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Sensor Fusion for Vehicle Tracking with Camera and Radar Sensor

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Abstract: In recent years, as demands for the vehicle safety and autonomous driving of the automobile industry have increased, it becomes important to more accurately recognize the position and velocity of surrounding vehicles. In this paper, heuristic fusion with adaptive gating and track to track fusion are applied to track fusion of camera and radar sensor for forward vehicle tracking system and the two algorithms are compared. To compare the two algorithms, simulation was carried out in 10 scenarios and the accuracy of sensor fusion results was measured with optimal subpattern assignment (OSPA) metric. The results of this metric are compared to show that the track to track fusion is superior to the adaptive gating for the target estimation.

Keywords: Sensor Fusion, Track to track fusion, Data association, Adaptive gating, Vehicle tracking

1. INTRODUCTION

As the society's demand for vehicle safety and autonomous driving continues to increase, the significance of technology for accurate recognition of the surroundings of vehicles is become more important. Thus, there are various types of vehicle recognition sensors, and the performance of each sensor is gradually improving. Typical sensors used in cognitive systems are cameras, radar, lidar, and ultrasonic sensors. However, because each sensor has its limitations in certain situations, it does not recognize the vehicle properly when used independently. For this reason, it is common to use the fusion result of recognition of various sensors [1].

Among many fusion algorithms, heuristic fusion with adaptive gating is widely used because of its implementational simplicity. This is the way to use the empirically chosen gate size for fusion. Another algorithm is track to track fusion [3], which performs data association and track fusion using covariance matrices that contains sensor reliability information of the sensors [4]. Although both algorithms are already used in the industry, few studies have directly compared these two algorithms in multi-target tracking. Therefore, in this paper, we apply the two algorithms to the front vehicle tracking problem using radar and camera, and compare the performance in 10 scenarios using optimal subpattern assignment (OSPA) metric [5], which is a widely used to evaluate the performance of multi-target tracking system.

The rest of this paper is organized as follows. Section 2 describes the heuristic fusion with adaptive gating and the track to track fusion algorithm, and introduce their features. Section 3 compares OSPA results by applying those two algorithms applied to simulation data of camera and radar sensor. Finally, the conclusions of the paper are presented in section 4.

2. PRELIMINARY FUSION ALGORITHMS

2.1 Heuristic Fusion with Adaptive Gating

The process of heuristic fusion can be roughly divided into data association and combining associated sensor data. Data association mainly used to match track and measurement in multi-target tracking. In sensor fusion, however, data association determines whether the track of each sensor is derived from the same target.

Heuristic fusion algorithm uses adaptive gating as data association method. This method determines the gate size by experimentally measuring the distance difference between two sensors for one target. Specifically, measure the distance between the longitudinal direction and the lateral direction of the radar value from the same target according to the camera longitudinal distance value, and then select the distance value covering the distance as the gate size.

The gate size of the x and y axes selected through our own experiments are

$$GateSize_x = \begin{cases} 0.125 \times x^{camera} + 5, & x^{camera} \le 80, \\ 15, & x^{camera} > 80, \end{cases} \quad (1)$$

$$GateSize_y = \begin{cases} 0.015 \times x^{camera} + 1, & x^{camera} \le 100, \\ 2.5, & x^{camera} > 100, \end{cases} \quad (2)$$

where

x^{camera} represents camera longitudinal distance.

The nearest track of the radar track entering the camera gate is determined as the value coming from the same target, and the two values are fused.

After data association via adaptive gating, the two associated tracks must be fused appropriately. The method of summing the camera and radar sensor values by giving a heuristic weight is used. In general, dichotomous fusing is usually done based on the assumption that the lateral direction of the camera and the longitudinal data of the radar are more accurate than each other. In the simulation of chapter 3, the dichotomous fusion method was used. Fig. 1 shows the result of heuristic fusion applied to the simulation data. Red and blue dotted lines represent boundaries of camera and radar sensor respectively. As the camera longitudinal distance increases, the size of the rectangular gate increases.

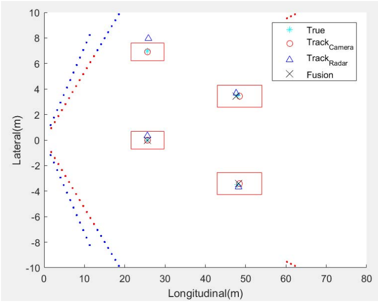

Fig. 1 Heuristic fusion with adaptive gating result.

2.2 Track to Track Fusion

In track to track fusion, the association does not use the experimentally determined gate size but the covariance of the track data. Since the covariance contains the probability information of the sensor estimate, it is known how far the true value is from the sensor track. It is determined whether the track data of the two sensors came from one target as follows:

$$D \triangleq \hat{\Delta}^{ij}(k)'[T^{ij}(k)]^{-1}\hat{\Delta}^{ij}(k) \leq D_a, \quad (3)$$

where

$$\hat{\Delta}^{ij}(k) = \hat{x}^i(k) - \hat{x}^j(k),$$
$$T^{ij}(k) = P^i(k) + P^j(k).$$

In Eq. (3), $\hat{x}^i(k)$ and $\hat{x}^j(k)$ are estimates of i and j sensors, respectively. In the simulation of section 3, longitudinal distance, lateral distance, longitudinal velocity and lateral velocity are used. D is the Mahalanobis distance between the i and j sensor's estimates, and D_a is a probability constant that follows the chi-square distribution. In this simulation, the order of the state is 4, and D_a is set to 13.28 for gating to the range of 99% of the camera track and the radar from the same target. This is because the gate size is selected based on the probability of the estimated value, which is different from the adaptive gating in which the gate size varies depending on the longitudinal position.

The track to track fusion algorithm uses the estimation and covariance values when combining the associated values. The smaller the covariance is, the better the reliability of the estimated value is. The sensor value with higher reliability is weighted as follows:

$$\hat{x} = P^j(P^i + P^j)^{-1}\hat{x}^i + P^i(P^i + P^j)^{-1}\hat{x}^j, \quad (4)$$
$$P = P^i(P^i + P^j)^{-1}P^j. \quad (5)$$

Since track to track fusion considers the reliability of each sensor's orientation, the reliability of the fusion results can be improved rather than empirically changing the weight. Fig. 2 shows the simulation results of the track to track fusion algorithm. The red circles show the camera tracks, and the blue triangles show the radar tracks. Each track has a longitudinal position, a lateral position, and a longitudinal velocity. The ellipses around the track represent the area where the probability of including a true value.

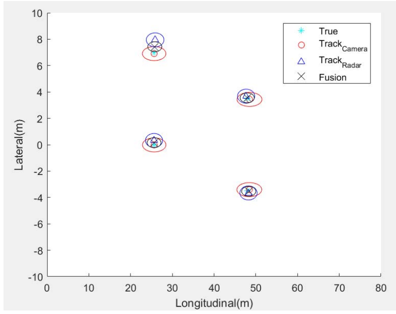

Fig. 2 Track to track fusion result

3. SIMULATION RESULTS

3.1 Simulation Environment

We obtained camera and radar sensor values in various situations using PreScan, which simulates road conditions and helped to develop advanced driver assistance systems (ADAS), and estimated each sensor measurement to obtain estimation and covariance. The track list composed of these values was applied to the heuristic fusion with adaptive gating algorithm and the track to track fusion algorithm respectively, and the results were compared.

Since comparing the position of an actual target is inappropriate in a multi-target situation, it is required a certified multi-target performance evaluation. The optimal subpattern assignment (OSPA) metric is widely used for multi-target performance evaluation because it expresses the cardinality error (CE) indicating the target tracked or not and the localization error (LE) indicating fusion the distance between the fusion value and the true value as one distance [5]. The OSPA distance is calculated by

$$\bar{d}_p^c(X,Y) := \left(\frac{1}{n}(LE + CE)\right)^{\frac{1}{p}}, \quad (6)$$

where

$$\text{LE} = \min_{\pi \in \Pi_n} \sum_{i=1}^{m} d^c(x_i, y_{\pi(i)})^p,$$
$$\text{CE} = c^p(n - m).$$

In this equation, n is the number of true values, d is the distance, m is the number of estimates, x is the true value, y is the estimate, p is the order, and c is the cutoff value. In this simulation, $p = 1$ and $c = 10$ were set in consideration of the maximum error of the sensor. The smaller the OSPA distance is, the better the estimation is.

3.2 Simulation Results

Heuristic fusion with adaptive gating and track to track fusion algorithm were repeated 5 times for 10 scenario to measure the OSPA distance of each step. Fig. 3 and Fig. 4 shows OSPA distances of each algorithm.

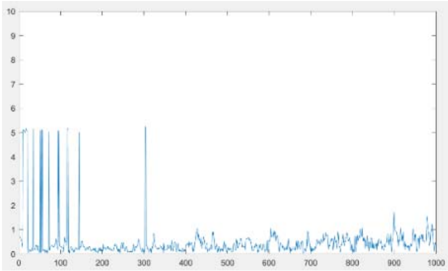

Fig. 3 OSPA distance of heuristic fusion result. (scenario (3)). The horizontal axis represents the time step and the vertical axis represents the OSPA distance.

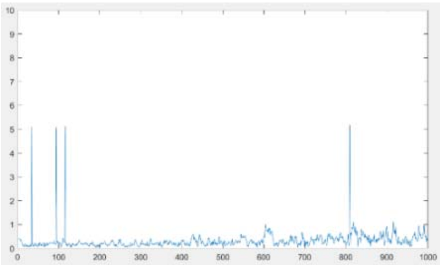

Fig. 4 OSPA distance of Track to track fusion result. (scenario (3)) The horizontal axis represents the time step and the vertical axis represents the OSPA distance.

The average OSPA distance of track to track fusion based on the average OSPA distance of heuristic fusion for each scenario is calculated by

$$\frac{\left(mean\ OSPA_{Error_{HG}} - mean\ OSPA_{Error_{T2Tf}}\right)}{mean\ OSPA\_Error_{HG}} \times 100. \qquad (7)$$

The description of each scenario and the average OSPA accuracy improvement rates are summarized in Table 1.

Simulation results show that the track to track fusion algorithm is better than the heuristic fusion with adaptive gating algorithm by 29.39%. In the OSPA distance graph in Fig. 3 and Fig. 4, the sudden surge in the middle of the error means the data association failure, and this surge is reduced in the track to track fusion algorithm.

Heuristic fusion with adaptive gating uses a predefined gate, so if the test environment is different, there is a big drawback that the developer must heuristically change the gate size to get the best result. In addition, there is a limitation in not reflecting the estimated reflecting the estimated reliability of the track data of the sensor.

In the track to track fusion algorithm, the sensor size that depends on the situation is reflected in the gate size. Thus, the data association is parameter-independent. There is no negative average accuracy improvement rate in Table 1, which indicates that track to track fusion is robust to changes compared to heuristic fusion with adaptive gating.

4. CONCLUSION

In this paper, we introduce heuristic fusion with adaptive gating and track to track algorithm for sensor fusion algorithm for forward vehicle tracking, and directly compare performance by applying each algorithm to camera and radar sensor fusion. The simulation results show that the track to track algorithm can yield better performance and reasonable fusion results than the heuristic fusion with adaptive gating.

The advantages of track to track fusion can be summarized in two ways. First, using track to track fusion reduces the probability of data association failure with gating which is reflecting probability information. Second, reliability of the fusion result can be improved by reflecting the reliability of each data direction rather than dichotomous combining camera and radar data using the camera lateral distance and radar longitudinal distance. These results can also be extended to real vehicles.

Table 1 OSPA accuracy comparison. (1)~(5) are two targets, (6)~(10) are four or more multi-target situations.

	scenario	average accuracy improvement rate (%)
(1)	stop	19.63
(2)	linear movement	47.86
(3)	curvilinear movement	15.40
(4)	birth	43.47
(5)	deletion	47.11
(6)	4 targets linear movement with different velocity	26.32
(7)	4 targets birth, deletion	32.26
(8)	4 targets cut-in, cut-out, cross	31.56
(9)	8 targets move slowly	13.74
(10)	4 targets near sensor detection range	16.56

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