다중주기 칼만 필터를 이용한 비동기 센서 융합

Asynchronous Sensor Fusion using Multi-rate Kalman Filter

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Abstract - We propose a multi-rate sensor fusion of vision and radar using Kalman filter to solve problems of asynchronized and multi-rate sampling periods in object vehicle tracking. A model based prediction of object vehicles is performed with a decentralized multi-rate Kalman filter for each sensor (vision and radar sensors.) To obtain the improvement in the performance of position prediction, different weighting is applied to each sensor's predicted object position from the multi-rate Kalman filter. The proposed method can provide estimated position of the object vehicles at every sampling time of ECU. The Mahalanobis distance is used to make correspondence among the measured and predicted objects. Through the experimental results, we validate that the post-processed fusion data give us improved tracking performance. The proposed method obtained two times improvement in the object tracking performance compared to single sensor method (camera or radar sensor) in the view point of roots mean square error.

Key Words : Multi-rate, Kalman filter, Object vehicle tracking, Sensor fusion

1. 서 론

HRobust and reliable object tracking solution is crucial to the performance of collision avoidance, path generation, adaptive cruise control. Object tracking with the use of radar and vision processing systems has been researched [1] - [5]. Radar and vision have the complementary characteristics in directional measurement's accuracy : the vision system provides accurate lateral information, whilst the radar system gives accurate range information of objects. The vehicle detection and tracking methods using only vision sensor were developed [6], [7]. The methods were designed based on an edge-based constraint filter. However, the vision system cannot guarantee satisfactory performance under various environmental conditions such as light change in the day and night times, poor weather conditions, and lack of light source. On the other hand, the radar provides an unnecessary object information resulting from reflections on crash barriers and other cars [1]. The radar and vision sensor systems commonly used in industrial applications have uncertain and slow update

rate compared to the vehicle electronic control unit (ECU). Thus it may be difficult for the radar and vision sensor systems to be synchronized together with lateral and longitudinal control systems. Furthermore, the slow update rate may limit the high performance of the vehicle control system.

The fusion of two sensors can complement each sensor's properties. The conventional approach to the sensor fusion is the method which is not synchronized and updates the fused data at the slow sensor. Thus the fusion structure of two sensors may result in slow object detection then unavoidable collision may arise. In [2], the vision data was only used to compensate for the object vehicle information from the radar data. They used a radar to detect relevant object vehicles, then used a vision sensor to validate object vehicles' lateral position, dimensions, and boundary of targets. Amditis et al. presented a multi-sensor collision avoidance system [8]. They solved the sensors' asynchronization problem through time based generation but they fused raw data from sensors at only commonly updated instance. Richter et al. present a tracking algorithm through combination of asynchronized observation data using a movement model [4]. They integrated the longitudinal and lateral velocity measurements to obtain object positions at the required instance. The major problem with this integration method is that bias errors and noises in the sensors will result in serious drift in the position estimates.

This paper investigates multi-object vehicle tracking

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using a fusion of asynchronous sensors such as radar and vision sensors. We propose a multi-rate sensor fusion using a Kalman filter for object vehicle tracking. The multi-rate Kalman filter is developed proximately to synchronize the sensors with a higher sampling rate synchronized to the ECU. A model based prediction of object vehicles' future behavior is performed by designing the decentralized multi-rate Kalman filter for each sensor (vision and radar sensors.) To obtain an improvement in the estimated object position, different weighting is applied to each sensor's predicted object position from the multi-rate Kalman filter: large weighting on the lateral position from vision and longitudinal position from radar. The proposed method allows us to implement prediction and correction steps at the ECU sampling rate [9] [10]. It is experimentally validated that the proposed method provides the improved estimation of object positions at every sampling time of the ECU. For object tracking, it is necessary for each sensor to link between measured objects and predicted ones at every time when sensor information is updated. In this paper, we use the Mahalanobis distance in determining correspondence among the measured and estimated [11]. Through the experimental results, we validate that the post-processed fusion data has improved object tracking performance. The proposed post-processing method can be helpful in providing collision warning and/or take collision avoidance action by predicting the position and motion of an object vehicle even with intermittent sensor information. We obtained two times improvement in the object tracking performance compared to the single sensor method (camera or radar sensor) in the view point of roots mean square error.

2. System Structure

In the proposed method, vision and radar sensors are used. Fig. 1 shows the schematic block diagram of the proposed multi-rate sensor fusion system for object tracking. The structure is composed of six function modules: (a) two sensor modules, (b) two validity determination modules for filtering object vehicles within specified ranges (c) two correspondence determination modules for matching the correspondence between measured data and object data recorded in previous frame, (d) two multi-rate Kalman filters for prediction of object vehicle's position, (e) a module treating interaction correspondence algorithm for finding the commonly measured object by vision and radar, and (f) a sensor fusion module that improves the position estimation by fusing the weighted position information from vision and radar.

Fig. 1 Structure of multi-rate sensor fusion system for object tracking

3. Object Modeling

Input data set of the post-processor are identity (ID) and information of object from each sensor. In this paper, variable with superscript $[l_v]$ denotes a variable from vision corresponding to the object with ID of l_v while variable with superscript $[l_r]$ denotes a variable from radar as follows

$$\begin{aligned} l_v &\in \Omega_v = \{1, 2, \dots, n_v\} \\ l_r &\in \Omega_r = \{1, 2, \dots, n_r\}. \end{aligned} \quad (1)$$

The relative distance, angle, and velocity from the ego vehicle to the measured object are obtained from a radar. From Polar-to-Cartesian conversion of the (distance, angle) information, we can obtain longitudinal distance, x , lateral distance, y , longitudinal relative velocity, $\dot{x}$, and lateral relative velocity, $\dot{y}$. The vision processor gives the relative position (x, y) of the object in Cartesian coordinate. Fig. 2 shows the coordinates of objects position with respect to the ego vehicle, and the both sensors' configurations of the range and field of view.

Generally, the relative velocity of each object with respect to the ego vehicle does not vary significantly within a short time. Thus, we can describe the motion of

Fig. 2 Configuration of the vision and radar sensors

object vehicles from vision processing system using the nonmaneuver target dynamic model [12] in terms of the state vector $X^{[l_r]} = [x^{[l_r]} \ y^{[l_r]} \ \dot{x}^{[l_r]} \ \dot{y}^{[l_r]}]^T$ as follows

$$\begin{aligned} \dot{X}^{[l_r]} &= A_l X^{[l_r]} \\ Y_v^{[l_r]} &= C_v X^{[l_r]} + \omega_v \end{aligned} \quad (2)$$

and its system matrix A_l is given by

$$A_l = \begin{bmatrix} 0_{2 \times 2} & I_{2 \times 2} \\ 0_{2 \times 2} & 0_{2 \times 2} \end{bmatrix}. \quad (3)$$

In regard to measurement matrix, we have $C_v^{[l_r]} = [I_{2 \times 2} \ 0_{2 \times 2}]$. ω_v denotes the measurement noise of vision which is assumed to be zero mean Gaussian white noise with covariance Q_v , $N(0, Q_v)$.

We can describe the object vehicles from radar in terms of the state vector $X^{[l_r]} = [x^{[l_r]} \ y^{[l_r]} \ \dot{x}^{[l_r]} \ \dot{y}^{[l_r]}]^T$ as follows

$$\begin{aligned} \dot{X}^{[l_r]} &= A_l X^{[l_r]} \\ y_r^{[l_r]} &= C_r X^{[l_r]} + \omega_r \end{aligned} \quad (3)$$

where the superscript $[l_r]$ denotes the object with an ID of l_r and A_l is the same as in (2). For radar, we have output matrix $C_r = [I_{4 \times 4}]$ or $C_r = [I_{2 \times 2} \ 0_{2 \times 2}]$. ω_r denotes measurement noise of radar which is assumed to be zero mean Gaussian white noise with covariance Q_r , $N(0, Q_r)$. Then, for the sampling time T_c of the car ECU, one can obtain the zero order hold equivalent discrete-time model matrices (Φ_l, C_v, C_r) from (A_l, C_v, C_r) .

4. Multi-rate Sensing and Processing

In this section, the multi-rate Kalman filters for both radar and vision systems are proposed to achieve the prediction of the object's motion at the fast sampling rate of ECU.

4.1 Design of Multi-rate State Estimator

(a) Asynchronous period of vision and radar sensors

(b) Synchronization of vision and radar sensors from multi-rate Kalman filters

Fig. 3 Update period of ECU, and vision and radar sensors

Fig. 3 (a) shows the update period of each ECU, radar, and vision. The radar provides the object information at a sampling period of T_{rad} while the vision processing system measures that at a sampling period of T_{cam} . As Fig. 3 (a), the sampling times are asynchronous. The vision processing system provides an approximately one sample delayed information in the view point of ECU sampling rate. We thus need to design a multi-rate state estimator for the each object dynamics (2) and (3) to estimate objects' position information at the same sampling period as T_c of the car ECU.

Assumption 1: The update periods of radar and camera are fixed integer multiples of T_c such as

$$\begin{aligned} T_{cam} &= R_{mv} T_c \\ T_{rad} &= R_{mr} T_c \\ \text{where } R_{mv}, R_{mr} &\in \mathbb{N} \text{ and } R_{mv}, R_{mr} \geq 1 \end{aligned} \quad \diamond$$

Then, under the Assumption 1, we can represent a time instant, t , such as

$$\begin{aligned} t &= (k_v + i/R_{mv}) T_{cam} \\ &= (k_r + j/R_{mr}) T_{rad} \end{aligned}$$

for

$$\begin{aligned} k_v, k_r &= 0, 1, \dots \\ i &= 0, 1, \dots, R_{mv} - 1 \\ j &= 0, 1, \dots, R_{mr} - 1, \end{aligned}$$

where k_v and k_r denote the vision and radar update instants, respectively. i and j indicate the control update instants for the vision and radar, respectively. We design two multi-rate state estimators: one for the vision sensor and the other for the radar sensor. The multi-rate state estimator for the vision consists of two procedures. One is a prediction based on model (2) as (4)-(a):

$$\bar{X}_v^{[l_v]}(k_v, i+1) = \Phi_l \hat{X}_v^{[l_v]}(k_v, i) \quad (4)-(a)$$

$$\begin{aligned} \hat{X}_v^{[l_v]}(k_v, i) &= \bar{X}_v^{[l_v]}(k_v, i) \\ &+ L_v (y_v^{[l_v]}(k_v, 0) - C_v \bar{X}_v^{[l_v]}(k_v, 0)) \end{aligned} \quad (4)-(b)$$

The prediction error is corrected as (4)-(b) by a multi-rate state estimator gain, L_v , based on the given measurement data at $(k_v, 0)$ instance such as The prediction error is computed based on the predicted states at $(k_v, 0)$. This computation enables the correction states to avoid oscillation. Similarly we have the following prediction and correction for the radar system as

$$\begin{aligned} \bar{X}_r^{[l_r]}(k_r, j+1) &= \Phi_l \hat{X}_r^{[l_r]}(k_r, j) \\ \hat{X}_r^{[l_r]}(k_r, j) &= \bar{X}_r^{[l_r]}(k_r, j) \\ &+ L_r (y_r^{[l_r]}(k_r, 0) - C_r \bar{X}_r^{[l_r]}(k_r, 0)). \end{aligned} \quad (5)$$

We apply a discrete-time lifting procedure, then (4) and (5) lead to a lifted model

$$\begin{aligned} \bar{X}_v^{[l_v]}(k_v+1, 0) &= \left(\tilde{\Phi}_{l,v} - \sum_{n=1}^{R_{mv}} \Phi_l^n L_v C_v \right) \bar{X}_v^{[l_v]}(k_v, 0) \\ &+ \sum_{n=1}^{R_{mv}} \Phi_l^n L_v y_v^{[l_v]}(k_v, 0) \\ \bar{X}_r^{[l_r]}(k_r+1, 0) &= \left(\tilde{\Phi}_{l,r} - \sum_{n=1}^{R_{mr}} \Phi_l^n L_r C_r \right) \bar{X}_r^{[l_r]}(k_r, 0) \\ &+ \sum_{n=1}^{R_{mr}} \Phi_l^n L_r y_r^{[l_r]}(k_r, 0) \end{aligned} \quad (6)$$

where

$$\tilde{\Phi}_{l,v} = \Phi_l^{R_{mv}}, \quad \tilde{\Phi}_{l,r} = \Phi_l^{R_{mr}}.$$

Here, we define

$$\begin{aligned} \tilde{\Phi}_{l,v} \tilde{L}_v &:= \sum_{n=1}^{R_{mv}} \Phi_l^n L_v \\ \tilde{\Phi}_{l,r} \tilde{L}_r &:= \sum_{n=1}^{R_{mr}} \Phi_l^n L_r. \end{aligned}$$

Then, we can reduce the multi-rate problem to the single-rate, then and determine L_v and L_r from

$$\begin{aligned} L_v &= \left(\tilde{\Phi}_{l,v}^{-1} \sum_{n=1}^{R_{mv}} \Phi_l^n \right)^{-1} \tilde{L}_v \\ L_r &= \left(\tilde{\Phi}_{l,r}^{-1} \sum_{n=1}^{R_{mr}} \Phi_l^n \right)^{-1} \tilde{L}_r \end{aligned}$$

that guarantees $\tilde{\Phi}_{l,v} - \sum_{n=1}^{R_{mv}} \Phi_l^n L_v C_v$ and $\tilde{\Phi}_{l,r} - \sum_{n=1}^{R_{mr}} \Phi_l^n L_r C_r$ to be convergent [9], [13]. From the designed decentralized multi-rate Kalman filters, we can obtain the synchronized information of object's position at every sampling time of T_c as shown in Fig. 3 (b). The update periods of a radar and camera are generally uncertain and vary at every update instant. The same authors showed that multi-rate state estimator are robust against Assumption 1, that is, uncertain update period [14].

4.2 Correspondence between Measurements and object Vehicle

For the object detection and tracking, the determination of correspondence between measured objects and object list is a necessary procedure. Vision processor and radar systems give each list of measured objects at every update instant. In the validity determination step, the only data corresponding to objects within the pre-defined range are passed. In this paper, variable with superscript $[m_v]$ denotes variable from vision corresponding to the object with ID of m_v while variable with superscript $[m_r]$ denotes variable from radar.

Here,

$$\begin{aligned} m_v \in \Omega_v' &= \{1, 2, \dots, n_v'\} \\ m_r \in \Omega_r' &= \{1, 2, \dots, n_r'\}, \end{aligned} \quad (7)$$

and, in general, $n_v' \neq n_r'$. In regard to the measurement correspondence that finds a measurement - object vehicle link, we are to use the Mahalanobis distance [11] for the vision's correspondence algorithm in Fig. 1 as follows:

$$d_{M,v}(m_v, l_v) = (y_v^{[m_v]} - C_v \hat{X}_v^{[l_v]})^T Q_v (y_v^{[m_v]} - C_v \hat{X}_v^{[l_v]})$$

and in the radar's module such as

$$d_{M,r}(m_r, l_r) = (y_r^{[m_r]} - C_r \hat{X}_r^{[l_r]})^T Q_r (y_r^{[m_r]} - C_r \hat{X}_r^{[l_r]}),$$

where Q_v and Q_r are the measurement noise covariances of vision and radar systems, respectively. Given object with ID of l_v , the measurement ID of m_v which minimizes the Mahalanobis distance such as:

$$\operatorname{argmin}_{m_v \in \Omega_v} d_{M,v}(m_v, l_v)$$

that corresponds to a candidate measurement for the object vehicle with ID of l_v . In the case of radar, the same principle is adopted to determine the ID of m_r corresponding to the vehicle with ID of l_r such as:

$$\operatorname{argmin}_{m_r \in \Omega_r} d_{M,r}(m_r, l_r).$$

If the Mahalanobis distance exceeds a threshold value for all existing object vehicles, then we find that either a new object that corresponds to the measurement appears or disappears [11]. If there are remaining measurements which could not be assigned to any existing predicted object lists, they are candidates for new object. Among the prediction list, if there is a vehicle which is not linked to the measurements, it may run in the out of range or filed of view.

4.3 Vision and Radar Sensor Fusion

A prior procedure to sensor fusion is determining the interaction correspondence between objects from radar and vision. Due to the different range of view and field of view between the radar and camera, the number of object vehicles may be different. The sensor fusion should be applied to the object vehicles measured by the both sensors. Radar treats all of crash barriers and reflected ones as objects, while the vision system can give a list of objects including only object vehicles by using such as the edge-based constraint filter [6]. In general, $n'_v < n'_r$ in (7). Through Mahalanobis distance decision analysis, we can get a list of objects that are commonly included in both sensor's list. We define the Mahalanobis distance for fusion such as

$$d_{M,f}(l_v, l_r) = (C_v \hat{X}_v^{[l_v]} - C_r \hat{X}_r^{[l_r]})^T Q_s (C_v \hat{X}_v^{[l_v]} - C_r \hat{X}_r^{[l_r]}), \quad (8)$$

where $C_v = C_r$. Then, given object ID in radar, l_r , the ID that minimizes (8) is designated as common ID, l , for fusion as following:

$$l = \operatorname{argmin}_{l_r \in \Omega_r} d_{M,f}(l_v, l_r). \quad (9)$$

The radar and vision have complementary characteristics: The radar has a long range of view but its angle resolution is relatively low compared to vision system. Thus the radar sensor has large measurement uncertainty in lateral direction due to the radar beam forming problem while it allows for good estimations of distance and relative velocities of objects in the longitudinal direction of the ego vehicle. Vision's application in the field of object detection results in large longitudinal position error due to the digitization error and short range of view. On the other hand, the camera provides the object vehicles' positions in lateral direction from the ego vehicle with high accuracy compared to the radar.

With the considerations of these complementary characteristics, we propose a sensor fusion scheme to combine the estimated states: a high weighting for the range data, a higher weighting for the lateral data from the vision sensor from the radar sensor as following:

$$\hat{X}^{[l]} = \Xi^{[l]} \hat{X}_v^{[l]} + (I - \Xi^{[l]}) \hat{X}_r^{[l]}, \quad \exists X_v^{[l]}, X_r^{[l]}$$

where $0 < \Xi^{[l]} = \operatorname{diag}(\xi_x^{[l]}, \xi_y^{[l]}, \xi_x^{[l]}, \xi_y^{[l]}) < I$ is a diagonal weighting matrix and $0 < \xi_x^{[l]} < 1$, $0 < \xi_y^{[l]} < 1$, $0 < \xi_x^{[l]} < 1$, and $0 < \xi_y^{[l]} < 1$.

5. Experimental Results

(a) Raw data from vision and radar

(b) Measured and estimated objects

(c) Estimated and fused objects

Fig. 4 Experimental result at 3.0 [sec]

(+:measure from vision, *:measure from radar, ○:estimation from vision, □:estimation from radar, ◇:fusion)

Table 1 Comparison of three methods

	Method	RMSE
X	Radar	0.6723
	Camera	0.8255
	Fusion	0.2680
Y	Radar	0.2764
	Camera	0.0797
	Fusion	0.0268

(a)

(b)

Fig. 5 Experimental result of $l=1$

The proposed multi-rate estimators and sensor fusion methods were validated via experiments. The vision processing was updated every 60~80msec, while the radar signal was updated every 50msec. The vision had range of view of 120m, R_v^v , and field of view of 38 deg while the radar had range of view, R_v^r , of 200 m and field of view of 26 deg as shown in Fig. 2. In order to evaluate the estimation performance of each method, we adopt the laser scanner as the reference since the laser scanner has relatively high accuracy object tracking performance within 0.04 m.

The vehicle ECU operated at a time period of 10 msec. Fig. 4 shows object's position data expressed in terms of local coordinate systems where (0,0,0) coincides with the ego vehicle at 3[sec]. At that moment, there were totally 6 object vehicles including one ego vehicle on a straight road with three lanes. Fig. 4 (a) shows raw data from vision and radar. Fig. 4 (b) shows measured data, $y_{v,r} \hat{X}^{[l_{v,r}]}$, and estimated data, $C_{v,r} \hat{X}^{[l_{v,r}]}$. Performing the validity determination procedure resulted in the only valid data that were within the range of ± 5 m according x-axis and 120 m according y-axis, respectively. The estimated object's position was obtained through multi-rate Kalman filtering. Fig. 4 (c) shows the result data after interaction correspondence and sensor fusion procedures. In the procedure of interacting correspondence determination, the common objects from both sensors were retained and they were given ID of l as the same as l_v by the ID determination rule (9). It was observed that the fusion data was positioned near the radar data compared to the vision data according to y-axis. This fusion result can be predictable because we weighted more weighting on the radar's longitudinal data with consideration for directional accuracy.

Fig. 5 (a) and (b) show the lateral and longitudinal

information of $l=1$, respectively. In Fig. 5, the green solid line shows fusion data while blue, red and black solid line show vision, radar and laser scanner's data, respectively. The object information was updated at every 10 msec as shown in Fig. 5. The roots mean square errors (RMSEs) of three methods are shown in Table. 1. It was observed that the proposed method, fusion, had the smallest RMSE among three methods.

5. Conclusions

We propose a multi-rate sensor fusion of vision and radar using Kalman filter to solve problems of asynchronized and multi-rate sampling periods in object vehicle tracking. A model based prediction of object vehicles is performed with a decentralized multi-rate Kalman filter for each sensor (vision and radar sensors.) We developed weighting to each sensor's predicted object position from the multi-rate Kalman filter. The Mahalanobis distance was used to make correspondence among the measured and predicted objects.

Through the experimental results, we validated that the post-processed fusion data give us improved tracking performance. We expect that the proposed multi-rate object tracking method with the optimal active steering controller [15] and the road lane estimation [16] will significantly contribute to realize the autonomous intelligent vehicles.

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