A Data Association Method for Vehicle Detection Based on Millimeter Wave Radar

Chuan Li¹*, Feng Luo²

¹Continental Automotive Co, No.55 Huiyuan Road, Shanghai City, PR China
²Tongji University, No.1239, Siping Road, Shanghai City, PR China
¹*Luntanyong88@163.com, (86)13817624538
²luo_feng@tongji.edu.cn, (86)13817053378

ABSTRACT This paper proposes a vehicle object association method based on millimeter wave radar detection, which can improve the accuracy of driving assistance functions that take vehicle targets as input. This method is used to judge the data association of the target tracking group through Kalman filtering. The L-shaped model is used to initially determine the outline of the measurement object, and the close object clusters are segmented according to the standard vehicle parameters and the related speed. Furthermore, a Gate algorithm is used to associate the hypothetical object within a certain area with the target. Road test experiments show that the data association method has high accuracy for detected vehicles.

1. INTRODUCTION

With the increasing popularity of vehicles in recent years, the number of traffic accidents has also increased. The application of advanced driver assistance systems can greatly reduce the incidence of accidents. The system's perception consists of external sensors such as high-definition cameras and millimeter-wave radar. It detects, recognizes, and distinguishes all objects in the direction of the vehicle, and outputs them to the decision-making section for functional implementation. So the output quality of the sensing part is very important for the realization of the final function and the safety of the vehicle.

In the realization of multi-target tracking, the state of the multi-target is estimated by the detection results of the millimeter wave radar. Target tracking provides the perception of the surrounding traffic environment for the decision algorithm based on the results of radar detection. The purpose of the tracking algorithm is to detect and confirm real targets, and collect observation sets from the same target into the tracking. From these tracking, estimate the amount of interest, such as target position and motion, future predicted paths and object features [1].

The data association method proposed in this paper is an important part of multi-target tracking. Data correlation is for initial verification of the target. Correlation should include when the detection occurred and the target data available to the radar at that moment, as well as the degree of uncertainty associated with these data.

If the association does correspond to a trusted object or target, the target can be detected multiple times in succession. Therefore, the association that is not verified by another association is discarded, and multiple associations that are considered to belong to the same target are fused together into a track. Tracking refers to the data source of a single target, from multiple associations, and can be updated appropriately with reference to other associations. It will contain the same general data as the
data contained in the association, as well as data that does not appear in any association but is inferred from the association collective. Tracking includes an estimate of the speed of the target, which is derived from an association that contains only position data. The trace will contain some other data, such as when it was initialized, when it was last updated, and how confident the system is that the trace represents a real target.

Through the introduction of the multi-target tracking process, first, the boundary of the target vehicle is selected by L-fitting. Secondly, the objects within the contour range are reasonably segmented by a certain threshold, and the gate control and association probability algorithm are further used. The corresponding targets were subdivided, and the correlation algorithm was finally verified by road tests.

2. Multi-target tracking
This article divides the tracking into three life cycles of initialization, update and deletion[2]. First, when the radar detects a newly discovered object and judges that it is associated with an existing target, a new track is generated to monitor the object, and it is temporarily determined that the monitored object is not included in any other track. Update tracking For multiple tracking at the same time, you need to compare the relevant data between the object and different targets to determine which tracking is associated with it. If such new associations do not occur within a certain period of time, the tracking may be discarded because the radar may not be able to see the target due to being damaged or exceeding the detection range of the radar, or due to harsh environmental conditions. The general process is shown in Figure 1.

When initializing or updating the trace, no data is saved immediately. The tracking update is done by referring to the historical (uncertainty) and associated data of the trace as a result of assigning a new association to it. The new data tracked is a trade-off between historical data and associated data. Regarding the continuous evaluation characteristics of the target, such as its position and speed, the trade-off takes the form of a weighted average between the measured value and the value predicted from past data. The weight assigned to the measured and predicted values is the key to data fusion. Associated objects must be assigned to other associated objects to initialize traces, and associated objects must be assigned to traces to update these traces [3].

By predicting and observing the measurement results, they must be correlated with each other to resolve the uncertainty of the source of the observation. Check whether the pairing (predictive observation pair) is statistically compatible by calculating the pairing difference and its associated uncertainty.

Measure the difference between predicted \( \hat{z}_i(k) \) and observed \( z_i(k) \):

\[
v[i,j](k) = z_i(k) - \hat{z}_i(k)
\]  
(1)

The related covariance estimates are called:

\[
\hat{S}_{ij}(k) = H(k)\bar{P}_{ij}(k+1|k)H^T(k) + R_i(k)
\]  
(2)

Where \( H(k) \) is the observation matrix, \( \bar{P}_{ij}(k+1|k) \) is the predicted covariance, and \( R_i(k) \) is the covariance matrix.
2.1 Border Limit

We propose an L-shaped fitting method for vehicle tracking\cite{6} to obtain the contour of the target vehicle. First, L-shaped feature extraction is an abstract process of raw data. Second, the L-shaped tracker estimates the dynamic state of the trajectory through dynamic models and shape models by using L-shaped measurements. Finally, the L-shaped trajectory is converted into a box-shaped trajectory to represent the precise position and speed of the target.

Figure 2 shows the specific extraction method of L-shape fitting. First, we select point B with the smallest angle and point A with the largest angle as the two endpoints of the aggregation. Connect point A and point B to form a reference line. By calculating the distance from each object point in the object group to the reference line, get point C as the farthest point from the reference line, and set the bounding box to a preset small passenger. The length (4.5 meters) and width (1.8 meters) of the car determine the extent of the bounding box.

After obtaining the target box, determine whether the current position is correct by using its geometry and reflection center. By weighting the two centers based on the position of the object in the field of view and the average calculation of the current target (L-shaped model), the calculated weight is the product of two parameters, one depends on the longitudinal coordinates and the other depends on the azimuth position. According to the results, it is considered that the geometric center position is reasonable, and the abscissa of the target position is set as the center of the line at the bottom of the bounding box.

2.2 Object Segmentation

The segmentation method is used to solve the coincidence problem of two tracking points pointing to the same detection object. There are two cases that will cause this problem to occur. The first case is when two targets point to the same detection object due to incorrect segmentation. In this case the two traces must be maintained and the (possibly missing) detections must be handled properly so that the
two traces can be updated correctly. Another case is that the current tracking may correspond to a portion of a real object that was not correctly detected in a previous time step due to excessive segmentation. In this case, a new trace must be created and the existing trace must be deleted.

Similar ambiguities arise when a single trace is assigned to two or more detections. Each detection may correspond to a part of an object that was previously tracked correctly, or to a small object that actually exists in the past, detected with other objects.

For each acquired test, confirm whether it originates from a tracked target, or merge two (or more) tests of a tracked object, or a new previously unrecognized object, or clutter.

![Figure 3 Tracking Segmentation Strategy](image)

As shown in Figure 3, all detection objects with a longitudinal distance of less than 12 meters are generally selected as the set of objects to be determined. It is assumed that it is an extra-long vehicle (such as a trailer), and the two with the largest adjacent distance among them are selected. The vertical distance between objects is verified (there is no other object between the two). If the vertical distance between the two is greater than 6 meters, or the horizontal distance is greater than 1.5 meters, the object set should be considered to consist of at least two different targets. The object set is divided into two corresponding parts, and the target is associated with reference factors such as other related elements and boundaries.

2.3 Gate and Association
A method of excluding the possibility of allocating measurements to tracking by gating\[4\][5] a large amount of statistical data. The area in the measurement space where measurements can be assigned to targets is called a gate. This article can give a rough door through the assumption of the maximum speed of the target. Use predicted measurements and tracked measurements to predict covariance to form more detailed gates.

If the Mahalanobis distance between the object and the target is less than 1 (dimensionless), the object is associated with the target. The Mahalanobis distance is proposed by Indian statistician Mahalanobis and represents the covariance distance of the data. Mahalanobis distance is a method that can effectively calculate the similarity between two unknown sample sets. What is different from Euclidean distance is that it considers the relationship between various characteristics and is scale-independent, that is, it is independent of the measurement scale.

Mahalanobis distance is calculated as

$$d_{kl}^2 = v_{kl}(k)^T S_{kl}(k)^{-1} v_{kl}(k)$$

Compare this to the correct threshold for a distribution

$$d_{kl}^2 \leq \frac{1}{2}$$
The three oval shapes in figure 4 represent doors constructed by a door calculation module. The prediction target is located in the center of the gate. Some parts of the three doors overlap each other. Object 1 and object 4 both land in the overlapping area of the door. In this case, all predictions at the center of the relevant gate are qualified candidates associated with object 1 and object 4 falling in the overlapping area. At the same time, the source information of each measured target needs to be considered. The degree of aggregation of multiple traces must be considered when estimating the probability of interconnection. The weighted value of the degree of aggregation must be reduced to reflect the aggregation of the measurement by other targets degree. The weighted average fusion of the target parameters is realized according to the joint probability data association.

That, $D_{ij}$ represents the Mahalanobis distance from object $i$ to object $j$, and $P_{ij}$ represents the probability of association from object $j$ to object $i$.

The number of targets is 3 and the number of valid objects is 5. The correlation matrix $\Omega$ can be defined as a $4 \times 5$ matrix, where 4 columns represent false alarms (assuming all object measurements are wrong) and target 1, target 2, target 3, target 4, target 5. "1" indicates that the object $j$ falls within the tracking gate of the target $i$, and "0" indicates that the object $j$ does not fall within the tracking gate of the target $i$.

\[
\Omega = \begin{bmatrix}
1 & 1 & 0 & 1 & 1 \\
1 & 1 & 0 & 0 & 1 \\
1 & 1 & 0 & 0 & 1 \\
1 & 0 & 1 & 0 & 1 \\
\end{bmatrix}
\]  \hspace{1cm} (5)

The association probability is calculated as

\[
P_k = P[\hat{z}_k (k) | z^k]
\]  \hspace{1cm} (6)

The measurement $Z (object)$ of the joint event $\hat{z}_k (k)$ comes from the association of a real target. Measure the fusion of objects is calculated as

\[
\bar{x}_{\text{fused}} = \bar{X} = \frac{\sum_k P_k \bar{x}_k}{\sum_k P_k}
\]  \hspace{1cm} (7)

Covariance of the measure object is calculated as

\[
\Omega_{\text{fused}} = \frac{\sum_k P_k \Omega_k = \sum_k P_k \Omega_k}{\sum_k P_k}
\]  \hspace{1cm} (8)

Wrong association is calculated as

\[
P_{\text{nd}} = 1 - \sum_k P_k
\]  \hspace{1cm} (9)

This paper uses joint probabilistic data association\cite{7} to implement in software. Its characteristics are to avoid possible association errors caused by the uniqueness of the nearest neighbor algorithm. It's easier to track the class goals.
The data association algorithm (shown in Figure 5) uses the probability matrix data to calculate the longitudinal and lateral position of the target vehicle, the probability of existence, the probability of obstacles, and the Mahalanobis distance to determine whether to aggregate related targets. The distance and the related probability are obtained by sorting the longitudinal distance of the target to obtain dynamic variables such as the relative longitudinal speed of the target and combining it with its polar coordinate position to calculate the relevant target (within a longitudinal or lateral distance of less than 3 meters and a relative speed of 20 km/h). The Markov distance, if the Markov distance is greater than 1, the two are considered to be unrelated; otherwise, the probability of their existence is calculated. If the object has not been merged before, the probability value is assigned to the object.

3. Vehicles Test
In the test, we used the following tools to set up a test environment: 77GHz millimeter-wave radar; Canalyzer equipment used for monitoring and analysis of target output; USB camera for actual comparison with targets detected by millimeter-wave radar; measurement test simulation equipment for output Various detected targets, environments and attributes.

3.1 Test Case
The test site is a two-way, four-lane road on a public road. A test vehicle equipped with radar has multiple vehicles in different directions in front of the road, as shown in Figure 6.
3.2 Test Expect Result
Able to accurately distinguish the target. There is a car in front of the test vehicle in this lane, a car in the adjacent right lane, and a car in front of the adjacent right.

According to national highway engineering technology standards, the standard lane is 3.5 to 3.75 meters; the length is less than the standard length of 4.5 meters; the width is less than the standard width of 1.8 meters; the longitudinal relative speed difference is less than the standard tolerance of 0.5 meters/second; the lateral relative speed difference is less than the standard tolerance of 2.0 meters/second; it can associate objects that meet all of the above requirements into one target.

3.3 Test Data
The radar detected targets 27, 28, and 30. Obtain the longitudinal distance, lateral distance, longitudinal relative vehicle speed, and lateral relative vehicle speed parameters of the object 24, object 26, object 29, and object 36 as shown in Table 1.

| Attribute                        | Target 24 | Target 26 | Target 29 | Target 36 |
|----------------------------------|-----------|-----------|-----------|-----------|
| Longitudinal distance /m         | 23.71     | 24.31     | 25.62     | 27.08     |
| lateral distance /m              | -3.87     | -4.87     | -3.84     | -3.42     |
| Longitudinal relative vehicle speed /m/s | 3.70   | 3.72     | 3.69     | 3.69     |
| lateral relative vehicle speed /m/s | -0.16 | -0.17     | -0.17     | -0.16     |
| Dynamic State                    | Moving    | Moving    | Moving    | Moving    |
| Ambiguity                        | Low       | Low       | Low       | Low       |

Obtain the longitudinal distance, lateral distance, longitudinal relative vehicle speed, and lateral relative vehicle speed parameters of target 27, target 28, and target 30. The target types, confidence, length, width, movement status, and life cycle are shown in Table 2.

| Attribute                        | Object 27 | Object 28 | Object 30 |
|----------------------------------|-----------|-----------|-----------|
| Longitudinal distance /m         | 23.46     | 23.8      | 47.7      |
| lateral distance /m              | -0.36     | -3.95     | -4.02     |
| Longitudinal relative vehicle speed /m/s | 0.35 | 3.71     | 1.71     |
| lateral relative vehicle speed /m/s | 0.06  | -0.17     | 0.20     |
| Object Type                      | Vehicle   | Vehicle   | Vehicle   |
| Probability/%                    | 100       | 100       | 100       |
| Vehicle Length/m                 | 4.5       | 4.5       | 4.5       |
| Vehicle Width/m                  | 1.8       | 1.8       | 1.8       |
| Dynamic State                    | Moving    | Moving    | Moving    |
| Vehicle Life/s                   | 67        | 13        | 35        |

3.4 Test Result
According to the data analysis, the algorithm can accurately detect that the target 27 is in front of the test vehicle in this lane, the target 28 is in the adjacent right lane, and the target 30 is in the adjacent right lane, as shown in figure 7.
Figure 7 Target vehicle recognition and segmentation analysis.

The horizontal distance between target 27 and target 28 is approximately 1.9 meters, and the longitudinal distance is approximately 19 meters.

Target 28 correlation test results (see Table 3): Based on subject 24, subject 26, subject 29, and subject 36, the maximum longitudinal distance difference of 3.37 meters is less than the standard length of 4.5, and the maximum lateral distance difference of 1.45 meters is less than the standard width of 1.8 meters. The longitudinal relative vehicle speed difference of 0.03 is less than the standard tolerance of 2.0 m/s, and all objects are moving and the ambiguity is low. In summary, the four objects are associated as the target vehicle 28.

Table 3 Test results for side-by-side subjects

| Attribute                           | Max. Difference | Pass Condition | Result |
|-------------------------------------|-----------------|----------------|--------|
| Longitudinal distance /m            | 3.37            | < 4.5          | Pass   |
| Lateral distance /m                 | 1.45            | < 1.8          | Pass   |
| longitudinal relative vehicle speed /m/s | 0.03            | < 0.5          | Pass   |
| Dynmic State                        | Moving          | Moving         | Pass   |
| Ambiguity                           | Low             | Low            | Pass   |

4. Conclusion

The state of the target is estimated by the Kalman filtering method, and the related targets with similar characteristics are associated, and then the target is given different attribute values. The simplest and most widely used method for tracking and tracking associated measurements is the global nearest neighbor algorithm. This method forms the most likely measurement tracking and new tracking assumptions. In the joint probability data association algorithm, multiple trace-to-measure hypotheses are generated. We calculate the hypothesis probability and then merge the distribution hypotheses for each track. With this method, by using the weighted sum of each hypothesized trajectory estimate, all tracking measurements are used to update the tracking state. These two methods form a tracking estimate of each tracking hypothesis.

References
[1] Danielsson, L. 2010. Tracking and radar sensor modelling for automotive safety systems. ISBN 978-91-7385-383-5
[2] Khan, J., Niar, S., Saghir, M. et al. 2010. Trade-Off Exploration for Target Tracking Application in a Customized Multiprocessor Architecture. J Embedded Systems 2009, 175043. DOI= https://doi.org/10.1155/2009/175043
[3] Peters, D. J. 2001. A Practical Guide to Level Once Data Fusion Algorithms, DREA Technical Memorandum (TM 2001-201), DRDC Atlantic, Dartmouth N.S.Canada.

[4] Michael Livshitz, 2017. Tracking radar targets with multiple reflection points,. Texas Instruments, Incorporated.

[5] C. Kim, F. Li, A. Ciptadi, and J. M. Rehg, “Multiple hypothesis tracking revisited,” in Proceedings of the IEEE international conference on computer vision, pp. 4696–4704, 2015.

[6] Gan Z.M., Wang C.X., Yang M., 2009. Lidar-based Vehicle Tracking and Recognition, Journal of Shanghai Jiaotong University. https://doi.org/10.16183/j.cnki.jsjtu.2009.06.016.

[7] JTGB01-2003 Highway Engineering Technical Standard.