Multi target tracking with CPHD filter based on asynchronous sensors

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Abstract—In this paper, the problem of targets road tracking based on multiple asynchronous sensors is addressed. A method based on Cardinalized Probability Hypothesis Density (CPHD) filter improved with probability of target type is presented. Using the sensor classification, the probability of target type is recursively computed by Bayesian rules. This probability is used to improve the performance of the Multi Target Tracking (MTT) filter and the understanding of the observed area. The tuning of filter parameter depending of sensor is explained and the particular case of non detection due to occlusion with camera is developed. Our system has been validated with real measurements from a smart camera and a radar in real traffic conditions with real time computation.

I. INTRODUCTION

The number of vehicles equipped with ADAS (Advanced driver assistance system) is increasing. Most of these systems are based on sensors information to detect relevant entities around the vehicle. The ADAS relies on a good estimation of the location of the surrounding cars. Sensors have to detect all the relevant entities, called “targets”, around the car and also to estimate the position and speed of these targets. To make the sensors information more reliable, different kinds of sensors are used at the same time. In this paper, two typical sensors are used, one passive and one active. A camera and a radar detect vehicles and pedestrians in front of the vehicle. Each sensor provides their own list of detected target. They estimate the position and the speed of each detection.

A multi target tracking (MTT) based on both sensors is chosen to fuse both sensors information. The filter will be fed with the sensor module output and will be able to compensate the drawback of sensor, occlusion with camera detection for example. The main issue to succeed the information fusion is the data association between a global track and information on target detection provide by the sensor.

A Multi target tracking (MTT) based on the Kalman filter, like nearest neighbor Kalman filter, may be used to solve this issue [1]. However, the data association in this filter is too simple to proceed our data because of some detection errors. Sensors can detect a target which do not correspond to a real object, called false alarm, and it may not detect real objects, called non detection. A Probabilistic Data Association (PDA) filter or inherent filters like Joint Probabilistic Data Association (JPDA) can be used [2] to avoid this error. However, these filters assume a fixed number of targets whereas the number of targets in road context is unknown. So the birth and the death of each target has to be managed in addition to the processing of these filters. Some MTT filters natively estimate the number of target with targets state. For example the Multiple Hypothesis Tracker (MHT) introduced by Blackman in [1] or the Cardinalized Probability Hypothesis Density (CPHD) recently developed by Mahler [3]. Due to a recent comparison between both filters [4], the CPHD will be used in the following to proceed our data.

Besides the result of the sensor classifier will be used to improve the results of the tracking filter and to improve the understanding of the scene. In [5], the result of the sensor classification is directly used by a MHT filter. In our contribution, a similar approach is proposed for the CPHD. The classification information will be introduced to estimate the width of targets and will be integrated to the likelihood of each association between measurements and predicted tracks.

The CPHD will be used in this paper to fuse information provided by two different sensors. Some CPHD filter parameters are based on sensor behavior and need to be estimated to make the filter works. For example the probability of detection, or the false alarm density have to be analyzed. In case of sensor sensitive to occlusion, these parameters will be also modified using the predicted state of target.
The main contribution of this paper is to present a fusion method based on a CPHD filter robust to occlusion and using additional sensor attribute to estimate the number and the state of the pedestrians, car, trucks and bicycles present on the road in front of the car. This method will be tested and analyzed with real data provided by a radar and a camera.

The paper is organized as follows; first the MTT filter, based on GMCPHD filter, an implementation of the CPHD filter, is introduced in Section II with the addition of target attribute. Section III is dedicated to the sensors fusion. Section IV presents filter results with real data. Conclusions are drawn in Section V.

II. MULTI TARGET TRACKING

In this paper, targets set is defined as a Random Finite Set (RFS), a finite set of variables with unknown cardinality. The Probability Hypothesis Density (PHD) filter, developed by Mahler in [3], is defined as the first order moment of the prior multivariable density function of the targets set. In case of non detection, this filter tends to decrease a lot the number of targets. Mahler [3] introduces probability density function (pdf) of the number of targets in the propagation of existing targets. Malher [3] is defined as the first order moment of the prior multivariable density function of the targets set. Set (RFS), a finite set of variables with unknown cardinality.

Section V. introduced in Section II with the addition of target attribute. on GMCPHD filter, an implementation of the CPHD filter, is with real data provided by a radar and a camera. in front of the car. This method will be tested and analyzed of the pedestrians, car, trucks and bicycles present on the road additional sensor attribute to estimate the number and the state of the.

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A. Cardinalized Probability Hypothesis Density (CPHD)

The aim of the CPHD filter is to recursively compute the first order moment of the prior multivariable density function of the targets set \( v(x) \), and the probability distribution of the number of targets \( p(n) \) too. Predicted equations of the filter are:

\[
v_{k|k-1}(x) = b(x) + \int f(x|\zeta)P_s(\zeta)v_{k-1|k-1}(\zeta)d\zeta
\]

\[
p_{k|k-1}(n) = \sum_{j=0}^{n} P_T(n-j) \ast \Lambda
\]

\[
\Lambda = \sum_{l=j}^{\infty} C^l_j \left( \frac{P_s}{1-P_s} \right)^j \left( \frac{1-\left( \frac{P_s}{1-P_s} \right)}{1, v_{k|k-1}} \right)^{l-j} p_{k-1|k-1}(l)
\]

\( P_T(\zeta) \) is the surviving probability of a target having the previous state \( \zeta \), \( f(x|\zeta) \) is the transition function of a target knowing its previous state and \( b(x) \) is the intensity function of birthing target. \( P_T(n-j) \) is the probability of having \( (n-j) \) birthing target. The number of targets probability is defined thanks to the total probability law applied to each hypothesis: knowing there are \( (n-j) \) new targets and \( l \) targets at time \( k \), each hypothesis identifies \( (l-j) \) dead targets among the \( l \) old targets, assuming each hypothesis is equally probable. \( C^l_j \) is the binomial coefficient indexed by \( l \) and \( j \).

The posterior intensity function \( v_{k|k} \) can be defined with the prior intensity function, the observation at the time \( k \), named \( Z_k \) and the prior number of targets probability \( p_{k|k-1} \) too:

\[
v_{k|k}(x_i) = \frac{\langle \psi^1_k \left[ v_{k|k-1}, Z_k \right], p_{k|k-1} \rangle (1-P_d)v_{k|k-1}(x_i)}{\langle \psi^0_k v_{k|k-1}, p_{k|k-1} \rangle}
\]

\[+ \sum_{z \in Z_k} \frac{\langle \psi^1_k \left[ v_{k|k-1}, Z_k | z \right], p_{k|k-1} \rangle}{\langle \psi^0_k v_{k|k-1}, p_{k|k-1} \rangle} \psi(z)v_{k|k-1}(x_i)
\]

\[
p_{k|k-1}(n) = \frac{\psi^0_k \left[ v_{k|k-1}, Z_k \right] (n) \cdot p_{k|k-1}(n)}{\langle \psi^0_k v_{k|k-1}, p_{k|k-1} \rangle}
\]

\( \Psi^1_k \left[ v_{k|k-1}, Z_k \right] (n) \) is the likelihood of measurements \( Z_k \) according to \( v_{k|k-1} \), assuming there are \( n \) targets. \( \langle \psi^1_k \left[ v_{k|k-1}, Z_k \right], p_{k|k-1} \rangle \) is a normalization term and \( (1-P_d) \) is the probability not to detect target.

B. Gaussian Mixture Cardinalized Probability Hypothesis Density (GMCPHD)

The initial CPHD equations are difficult to implement. Many implementable versions of this filter are available [6]. For example a Monte Carlo method is used by Reuter and Dietmayer in [7]. Gaussians mixture is also used to model the intensity function, this filter is named GMCPHD filter, and was introduced by Mahler in [3]. The posterior intensity of a RFS is a mixture of gaussians \( v_k = \sum \omega_{k,i} N(x, m_{k,i}, P_{k,i}) \). In the following, the only equation of this filter will be described, the hypothesis of this implementation can be found in [3]. The predicted equations of the GMCPHD are:

\[
v_{k|k-1}(x) = \nonumber\]

\[P_s \sum_{j=1}^{n} w_{k-1|k-1,i} N(x, m_{k|k-1,i}, P_{k|k-1,i}) + \gamma_k(x)
\]

\[
p_{k|k-1}(n) = \nonumber\]

\[\sum_{j=0}^{n} P_T(n-j) \sum_{l=j}^{\infty} C^l_j (1-P_s)^{l-j} P_s^{l} p_{k-1|k-1}(l)
\]

Likewise, the update equations are:

\[
p_{k|k}(n) = \frac{\psi^0_k \left[ w_{k|k-1}, Z_k \right] (n) \cdot p_{k|k-1}(n)}{\langle \psi^0_k w_{k|k-1}, p_{k|k-1} \rangle}
\]

\[
\Psi^1_k \left[ w_{k|k-1}, Z \right] (n) = \sum_{j=0}^{\min(n, |Z|)} \frac{\omega_j (1-P_d)^{n-j+u} \cdot \langle \xi v_{k|k-1} \rangle}{\langle 1, \xi v_{k|k-1} \rangle^{u+1}} e_j(\xi(v_{k|k-1}, Z))
\]

\( p_c(|Z| - j) \) is the probability to have \( (|Z| - j) \) false alarms, \( |Z| \) is the measurements set cardinal and \( e_j(\xi(v, Z)) \) used in the equation is the elementary symmetric function.

\[
e_j(Z) = \sum_{S \subseteq Z, |S| = j} \prod z
\]
\[ \mathbb{Z}(v_{k}\mid k-1, Z) = \{ P_d w_{k}^T q_k(z), z \in Z \} \]

\[ w_{k-1} = [w_{k-1}^{(1)}, \ldots, w_{k-1}^{(j)}]^{T} \]

\[ q_k(z) = [q_k^{(1)}(z), \ldots, q_k^{(j)}(z)]^{T} \]

\[ q_i(z) = N(z, H w_{k-1}^{(j)} + R + HP_{k-1}^{(j)}H^{T}) \]

\[ H \] is the observation matrix, \( R \) is the covariance matrix of the sensor noise.

For each measurement, \((z)\) new Gaussians are created (corresponding to the update of predicted Gaussians and because one Gaussian is also created corresponding to the non detection of predicted Gaussian).

\[ w_{k-1}^{(j)} = \frac{P_d w_{k}^{(j)} q_k(z)}{c_k(z)} \]

\[ c_k(z) \] is the false alarm density.

\[ w_{k-1}^{(j)} = (1 - P_d) \frac{\langle \Psi_k^T \mid w_{k-1}^{(j)}, Z_k \rangle, p_{k-1} \rangle}{\langle \Psi_k^T \mid w_{k-1}^{(j)}, Z_k \rangle, p_{k-1} \rangle} \]

Finally, to allow real-time computation, some simplifications are done to reduce the number of Gaussians describing updated tracks: a pruning and a merging step.

MTT filter has already been used to fuse multi-sensors data.

C. Improvement with target classification

With our application, used sensors module detect and estimate the state of the detected target, and they also classify these target. Indeed, on the road, sensors have to detect several types of obstacle: pedestrian, car, truck, and bicycle, and each sensor classifies target from their measures. The output of the sensor module is a list of detected target with state estimation and result of sensor classifier.

The camera classification is based on the target appearance whereas the radar classification is based on target speed. Radar can only distinguish pedestrians from other targets.

This classification can improve the data association of the MTT filter and the understanding of the scene. The classification of one target made by the sensor can be itself erroneous and is likely to change during time. So it is not efficient to apply different MTTs for all possible types of targets. This can neither support change of target type. In [5] authors introduce attribute of target in the processing of the MHT filter through a new computation of the likelihood. Similar change will apply to our tracking filter. As far as we know, although Mahler have suggested the idea in [6], additional information has been never used with CPHD filter.

A new discrete probability of target type will be associated to each Gaussian.

\[ x_{type} \in \{ t_0, t_1, t_2, t_3, t_4 \} \]

with \( t_0 \) unknown, \( t_1 \) pedestrian, \( t_2 \) bicycle, \( t_3 \) car, \( t_4 \) truck.

When a new Gaussian is created (MTT birth step), the associated pdf is set as a uniform function, because no information about the target type is available.

During the MTT update step, when new measurements are available the pdf of target type is updated with Bayesian rule.

\[ P_k(X_{type} = t_i) \]

\[ = \frac{P(Z_{type} \mid X_{type} = t_i) P_{k-1}(X_{type} = t_i)}{\sum_{j=0}^{4} P(Z_{type} \mid X_{type} = t_j) P_{k-1}(X_{type} = t_j)} \]

\[ P_k(X_{type} = t_i) \] is the probability that the type of the associated Gaussian is \( t_i \) at time \( k \). \( P(Z_{type} \mid X_{type} = t_i) \) is the likelihood of the measurement classification result according to the type of the Gaussian. This value comes from the confusion matrix describing the sensor classifier system. This matrix is provided by a previous analysis of the performance of the sensor classifier, each component of this confusion matrix is defined by:

\[ C_{t_i} = P(Z_{type} = t_i \mid x_{type} = t_i) \]

\[ P_k(X_{type} = t_i) \] can also be used to improve the association between targets and between tracks and measurements. The likelihood \( q_i(z) \) used by the MTT update equation is modified with this probability.

\[ q_i(z) = q_{state}(z_{state} \mid x_{state}) q_{type}(z_{type} \mid x_{type}) \]

\[ q_{state}(z_{state} \mid x_{state}) \] is the kinematic likelihood, and \( q_{type}(z_{type} \mid x_{type}) \) is the type likelihood defined by:

\[ q_{type}(z_{type} \mid x_{type}) = \sum_{j=0}^{4} P(Z_{type} \mid x_{type} = t_j) P_{k-1}(x_{type} = t_j) \]

Similarly, the distance computed in the GMCPHD merging step is modified with the target type. The previous used Mahalanobis distance between two tracks state is multiplied with the type distance defined as the Bhattacharya distance between two discrete probability density functions.

To conclude, the use of sensor classification result allows a better understanding about target in front of the vehicle.

Besides, the MTT equations are modified by the inclusion of the type of target in the distance and in the likelihood computing. These modifications impact on the association between tracks and measurements, on the existence probability of track, and on the estimated number of targets, due to the use of the likelihood. With sensor fusion, the target classification is necessary because sensor behavior change with target type.

III. SENSOR FUSION

The previous section has introduced the PHD and the CPHD filter. In related works, these filters have already been used to solve multi sensor multi target issue. Most of the time the filter is used with synchronized or aligned data coming from multiple sensors. In this case, the generalization of PHD or CPHD with multi sensors seems difficult [8], [9]. In [10], [11], [12] authors use an iterative corrector approach to approximate the multi sensor generalization; the corrector equation are iterated for each sensors. In our work, data from different sensors are not aligned. Thus the MTT filter is fed with the first data received. No synchronization is required [13], and the basic MTT filter can be used to fuse our sensors.

A. Sensors studies

To make the GMCPHD work, some parameter has to be defined: some parameters depend on the sensor, the other depend on the context. The context parameters don’t change with sensor. So, the state vector of each target \( X_t \) is composed of the position and velocity in Cartesian coordinates \( X_t = (x, v_x, y, v_y) \). The dynamic equation is written as: \( X_{t+1} = AX_t + W_t \), Where \( A \) is the transition matrix and \( W_t \) is a zero-mean white Gaussian noise. A model of constant velocity is chosen. Besides, the GMCPHD filter require the definition of the maximum number of targets (set to 12 in our tests). This parameter allows a constant computational complexity whatever the number of detected targets. So the assumption that there are less than 12 targets in front of our vehicle is made.
However, the detection probability $P_{d}$, the surviving probability $P_{s}$ or the measure noise used in update equation of target state for example, depend on sensor and on targets state. Likewise a confusion matrix has to be defined evaluating the sensor classifier.

All this previous parameters need to be defined depending on the sensor but also depending on the type and on the state of target.

A study has been carried on to evaluate the sensor performance. The parameters are learned from comparison between sensor result and ground truth.

The result of this study has been submitted and is under review.

However, the study carries out on camera detection performance raises the problem of occlusion. In fact, most of non detection of target with camera are due to occlusion. This issue can’t be solved easily by a sensor study and need a real modification of the detection probability computation.

B. Occlusion

Optical sensor, as camera or Lidar, are sensitive to occlusion. It means that their detection ability of one target depends on the target state but also on the state of other targets in the scene.

In related work, partial occlusions with camera are handled directly in the target detection system. In these cases, shape detection in camera image can be successfully done to improve target detection [14], [15], [16]. However when the target is totally hidden approaches solving the occlusion issue with MTT filters have been considered, through a new computation of the detection probability. With Lidar data, probability of occlusion is usually binary and handled by occupancy grid and used in MTT filter [17], [18], [7]. With camera detection, the measurements of targets position are more affected by noise and this noise has to be taken into account. Besides there is also a problem of occlusion uncertainty due to the height of target shown in Figure 2. This figure shows a pedestrian behind a vehicle. Due to the height of the vehicle, the pedestrian is only partially occluded and may or may not be detected by the camera. In case the occlusion of the pedestrian is uncertain. Thus, the method presented in [19] provides a reliable solution to the occlusion problem in case of one type of target. This method is adapted, using $P_{h}(X_{type} = t_{i})$ (defined in section II-C) to compute the width of target and to provide a reliable solution to occlusion issue.

1) Detection map: In our work occlusion is considered as non detection and the map of sensor detection probability is modified by occlusion probability. So the GMCPHD equations do not need to be modified. The hypothesis and the reasoning of the new map computation are described in [19]. In the following, equations defining the new map of detection probability $P_{dacc}(x;y)$ are presented:

$$P_{dacc}(x;y) = P_{d}(x,y) \times \prod_{j}(1 - w_j P_{O}(x,y))$$

At point $(x,y)$ the new detection probability is computed from the occlusion probability of each target (see Fig. 3), and the sensor detection probability $P_{d}(x,y)$.

$$P_{O}(x,y) = (f_{G}^o * P_{U})(x')$$

The occlusion probability $P_{O}(x,y)$ due to target $j$ is the convolution between $f_{G}^o$, the marginal distribution function on axis $\Gamma$ of the position of the target $j$, $\Gamma$ is defined as the perpendicular to the line between $x$, $y$ and the sensor. $P_{U}$, the function representing the width of target $j$ (assumed to be a gaussian function with std $\sigma_u$). $w_j$ is the existence probability of the possible occluding target $j$ position.

$$P_{O}(x,y) = \exp\left(-\frac{(d')^2}{2\sigma_u^2 + \sigma_v^2}\right)$$

$P_{U}$ is defined as a not Gaussian function, with $\sigma_u$ as its standard deviation. $\sigma_v$ is the standard deviation of $f_{G}^o$. $d$ is the Mahalanobis distance between $x'$ (the projection of occluding Gaussian mean on the axis between $(x,y)$ and the sensor) and $f_{G}^o$. $\sigma_u$, $\sigma_v$ represent the width of occluding target, it is compute from the probability of target type and the typical width of this type.

$$\sigma_u = \sqrt{4 \sum_{i=0}^{4} P_{h-1}(X_{type} = t_i) L_i}$$

With this new detection probability map, a new detection probability associated to each Gaussian is computed. This new probability is the mean of the detection probability weighted by the target position probability. Then this probability is used by the update step of the GMCPHD filter.

This new detection probability of the camera combined with other parameters estimation result in a good fusion between both sensors.
IV. RESULTS

Our multi target tracking method is used with real data. To acquire these data, our vehicle prototype is set up with a smart camera with a 40 degree field of view. This camera estimates euclidean position, and the type of each target detected on the observed area. A radar is also used estimating euclidean position, and relative speed of targets.

The GMCPHD is based on predicted and updated equation of Kalman filter. So the performance on estimation of target state is similar to Kalman filter performance. The advantage of both sensor are used. The speed of target measure by radar improve the estimated speed of target whereas the lateral position of target or the target classification are improved by the camera. It is difficult to evaluate precisely this kind of improvement due to the lack of knowledge about the real state of target.

In the following, the performance concerning the estimation of number of target will be evaluated. Our MTT filter was tested with occlusion and target type management with radar and camera in real time, with C++ code. The frequency of radar is 30Hz, and the camera frequency is 11Hz. It was tested in two different situations. First, tests were conducted in controlled situation to accurately evaluate the results, the strengths and the weaknesses of the complete method. In a second step, this method was tested in an usual driving situation on highway, the results presented in the following focus on the management of the type of target inside the MTT. The filter parameter are tuned based on the sensor study introduced in the previous section.

A. Results in usual driving situations.

The algorithm was tested in usual scenario to assess several conclusion.

First, occlusion management does not lead to an increase of false alarms. Indeed, most of the time, when no occlusion occurs, our method works as well as the simple GMCPHD with type management. The results provided by both of the filters have the same number of targets estimation and the same precision. The processing of type management was analyzed. The results show an interesting processing of type management from an usual driving situation on highway. Furthermore, the case where one sensor detects a real target whereas the other sensor do not is also analyzed. For example, Fig. 7 shows the case of new target detected. Both sensors Field of view (FOV) are different. Camera detect the new car (Fig. 4a) and the radar doesn’t detect it (Fig. 4b). Because of the previous sensor study, the radar detection probability of this new target is around 0.2 whereas the camera detection probability is 0.95. So several camera detections of the new car lead to a new target birth (Fig. 4c).

Besides the application is real time even with several detected targets. The computational complexity is constant with GMCPHD whatever the number of detected targets. However the time required for occlusion management depends on the number of targets. Our tests have been conducted with almost 8 targets, so the method has been proved to be real time with almost 8 targets.

B. Results in controlled scenario : pedestrian and vehicle occluded

Test in controlled scenario were conducted to assess the improvement brought by the occlusion and type of target management in the camera radar fusion framework. Indeed previous tests results with only camera observations are shown in paper [19]. In this section, similar tests are analyzed with with data from camera and radar.

In the framework of pedestrian detection system, it could be interesting to plan the position of pedestrians in the typical scenario described by Fig 2. With this example, if the predicted position of the pedestrian is behind the predicted position of the car, the pedestrian may not be seen by the camera. Whereas, it can be expected that the pedestrian is going across the scene, and will be detected again on the other side of the car. Besides, radar has a low probability of pedestrian detection. As it is shown on Fig 2, the observed car is not moving, and the pedestrian starts on the right side of the car and is moving to the left.

At the beginning of the test, the target is classified as a pedestrian, so the corresponding radar detection probability is decreasing. Indeed, during the test, radar does not succeed to detect pedestrian.

Then, the pedestrian is occluded for a few frames. The birdview of the positions of both objects are represented on Fig. 5a. Positions of objects observed by the camera are shown in blue crosses and results of the filter are shown with red points.

During the occlusion, the positions of the pedestrian are predicted. The estimated number of targets does not decrease. Even if the pedestrian is not detected, the filter actually estimates that there are two targets. Besides, the detection probability can be estimated from the estimated position of pedestrian.

This result can be compared with result of this same filter without occlusion management (Fig. 6). Indeed without occlusion management, the camera detection probability is 0.8 whereas the pedestrian is not detection for several frame. It lead to the disappearance of the pedestrian, the estimated number of target is equal to 1 during the
This result is representative of occlusion scenario with expected radar non detection. In this case, occlusion and type management are necessary.

The Fig. 7 presents a second test in controlled environment : a car lane change. Several tests f the same situation are done. In the following two different results are presented.

Fig. 8 shows the result of one of the test. In this test, radar is expected to detect occluded target (because it is a car) and the radar detects the occluded car (see Fig 8a). Fig 8b and 8c show the filter result with the estimated number of targets with or without occlusion management. These results are similar in both cases, the estimated number of target is not decreasing during the occlusion because of the radar detection.

Fig. 9 shows the result of another of the test. In this test, radar is expected to detect occluded target (because it is a car) and the radar does not detects the occluded car (see Fig 9a). Fig 9b and 9c show the filter result with the estimated number of targets with or without occlusion management. These result is similar in both cases, the estimated number of target is decreasing during the occlusion because of the radar non detection whereas it was expected to detect the car (see sensor detection probability in both case in Fig. 9d and 9e ). However, the decreasing is faster without occlusion management.

V. CONCLUSION

In this paper, a multi target tracking filter based on a GMCPHD has been developed and tested with asynchronous camera and radar with real time computation. This paper has introduced the occlusion and type of targets management. Results have presented the advantage of these management in the sensor fusion with multi target tracking framework. Primary result have shown the good behavior of the filter in real road but further investigations have to be made to validate the filter with every possible situations.

As future works, this approach will be also extended to address the problem of prediction accuracy in case of occlusion, some GPS and map data could be introduced to improve the predicted state of target in case of occlusion.

REFERENCES


(a) Number of camera detections (blue crosses) and Radar detections (green crosses) for the scenario described in Fig.7. Radar detect the occluded car during the occlusion.

(b) Estimated number of targets. The probability of having 2 (resp 3, 1) targets is represented in red (resp purple, green) with occlusion management.

(c) Estimated number of targets. The probability of having 2 (resp 3, 1) targets is represented in red (resp purple, green) without occlusion management.

(d) Camera detection probability (blue) and radar detection probability (green) with occlusion management.

(e) Camera detection probability (blue) and radar detection probability (green) without occlusion management.

Figure 8: Filter results of experimentation described in Fig. 7 with and without our occlusion management method. During the occlusion, the occluded car is detected by the radar.

Figure 9: Filter results of experimentation described in Fig. 7 with and without our occlusion management method. During the occlusion, the occluded car is not detected by the radar.


