted information but it can be faced to the over-convergence problem. The fusion of interdependent states leads to quick convergence to an inaccurate value. In [8], A. Howard *et al* consider the problem of over-convergence. Every robot of the team can estimate the pose probability distribution of every other robot, relative to itself and broadcast this information to the team as a whole. In the case of circular update, for example a scenario in which the robot i observes the robot j, the robot j can update its pose distribution with the observation of the robot i. At this time the pose distribution of the robot j depends on the pose distribution of the robot i. After

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that, the robot j observes the robot i, this observation (pose distribution) can not be used by the robot i to update its pose distribution. This is due to the interdependence between the pose distributions of the two robots. In order to avoid this problem, the author maintains a *dependency tree* to update the history of distributions dependency. This approach have some limitations. The *dependency tree* assumes that distributions are only dependent on the distribution that was last used to update them, and are therefore independent on all other distributions. This assumption is restrictive as circular updates can still occur.

All the cited approaches suppose that the robots are able to localize and identify the other members of the group. In the case of road vehicles collective localization, direct identification of the detected vehicles is difficult to perform. In the next sections we present a state exchange based collective localization approach. It differs from the aforementioned approaches in the nature of the exchanged data and that the detected vehicles can not be directly identified.

Every vehicle in the group maintain an estimation of the group state using its own sensors. This estimation is shared with the other members of the group. As those estimations are totally independent, their fusion does never lead to any over-convergence.

The proposed approach takes also account of the possible delays or unavailability which can affect sensor data and communication.

III. The Proposed Approach

Let us consider an heterogeneous group of N vehicles V. Through out this paper, the following assumptions will be considered :

- Each vehicle can be able to localize approximatively itself in an absolute referential.
- Each vehicle can be able to localize approximatively its neighborhood vehicles relatively to its own position, but can not identify them.
- The vehicles can be equipped with communication devices in order to exchange information.
- Communication and sensor information can be affected with delays or can be temporarily unavailable.
- The total number N of vehicles in the group is unknown.

The goal is to maintain in every vehicle the most accurate pose estimation of the other group members taking into account sensor and communication constraints.

This is obtained by performing collective localization where the state of the group is viewed as a single system. Every vehicle makes (if possible) an estimate of the group state pose using its own sensor data and exchanges it (if possible) with the other members of the group. By fusing its group state estimation and the received ones, every vehicle obtains a global group state which combines its own sensors data with sensors data of all communicating vehicles of the group. This global group state takes also into account the interdependencies between the poses estimations distributions. This work will be divided in two parts. In the first part, the localization algorithm executed in a single vehicle of the team (estimation of its pose and the other vehicles poses) is detailed. In the second part the proposed collective localization approach is presented.

A. Group state estimation

This section describes the algorithm running in one vehicle of the group which is called self vehicle V_s (s means self), the same algorithm is executed in the other M vehicles V_{o_j} with j=1...M (o means other) where M=$N-1$ is the number of other vehicles of the group. The state of the vehicle V_s is represented by the vector $\underline{x}_s$=$[x_s, y_s, \varphi_s, v_s]^T$ and its covariance matrix $P_{s,s}$, where x_s and y_s are the coordinates of the vehicle V_s in an absolute reference, φ_s its orientation and v_s is the module of its speed. The state of the other vehicles is represented by the vector $\underline{x}_{o_j}$=$[x_{o_j}, y_{o_j}, \varphi_{o_j}, v_{o_j}]^T$ and its covariance matrix P_{o_j,o_j}, where j=1...M, x_{o_j} and y_{o_j} are the coordinates of the other vehicle V_{o_j} in an absolute reference, φ_{o_j} its orientation and v_{o_j} is the module of its speed.

To perform the collective localization, the group is represented by a single system $W_s = (\underline{X}_s, P_s, \mathbf{id}_s)$ where $\mathbf{id}_s$ is the vehicle V_s identifier, $\underline{X}_s$ is the state vector of the group and P_s its covariance matrix as in equations (1) and (2).

$$\underline{X}_s = [\underline{x}_s^T, \underline{x}_{o_1}^T, \underline{x}_{o_2}^T, ..., \underline{x}_{o_{m_s}}^T]^T \tag{1}$$

$$P_s = \begin{bmatrix} P_{s,s} & P_{s,o_1} & \dots & P_{s,o_{m_s}} \\ P_{o_1,s} & P_{o_1,o_1} & \dots & P_{o_1,o_{m_s}} \\ \dots & \dots & \dots & \dots \\ P_{o_{m_s},s} & P_{o_{m_s},o_1} & \dots & P_{o_{m_s},o_{m_s}} \end{bmatrix} \tag{2}$$

where m_s is the number of vehicles detected by the vehicle V_s.

The vehicle V_s maintains an estimation W_s of the group state. The state W_s is only updated with proprioceptive and exteroceptive sensors data of the vehicle V_s. The data fusion is done with an Extended Kalman Filter (EKF).

1) Group state evolution: The motion of the vehicles can be modeled by the function f_s (bicycle model) for the self vehicle V_s (equation (4)) and by the function f_o (constant speed kinematic model) for the other vehicles V_{o_j} of the group state (equation (5)). We assume that the error affecting the encoders data $\underline{u}_s$ can be modeled by :

$$\underline{u}_s \sim \mathcal{N}\ (\underline{u}_s^m, Q_s) \tag{3}$$

where $\underline{u}_s^m$ is the measured data and Q_s the covariance of the noise affecting it.

The evolution equation of the group state vector and its covariance matrix can be written as following

$$\underline{x}_{s_{k+1}}^- = f_s(\underline{x}_{s_k}, \underline{u}_{s_k}^m) \tag{4}$$

$$\underline{x}_{o_{j_{k+1}}}^- = f_o(\underline{x}_{o_{j\,k}}) \tag{5}$$

$$P^{-}_{s,s_{k+1}} = F_{s_{(\underline{x}_s)}} P_{s,s_k} F^T_{s_{(\underline{x}_s)}} + F_{s_{(\underline{u}^m_s)}} Q_{s_k} F^T_{s_{(\underline{u}^m_s)}} + B_s \quad (6)$$

$$P^{-}_{o_j,o_{j\,k+1}} = F_o P_{o_j,o_{j\,k}} F^T_o + B_o \quad (7)$$

where k represents the time, $\underline{x}^{-}_{s_{k+1}}$ and $\underline{x}^{-}_{o_{j_{k+1}}}$ are respectively the predicted $\underline{x}_{s_k}$ and $\underline{x}_{o_{j_k}}$, $F_{s_{(\underline{x}_s)}}$ and $F_{s_{(\underline{u}^m_s)}}$ are respectively the Jacobian of the function f_s with respect to the state $\underline{x}_s$ and $\underline{u}_s$, F_o is the Jacobian of the function f_o with respect to the state $\underline{x}_{o_j}$. B_s and B_o are the covariances of the noise affecting the motion model of the vehicle V_s and the other vehicles V_{o_j} respectively.

The obtained state is the prediction of the group state at the time $k+1$ using the group state estimation at the time k and the encoders data. This state will be updated with the exteroceptive sensors information.

2) Group state update: At the beginning of the application, the group state contains only the vehicle V_s pose estimation vector $\underline{x}_s$ and its covariance matrix $P_{s,s}$ as in equation (8). There is no other vehicle pose estimation in the group state (m_s=0).

$$\underline{X}_s=[\underline{x}_s], \quad P_s=[P_{s,s}] \quad (8)$$

When the vehicle V_s detects an other vehicle V_{o_1}, it can measure its relative pose $\underline{z}_r$ noised according to the model:

$$\underline{z}_r \sim \mathcal{N}\ (\underline{z}^m_r, B_z) \quad (9)$$

with $\underline{z}^m_r$=$(\Delta x, \Delta y, \Delta\varphi)$ the measured relative pose and B_z the covariance of the noise affecting it.

As the group state of the vehicle V_s contains only its own pose estimation, the state of the detected vehicle can be added to the group state without any ambiguity. In order to keep the inter dependencies between the poses estimations of the two vehicles, the group state estimation is updated as following.

- The group state is extended with an initial vehicle state $(\underline{x}_0, P_{0,0})$ set to an arbitrary values with a large covariance as in equation (10).

$$\underline{X}^{-}_{s_{k+1}}=\begin{bmatrix}\underline{X}^{-}_{s_{k+1}}\\ \underline{x}_0\end{bmatrix} \quad , \quad P^{-}_{s_{k+1}}=\begin{bmatrix}P^{-}_{s_{k+1}} & 0_{4\times4}\\ 0_{4\times4} & P_{0,0}\end{bmatrix} \quad (10)$$

  where $0_{n\times n}$ is an $n\times n$ dimension zeros matrix.
- The extended state is updated with the measured relative information $\underline{z}_{r_{k+1}}$ as in equations (11),(12) and (13).

$$K_{k+1} = P^{-}_{s_{k+1}} H^T (H P^{-}_{s_{k+1}} H^T + B_z)^{-1} \quad (11)$$

$$\underline{X}_{s_{k+1}} = \underline{X}^{-}_{s_{k+1}} + K_{k+1}(\underline{z}^m_{r_{k+1}} - H_{k+1}\underline{X}^{-}_{s_{k+1}}) \quad (12)$$

$$P_{s_{k+1}} = (I - K_{k+1}) P^{-}_{s_{k+1}} \quad (13)$$

  The update matrix H is given by the equation (14).

$$H \quad = \quad \begin{bmatrix}-I_{3\times4} & I_{3\times4}\end{bmatrix} \quad (14)$$

  where $I_{3\times4}$=$\begin{bmatrix}I_{3\times3} & 0_{3\times1}\end{bmatrix}$ and $I_{n\times n}$ is an $n\times n$ dimension identity matrix.

After the update, the obtained group state contains the state of the vehicle V_s and the state of the other vehicle V_{o_1}, the number of other vehicles in the group state estimation is then m_s=1.

From now on, when the vehicle V_s detects an other vehicle V_o, as it can't identify it directly, it must compare the pose of the vehicle V_o with the estimated poses of the other m_s vehicles present in the group state W_s. The pose of the detected vehicle V_o is estimated with the self pose estimation of the vehicle V_s and the measured relative information $\underline{z}^m_r$ = $(\Delta x, \Delta y, \Delta\varphi)$ as in equation (15).

$$\begin{aligned}\tilde{\underline{x}}_o&=(x_s+\Delta x, y_s+\Delta y, \varphi_s+\Delta\varphi)\\ \tilde{P}_{o,o}&=\tilde{P}_{s,s}+B_z\end{aligned} \quad (15)$$

Where $\tilde{\underline{x}}_o$ and $\tilde{P}_{o,o}$ are the estimated pose of the detected vehicle and its covariance matrix, $\tilde{P}_{s,s}$ is the covariance matrix of $\tilde{\underline{x}}_s$=$[x_s, y_s, \varphi_s]^T$. As the vehicle V_s is supposed unable to measure the relative speed of the detected vehicle, the obtained pose $(\tilde{\underline{x}}_o, \tilde{P}_{o,o})$ is compared to the poses $(\tilde{\underline{x}}^{-}_{o_{j_{k+1}}}, \tilde{P}^{-}_{o_j,o_{j\,k+1}})$ in the group state $(\underline{X}^{-}_{s_{k+1}}, P^{-}_{s_{k+1}})$. Where $\tilde{\underline{x}}^{-}_{o_j}$ and $\tilde{P}^{-}_{o_j,o_j}$ note respectively $\underline{x}^{-}_{o_j}$ and $P^{-}_{o_j,o_j}$ without the speed component v_{o_j}. This comparison is performed by computing the Mahalanobis distance between the poses estimations as in equation (16)

$$d^2_j= (\tilde{\underline{x}}_o - \tilde{\underline{x}}^{-}_{o_{j_{k+1}}})^T (\tilde{P}_{o,o}\tilde{P}^{-}_{o_j,o_{j\,k+1}})^{-1} (\tilde{\underline{x}}_o - \tilde{\underline{x}}^{-}_{o_{j_{k+1}}}) \quad (16)$$

where j=1...m_s. The comparison process generate's a set of m_s Mahalanobis distances which correspond to the m_s other vehicles in the group state estimation.

- If the minimum distance is lower than a specified threshold, it means that the detected vehicle already exists in the group state, the relative measure $\underline{z}^m_r$ is used to update pose of the corresponding vehicle according to equations (11),(12) and (13) with an update matrix H as in equation (17)

$$H=\begin{bmatrix}-I_{3\times4} & 0_{3\times(4(D-1))} & I_{3\times4} & 0_{3\times(4(m_s-D))}\end{bmatrix} \quad (17)$$

  where $1 \le D \le m_s$ is the position of the vehicle which corresponds to the minimum Mahalanobis distance in the group state. In this case, the number of vehicles in the group state m_s does not change.
- If the minimum distance is higher than the specified threshold, it means that the detected vehicle is not yet in the group state, it is then added according to the equation (18) and updated according to the equations (11),(12) and (13), with the update matrix H as in equation (19).

$$\underline{X}^{-}_{s_{k+1}}=\begin{bmatrix}\underline{X}^{-}_{s_{k+1}}\\ \underline{x}_0\end{bmatrix} , \ P^{-}_{s_{k+1}}=\begin{bmatrix}P^{-}_{s_{k+1}} & 0_{4(m_s+1)\times4}\\ 0_{4\times4(m_s+1)} & P_{0,0}\end{bmatrix} \quad (18)$$

$$H \quad = \quad \begin{bmatrix}-I_{3\times4} & 0_{3\times(4m_s)} & I_{3\times4}\end{bmatrix} \quad (19)$$

  In this case the number of vehicles in the group state is incremented (m_s=m_s+1).

In real applications, the observations can be affected with delays. This problem is solved by dating the observations in an absolute time reference, the observations are affected then to their true arrival date and put back in chronological order in an observations table. After that the group state is recomputed to take into account the new observation.

3) Group State Cleaning: In the previous sections III-A.1 and III-A.2, we shown how the vehicle V_s detects and add other vehicles in its group state estimation. Those vehicles are kept in the group state while the vehicle V_s can measure and update their pose. If their pose can not be measured and updated during several iterations, the error affecting their pose estimation becomes too large, and it can lead to wrong matchings (the Mahalanobis distance between the pose estimation of a detected vehicle and a pose estimation with a too large covariance is regularly lower than the specified threshold).
To avoid this problem a step of vehicle removal is performed. After the group update process, the poses estimations which have an error higher than a maximum allowed error are removed from the group state estimation.
The inability for the vehicle V_s to detect and update the pose estimation of an other vehicle can be due to:

- The sensor range limitation: the distance between the vehicle V_s and the other vehicle becomes higher than the *maximum sensing distance*.
- A wrong matching: the vehicle state was added to the group state after a wrong matching.
- A false positive detection: it is happened when the vehicle V_s makes a false detection and add the estimated pose in the group state, this pose will not be updated again.

The three process *Group state evolution*, *Group state update* and *Group State Cleaning* enable the vehicle V_s to maintain a group state estimation which describes its view of the environment. Those process are executed in the other vehicles of the group. The collective localization is obtained by combining those group states estimations.

B. Collective Localization

The vehicles of the group exchange their group states where are represented the poses estimation of every vehicle and its neighborhood in an absolute common referential. The vehicle V_s sends its group state estimation to the other vehicles and receives theirs. The vehicle V_s can fuse its group state with the received ones to obtain the most accurate group state estimation.

1) Group states fusion: Let us consider the self vehicle V_s which maintains the group state W_s=$(\underline{X}_s, P_s, \mathbf{id}_s)$ and receives L group states W_l=$(\underline{X}_l, P_l, \mathbf{id}_l)$ with l=1...L from other communicating vehicles present in the communication area.
The global group state estimation is obtained by fusing the L received group states W_l with the self group state W_s as in equation (20)

$$W^s \quad = \quad \mathcal{G}\ (W_s, W_1, W_2, ..., W_l, ..., W_L) \qquad (20)$$

W^s is the fused global group state estimation in the vehicle V_s, this state is shaped as in equation (21) , W_l is the group states received from the other vehicle $V_{\mathbf{id}_l}$ and $\mathcal{G}$ the fusion function.

$$W^s \quad = \quad (\underline{X}^s, P^s, \underline{\mathbf{id}}^s) \qquad (21)$$

where $\underline{X}^s$ is the global state vector, P^s its covariance matrix and $\underline{\mathbf{id}}^s$ is a set of identifiers of the vehicles in the global group state estimation.
The fusion of the group states is performed by updating the self group state W_s with the other ones as in the algorithm 1.

Algorithm 1 Function ($\mathcal{G}$) group states fusion

Inputs: $(W_s, W_1, W_2, ..., W_L)$
Output: W^s
  W^s initialization
  for $l = 1\ ...\ L$ **do**
    W^s=FUSE(W^s, W_l)
  end for
  return W^s.

Where W^s is initialized with W_s as in equation (22).

$$X^s{=}X_s, \quad W^s{=}W_s \quad \text{and} \quad \underline{\mathbf{id}}^s{=}[\mathbf{id}_s, 0, ..., 0]^T \qquad (22)$$

$\underline{\mathbf{id}}^s$ is a $(m_s + 1)$ dimensions vector of identifiers where null elements mean that the corresponding vehicles are not identified yet. *FUSE* is the function which updates the global group state W^s=$(\underline{X}^s, P^s, \underline{\mathbf{id}}^s)$ with the group state W_l=$(\underline{X}_l, P_l, \mathbf{id}_l)$ received from the vehicle $V_{\mathbf{id}_l}$. This function is detailed hereunder.
Let us consider that the group states W^s and W_l contain respectively M^s=$(m^s + 1)$ and M_l=$(m_l + 1)$ vehicles (one self pose estimation and respectively m^s and m_l other vehicles poses estimations). The number of vehicles and their positions in that group states can be different. To combine correctly the received states, a data association must be performed to find correspondences between the vehicles in W^s and the vehicles in W_l. Once the correspondences found, it becomes possible to update the fused global group state W^s by the received W_l at ones in order to take account of the possible interdependencies between poses estimations in the group states. The fusion process can be divided in two steps:

- *Vehicles matching:* The vehicle V_s browses the two states W^s and W_l looking for correspondences between the poses estimations. This is performed by computing the Mahalanobis distances between all the poses estimations in the two group states (of course, V_s does not compare it self pose with $V_{\mathbf{id}_l}$'s self pose). Two estimations match if the distance between those is lower than the same threshold in the group state building (section III-A.2).
- *Updating the state W^s by W_l:* The vehicles matching process leads to a *matching table* where can be two kinds of results:
  - The pose $(\underline{x}_{o_b}, P_{o_b,o_b})$ in the group state W_l matches with the pose $(\underline{x}_{o_a}, P_{o_a,o_a})$ in the global group state

W^s. It means that the corresponding vehicle was detected by at least two vehicles. The pose estimation $(\underline{x}_{o_a}, P_{o_a,o_a})$ will be updated by $(\underline{x}_{o_b}, P_{o_b,o_b})$.

– The pose $(\underline{x}_{o_b}, P_{o_b,o_b})$ in W_l does not match with any pose in W^s. It means that the vehicle detected by $V_{\mathbf{id}_l}$ was not present in the state W^s. For every unmatched pose estimation, the group state W^s is extended with an initial vehicle state $(\underline{x}_0, P_{0,0})$ set to an arbitrary values with a large covariance as in equation (23). The unmatched poses will correspond to the added ones.

$$\underline{X}^s = \begin{bmatrix} \underline{X}^s \\ \underline{x}_0 \end{bmatrix}, \quad P^s = \begin{bmatrix} P^s & 0_{N_s \times 4} \\ 0_{4 \times N_s} & P_{0,0} \end{bmatrix} \qquad M^s = M^s + 1 \tag{23}$$

After the extension, the global group state contains M^s poses estimations . The update matrix H can be built using the matching table and will be an $4M_l \times 4M^s$ dimensions matrix with $I_{4\times4}$ in the right places to update the poses estimation in W^s with corresponding ones in W_l. The global group state is updated according the equations (24), (25) and (26).

$$K = P^s H^T (H P^s H^T + P_l)^{-1} \tag{24}$$

$$\underline{X}^s = \underline{X}^s + K(\underline{X}_l - H\underline{X}^s) \tag{25}$$

$$P^s = (I - K)P^s \tag{26}$$

and finally

$$\underline{\mathbf{id}}^s(D) = \mathbf{id}_l \tag{27}$$

where D is the position of the pose of the vehicle $V_{\mathbf{id}_l}$ in the obtained W^s.

The global state $W^s = (\underline{X}^s, P^s, \underline{\mathbf{id}}^s)$ returned by the fusion function is shaped as in equations (28) and (29).

$$\underline{X}^s = [\underline{x}^{sT}, \underline{x}^{o_1 T} \ ... \ \underline{x}^{o_{N_s} T}]^T \quad , \quad \underline{\mathbf{id}}^s = [\mathbf{id}_s, \mathbf{id}_{o_1} \ ... \ \mathbf{id}_{o_{N_s}}]^T \tag{28}$$

$$P^s = \begin{bmatrix} P^s_{s,s} & P^s_{s,o_1} & \cdots & P^s_{s,o_{N_s}} \\ P^s_{o_1,s} & P^s_{o_1,o_1} & \cdots & P^s_{o_1,o_{N_s}} \\ \cdots & \cdots & \cdots & \cdots \\ P^s_{o_{N_s},s} & P^s_{o_{N_s},o_1} & \cdots & P^s_{o_{N_s},o_{N_s}} \end{bmatrix} \tag{29}$$

$\underline{X}^s$ is the global group state vector and P^s is its covariance matrix. The vector $\underline{\mathbf{id}}^s$ contains the identifiers of the vehicles pose estimations in the global group state. For example the vehicle in the second position is the vehicle $V_{\mathbf{id}_{o_1}}$. There can be unidentified vehicles in the fused global state represented by a null identifier. This happened when a vehicle is detected by V_s or an other communicating one and did not send its group state to the others.

Communication can be affected with delays or can be temporarily unavailable, the communicated group state are seldom if ever dated on the same time. To fuse the received states correctly, it is necessary to make evolve those states to the present time before the fusion.

IV. Results and Discussion

The proposed approach was implemented in simulation in the case of a group of four vehicles. Three vehicles are equipped with proprioceptive sensors which describe their motion and exteroceptive sensors enabling them to localize themselves in an absolute reference and to detect and localize (but not to identify) the other vehicles. The three vehicles are also equipped with communication devices to exchange information among the group. The fourth vehicle is not equipped with any sensor or communication device.

To show the effect of the group state exchange, we will make the following assumption:

- The equipped vehicles can not communicate when the distance between them is higher than the *maximum communication distance* set empirically, for the experiment this distance is set to 100 meters.
- The vehicles can not measure the relative poses of the other group members when the distance between them is higher than the *maximum sensing distance* which is smaller than the *maximum communication distance*, this distance is set to 50 meters.
- The sensors and GPS data and the communication can be affected with delays or can be temporarily unavailable.

The Four vehicles move according to a preset scenario. The figure 1 represents the evolution of the standard deviation of the pose estimation of the vehicle V_1 in its own fused global group state W^s during the experiment. The std (standard deviation) evolution is represented in the ideal case (no delays and data unavailability) in red (lower curve) and in real conditions simulation in blue (upper curve).

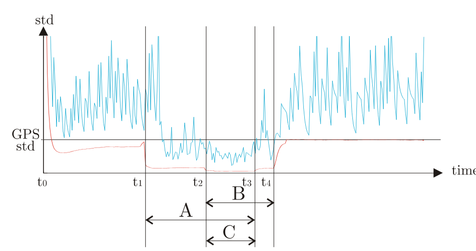

Fig. 1. The evolution of the standard deviation of pose estimation error of the vehicle V_1 in its fused global group state W^s. **A:** the vehicles V_1 and V_3 are able to estimate and exchange their relative poses. **B:** the vehicles V_1 and V_2 are able to estimate and exchange their relative poses. **C:** the three vehicles can measure and exchange their relative poses.

- At the initial time, the distance between the vehicles V_1,V_2 and V_3 is higher than the *maximum communication distance*. Every vehicle maintains its group state estimation where it updates its own pose and the poses of its neighborhood. The figure 2(a1), (a2) and (a3) represent respectively the group states W_s performed in the three vehicles V_1, V_2 and V_3 and figure 2(b1), (b2) and (b3) represent respectively the group states W^s fused in the three vehicles V_1, V_2 and V_3. We can see that the vehicle V_1 detects only the vehicle V_4 but it can not exchange any information with other the vehicles. This case is represented in figure 1 before t1. This can be assimilated with single vehicle localization.

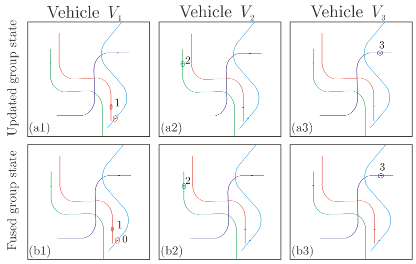

Fig. 2. A screen shot of the updated group states in (a1), (a2) and (a3) and the fused group states (b1), (b2) and (b3) in the vehicles V_1, V_2 and V_3 at the beginning of the application.

- The figures 3 represents the three updated and fused states in the three vehicles. We can see in figure 3(a1) that the vehicle V_1 detects the vehicles V_2 and V_3, in figure 3(a2) that the vehicle V_2 detects V_1 and V_3 and in figure 3(a3) that the vehicle V_3 detects the three other vehicles V_1, V_2 and V_4. By exchanging their maintained group states W_s, each communicating vehicle can combine the received group states to compute the fused global group state. We can see in figure 3(b1), (b2) and (b3) that the vehicle identification is well done (the vehicles are correctly identified) and that each of the three communicating vehicles obtains a more accurate estimation of it own pose and of the one of the other vehicles. We can see also that the fused global state of the vehicles V_1 and V_2 contains the pose estimation of the vehicle V_4 which is still observed by V_3, the vehicle V_4 is not identified because it never communicate its pose estimation ant its identifier to the other vehicles. This case is represented in figure 1 between t2 and t3, we can see that when the identification is well done, the relative poses exchange leads to the reduction of the pose estimation error, this is due to the fusion of several independent pose estimation of the same vehicle.

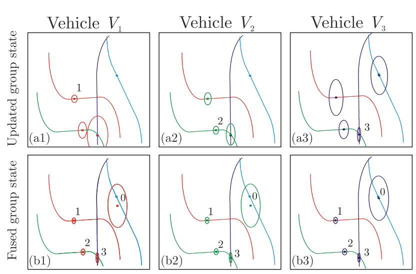

Fig. 3. A screen shot of the updated group states in (a1), (a2) and (a3) and the fused group states (b1), (b2) and (b3) in the vehicles V_1, V_2 and V_3 when the 3 vehicles measure and exchange their relative poses .

V. Conclusion

This paper describes a cooperative approach for the collective localization of an heterogeneous group of road vehicles while taking into account sensor imperfections as delays and data unavailability. To take advantage of the interdependencies between the vehicles poses, the group is viewed as a single system which contains the poses of the detected other vehicles. Each vehicle updates its group state with its own sensor data. When two vehicles meet, they exchange their views of the environment. The collective localization is obtained by fusing the received views with an Extended Kalman Filter.

This approach was tested in the case of four vehicles. Three of those vehicles are able to localize itself in an absolute reference and estimate the relative poses of the other vehicles. The fourth vehicle is not equipped with any sensing or communication devices. The obtained results show that the performed data association can solve the problem of identification of the detected vehicles and that the relative data exchange carries the reductions of the localization error among the group.

We are currently planning to make a real environment experimentation of this approach.

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